

In this book we discuss some AI implementations using popular machine learning models such as: Decision Tree Algorithm, Random Forest Algorithm, Deep Learning, and Convolution Neural Networks. Additionally, this work connects emotion recognition with cultural context. It delves into the current AI applications in the aerospace industry, focusing on enhancing safety, predictive maintenance, and development of the Smart Factory concept. Furthermore, it showcases how FIWARE and smart systems help the management of resources and development of Smart Cities. The potential of smart technologies, including IoT, UAVs, Raspberry Pi, and ensemble learning, in various domains such as agriculture, surveillance, and healthcare are also brought to light. In addition, the book addresses the challenges posed by the exponential growth of data in the energy sector and the role of Phasor Measurement Units in monitoring power transformation. The findings highlight the benefits of these technologies in improving efficiency, cost reduction, and innovative solutions in existing challenges. Similar to Part 1, readers can also benefit from a Python example that utilizes Transfer Learning with ResNet50.



Alexander I. Iliev

Artificial Intelligence in Smart Systems

Applied Use Cases | Part 2



Dr Alexander I. Iliev holds two patents in the Digital Audio Watermarking field. He has published a number of research papers in journals and international conference proceedings in the fields of DSP, Big Data Analytics, Smart Systems and Artificial Intelligence. He is affiliated to UC Berkeley, University of Miami, and University of Wisconsin.



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Artificial Intelligence in Smart Systems

Applied Use Cases

Part 2

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A note from the author:

This book, '**Artificial Intelligence in Smart Systems, Applied Use Cases | Part 2**', is the second book in a series focusing on applied use cases of artificial intelligence. The series began with '**Artificial Intelligence Smart Systems Design, Applied Use Cases | Part 1**'. Currently, both books are being utilized in the 'Big Data and Artificial Intelligence' master's degree program at the School of Technology within SRH Berlin University of Applied Sciences. They serve as the principal study textbooks for a course titled 'AI Use Cases'.

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The intersection of Python programming, Artificial Intelligence (AI), and the Internet of Things (IoT) has caused a paradigm shift in how we see and interact with the world around us in the fast-changing world of technology. This book looks at how Smart Systems, FIWARE, AI, IoT, Emotion Recognition, and their real-world uses in areas like Agriculture, Sports, Aerospace, and Smart-City Development fit together like a complicated puzzle. The main goal of this book is to explain the current state of these technology fields and how they are changing our world. The study also goes into the ethical issues that come up when building AI powered smart systems. This shows that the importance of responsible innovation is in high demand.

Smart Systems that can detect, analyze, and respond to their surroundings, have become an important part of today's technological infrastructure. Infusion of AI in these systems with the power of python programming helps to process huge amounts of data and derive valuable insights. This synthesis can be applied to various fields such as predicting maintenance in the field of agriculture, enhancing sport performances, and increasing the safety in aerospace industry. It can also be used for sustainable urban development through smart-city projects. When these technologies are combined, they improve efficiency, accuracy, and quality of life across all areas.

The FIWARE platform is a key part of this ecosystem. It acts as a trigger by giving developers and managers of IoT applications a standard way to build and manage their apps. Its open design promotes interoperability and scalability, which are the key features for smooth integration of different technologies. FIWARE acts as a strong foundation for harnessing machine learning algorithms in AI. This capability enables various applications such as emotion recognition, allowing machines to understand and respond to human emotions. This technology has a wide range of uses, from personalized marketing in agriculture, performance analysis in sports, utilizing parking spaces in smart cities, improving the passenger experience in aerospace, and optimizing urban services in smart-city settings.

The adoption of these technologies has a significant impact on different industries for example, precision farming techniques with AI and IoT has revolutionized the agriculture industry. Smart sensors collect information about the soil quality, weather conditions, and crop health, which enables farmers to make better decisions that improves output and sustainability.

In sports, AI-driven analytics identify performance patterns of the players, allowing coaches to develop better plans. AI-powered models help aerospace engineering by speeding up design iterations and safety checks. Smart cities, on the other hand, use AI-powered data analytics to improve resource allocation and urban planning. This leads to better services for citizens and less damage to the environment.

But as these technologies change the world and move humans forward, ethical concerns cast a shadow. Many papers detail the ethical aspects of AI powered smart systems. They expose problems such as data privacy, bias reduction, and transparency. For example, in emotion recognition systems, AI algorithms that work with private personal information need strong privacy protections. Addressing bias in the training data is crucial to prevent societal inequalities, so algorithms must be carefully designed. Transparency is also very important, not just to make sure that rules are followed, but also to increase public trust since these technologies are changing our lives.

At the end, this book discusses the fascinating world of Smart Systems, FIWARE, AI, IoT, and Emotion Recognition, and their applications in areas of agriculture, sports, aerospace, and smart-city development. Development of AI in the python environment accelerates the creation of innovative solutions that enhance efficiency, sustainability, and overall quality of life. However, this change is accompanied by social concerns that require responsible innovation. As these technologies continue to change the world in big ways, staying committed to ethical and inclusive growth is important. Through the materials presented in this book it is evident that we should be wise in the ways we develop, apply and explore the evermore sophisticated field of artificial intelligence, as we move through a world that is always changing, ensuring that our path is one of progress, wealth, and moral integrity.

2 Objectives

The primary objective of this study is to discuss smart systems and their current uses, while part of it is focusing on the FIWARE framework. This study provides a thorough look at the technological landscape, practical applications, benefits, challenges, and future possibilities. This research aims to enhance the understanding of smart systems that are rapidly transforming industries and societies and at the same time underlines the importance of the FIWARE framework.

The first goal of this study is to understand smart systems and what they mean in today's connected world. This requires a closer look at the underlying technologies in building a smart system such as the Internet of Things (IoT), artificial intelligence (AI), data analytics, and cloud computing. By discussing the fundamental concepts and principles of this topic, this study establishes a groundwork for the future research and more advanced applications.

The second goal is to investigate the diverse applications of smart systems in various fields. The study will analyze how urban planning, transportation, health care, agriculture, sports, and manufacturing use AI in the real world. By highlighting these applications, the study seeks to demonstrate the tangible advantages of smart systems, such as increased efficiency, better use of resources, better decision-making, and better user experiences.

The third goal is to identify the challenges and hurdles associated with the adoption of smart systems. These include technical, ethical, and legal issues. By addressing these problems, the study aims to explore solutions for navigating these challenges, ensuring that smart systems are used in a responsible and sustainable manner.

The fourth objective is to explore the emerging trends and opportunities in the domain of smart systems. This involves considering new technologies, possible disruptions, and new applications that have the potential to reshape both businesses and societies. The study seeks to deepen our understanding of the discussed technologies by offering insights into how smart systems may evolve in the future.

In conclusion, this study tries to meet these goals by thoroughly examining smart systems, its current applications, and the importance of FIWARE framework. By looking at

the technological, practical, and strategic aspects, this study provides a clear aspect on smart systems and its current applications, which has a huge impact in the technological transformation.

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3 Tasks

In this section, the tasks required for deeper understanding of these subjects are outlined:

1. The first task is to explore the influence of Python programming language, with its libraries and user communities in the developing field of AI and emotion recognition applications.
2. The second task involves gathering of knowledge and insights into smart systems and FIWARE framework in the energy sector.
3. For the third task, FIWARE-based smart Agriculture Systems using AI and IoT that potentially solves the challenges faced by farmers, including climatic changes, disease control, and inadequate irrigation facilities are discussed.
4. The fourth task is outlined as how FIWARE, and the concept of smart cities help urban development that promotes environmental preservation, sustainability, and improved quality of life.
5. The fifth task would be to answer the question of how smart systems using AI help improve the accuracy of referee decisions, better player analysis, and increase fan engagement.
6. The sixth task is to explore the extent of the potential and existing applications of smart systems in the aerospace industry.
7. The seventh task addresses the measures that can be taken to mitigate historical biases in the AI models and ethical decision making.

The tasks are also summarized as questions in the following list:

- How Python, with its libraries and users, is developing the field of AI and emotion recognition applications.
- Learn about how Smart systems and FIWARE are helping address the ongoing changes the Energy sector requires.

- How are FIWARE-based smart Agriculture Systems using AI and IoT to confront the challenges faced by farmers, including climatic changes, disease control, and inadequate irrigation facilities?
- How is FIWARE and the concept of smart cities helping urban development that promotes environmental preservation, sustainability, and improved quality of life?
- How do smart systems using AI help improve the accuracy of referee decisions, better player analysis, and increase fan engagement?
- How many potential and current applications of smart systems are in the Aerospace industry?
- What can be done to impede the historical biases in the AI models and ensure ethical decisions?

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4 Summary

Python is a popular programming language that is widely used for developing smart systems due to its flexibility and powerful libraries. It plays a crucial role in various aspects of smart system development, including data processing, machine learning, IoT, GUI development, and emotion recognition. Raspberry Pi being a cheap single-board computer is often used in conjunction with Python to develop smart system projects. Python libraries, such as Adafruit and PySerial, enable interaction with physical components. Additionally, Python offers GUI libraries like PyQt and Tkinter for creating user interfaces. Raspberry Pi's affordability and compatibility with Python have made it a preferred platform for innovative projects. The field of smart systems has advanced rapidly due to the combination of Raspberry Pi and Python.

Artificial intelligence (AI) and machine learning (ML) are crucial technologies for smart systems. Python provides libraries such as NumPy, SciPy, Pandas, Scikit-Learn and TensorFlow for data processing and ML model training. The combination of Raspberry Pi and Python has facilitated the implementation of machine learning projects in smart systems.

Emotion recognition is a subset of AI which focusses on analyzing facial expressions, tone of voice, and physiological signals to detect and interpret human emotions. Python and ML algorithms are used to recognize emotional states in smart systems. The applications of emotion recognition can be seen in virtual assistants, marketing, healthcare, education, entertainment, public safety, and robotics. However, it is necessary to address ethical and legal considerations regarding privacy and security when implementing emotion recognition in smart systems.

This book consists of several sections that discuss the topic of smartness, smart devices, and the role of technologies such as Raspberry Pi and AI in the development of smart devices and emotion recognition technology. The author emphasizes the need to define and understand the concepts of “smartness” and “smart systems” to analyze and design devices and systems effectively. This book also investigates the influence of digital transformation on individuals and organizations, highlighting the importance of digital agility, networking capability, and big data analytics in achieving successful transformation. It further examines the advancements in smart technologies and their contribution to the development of the smart ecosystem which specifically focusses on media personalization and recommendation systems. The potential

implications of smart workplaces are also discussed which emphasizes the importance of learning about technologies and tools to anticipate changes. The text also delves into the use of IoT and fuzzy control technology for optimizing irrigation systems in agriculture, highlighting the effectiveness in reducing water and energy consumption. Finally, the paper examines the applications of IoT and UAVs in agriculture, including water management, fertilizer usage, crop monitoring, and crop health management. Overall, the text provides insights into various aspects of smartness, digital transformation, smart technologies, and their impact on different domains.

Several research papers focussing on the applications of smart technologies in different domains are also discussed in this work. One of the research papers presents an overview of the use of ICT, fuzzy logic (FL), Internet of Things (IoT), and wireless sensor networks (WSN) in modernizing traditional agriculture. The proposed zoning irrigation system based on IoT and FL, with the use of WSN technology, shows promising results in minimizing water use and energy consumption while maintaining ideal soil moisture conditions for plant growth. Another paper explores smart agriculture using IoT and unmanned aerial vehicles (UAVs), highlighting their transformative impact on conventional farming methods. Analysis of various applications of IoT and UAVs in various aspects of agriculture, such as water management, fertilizer usage, pesticide usage, and crop health monitoring are also discussed.

Furthermore, there are research papers discussing the application of Raspberry Pi microcontrollers in smart systems. The effectiveness of smart irrigation system using Raspberry Pi in precise watering of plants and overcoming the limitations of traditional irrigation methods is better and better coverage in the literature. Another paper proposes a smart surveillance system using Raspberry Pi and infrared sensors showcasing its capabilities in detecting motion and triggering alerts for possible intrusions. Additionally, many papers nowadays discuss smart healthcare systems using Raspberry Pi and IoT aiming to improve the efficiency and cost-effectiveness of traditional healthcare systems.

Lastly, a research paper focuses on emotion recognition and data sentiment analysis. The authors present an ensemble learning approach for cross-corpus, multilingual speech emotion recognition systems. This study compares a novel performance to a traditional machine learning algorithms and highlights the efficacy of ensemble learning with majority voting in handling sentiments in multiple languages.

The above-mentioned summary of research papers analyzed and discussed in this book showcase the potential of smart technologies, including IoT, UAVs, Raspberry Pi, and ensemble learning, in various domains such as agriculture, surveillance, healthcare, and emotion recognition. The findings highlight the benefits of these technologies in improving efficiency, cost reduction, and innovative solutions in existing challenges.

Furthermore, this study delves into speech emotion detection exploring various machine learning techniques and features for accurate recognition. It was suggested that using MFCCs as features and SVM or ANN as machine learning techniques can provide high accuracy for speech emotion detection. In another study the focus is shifted towards visual emotion recognition using deep neural networks and presents a framework that achieves promising results in recognizing emotions from facial images. The authors use a pre-trained CNN and a dataset with labeled emotions to train and evaluate their framework. The study demonstrates the potential of deep neural networks in visual emotion recognition.

Additionally, several papers contributed to this work explore emotion recognition and cultural context. One such paper investigates the accuracy of emotion recognition using CNNs across different cultures and finds that the performance of CNNs can vary depending on the cultural background of the individuals' expressing emotions. Another paper focuses on emotion recognition using perceptual features and CNNs and evaluates the importance of different features in emotion identification. The results highlight the potential of CNNs and the significance of considering cultural differences in emotional expression.

Moreover, this study also discusses research that presents a system for emotion detection using wearable devices in an ambient intelligent system. This system collects physiological signals from users through a smart wristband and uses machine learning algorithms to classify their emotional states. The proposed system has shown promising results and has potential applications in ambient assisted living and affective computing.

There is also a paper that focuses on postpartum depression prediction through pregnancy data analysis. The authors highlight the importance of timely identification and treatment of postpartum depression and address the challenges in identifying women at risk. The study aimed to develop an emotion-aware smart system that can predict postpartum depression based on pregnancy data analysis.

The concept of Ambient Intelligence (AmI) is discussed as the next step for Artificial Intelligence (AI). AmI refers to the integration of technology into everyday environments to

enable more natural and intuitive human-machine interactions. This article emphasizes the potential of AmI to transform various settings, including homes, offices, and public spaces, by seamlessly integrating technology into the environment and adapting to user needs.

The authors argue that while some systems only incorporate a limited amount of Intelligence and focus primarily on operational technologies such as sensors and communications, AmI requires a balanced combination of operational technologies and AI. AmI systems receive information, interact with users, perform reasoning, and take actions based on the environment. To handle the complexity of these environments, AmI systems leverage operational technologies and AI methods and techniques.

Another article emphasizes the necessity for increased intelligence in AmI (Ambient Intelligence) systems to attain broader acceptance and enhanced effectiveness. By incorporating AI, AmI can provide more sophisticated and context-aware responses, enhancing the user experience and enabling advanced functionalities. The authors emphasize the importance of developing AmI systems that are capable of autonomous learning, adaptation, and decision-making.

The article presents AmI as an exciting and promising direction for AI, offering the potential to create intelligent environments that seamlessly integrate technology into our daily lives. The authors stress the significance of combining operational technologies with AI to unlock the full potential of AmI and achieve its goals of enhancing human-machine interactions and providing personalized and context-aware experiences.

The Integration of AI methods and techniques is crucial in achieving Ambient Intelligence (AmI) environments. AI plays a significant role in tasks such as interpreting the environment's state, representing information and knowledge and intelligent interaction with humans. Various AI techniques, including natural language processing, speech recognition, computer vision, and probabilistic models, are employed to handle language input, analyze visual data, and manage uncertain information.

Intelligent interaction in AmI systems entails context awareness, adaptation to users and situations, and learning from user observations. AI research areas, contribute to incorporating these capabilities into AmI systems, considering social and emotional factors. AmI environments presents an exciting challenge for the AI community, as the realization of AmI is not feasible without the integration of AI methods and techniques. Ongoing exploration of AI in diverse environments, such as hospitals, geriatric residences, homes, workplaces,

cultural-heritage sites, and tourist attractions, involves the application of various AI approaches, including multiagent systems, case-based planning, fuzzy systems, logic programming, hidden Markov models, and ontologies.

Furthermore, the use of IoT and facial emotion recognition has the potential to greatly assist people with special needs, including the elderly. With the increasing aging population, the need for elderly care is growing. IoT technology provides a solution for monitoring and ensuring the safety, comfort, and well-being of elderly individuals. The proposed smart system discussed in the text utilizes sensors placed around the house to collect data on the elderly person's behavior, which is then analyzed and processed by an IoT platform. Anomalies in behavior are detected, and alerts are sent to caregivers or family members in case of emergencies. The system's features i.e. the use of sensors for monitoring temperature, humidity, lighting conditions, motion, and door activity, as well as a smart doorbell for remote viewing and visitor management. By employing advanced technologies such as Raspberry Pi, Arduino, and machine learning algorithms, the system enhances security, facilitates wireless monitoring of appliances, and provides reminders for important daily activities.

The utilization of IoT and facial emotion recognition in assisting the elderly showcases the potential of AI-powered systems to ensure their safety, well-being, and independent living. These advancements contribute to the development of intelligent and supportive environments for various applications, benefitting individuals with special needs.

The importance of addressing global warming and building efficient models for energy production and consumption is discussed. It emphasizes the need for both traditional energy players and consumers to take responsibility for using energy efficiently. FIWARE, a platform that offers standard, reusable, and easily deployable models, is introduced as a solution for designing and implementing smart energy systems.

The challenges faced in the smart energy sector, such as the lack of IoT protocols, integration standards, data security concerns, and limited usability of end applications are highlighted. It also acknowledges the increasing complexity of energy technologies, including renewable energy systems and the rise of electric vehicles.

The concept of a smart grid is introduced as a cohesive system that optimizes energy supply to consumers through real time automation. Machine learning and big data analytics are discussed as tools for extracting useful information from collected data and improving decision-making processes in smart grid management.

This book discusses some machine learning models such as: Decision Tree Algorithm, Random Forest Algorithm, Deep Learning, and Convolution Neural Network – for predicting the stability of smart grids. The results indicate that regression and CNN models provide the best predictions for complex grids. Furthermore, the paper discusses the challenges posed by the exponential growth of data in the energy sector and the role of Phasor Measurement Units (PMUs) in monitoring power transformation.

The FIWARE technology is described as an open-source platform that supports the development of smart solutions in various domains. It offers generic enablers (GEs) and specific domain-specific enablers for implementing smart energy platforms. The FISMEP project is introduced in this book as a FIWARE-based initiative for building smart energy platforms. It focuses on the integration of renewable energy, decentralized energy, and active participation of end-users in managing their energy consumption. Several European cities, including Santander, Valencia, Trento, Bari, and Lisbon, are mentioned as examples of FIWARE implementation in smart city projects and energy management. This research also discusses future work, including FIWARE platform development, big data analytics, renewable energy integration, and fault detection in power systems. It suggests using machine learning algorithms to adjust smart grid systems based on weather forecasts. In summary, this research provides an overview of smart energy systems, FIWARE technology, the implementation of smart grids, machine learning models for prediction, and the future direction of research and development in the field.

The agricultural sector plays a crucial role in the world economy and is vital for human survival. However, challenges such as climate change, water scarcity, and soil testing have led to malnutrition in many parts of the world. To meet the increasing demands for food, the adoption of smart agriculture, which integrates technologies like IoT, artificial intelligence, and machine learning, is essential. Smart agriculture involves the use of IoT sensors, wearables, robots, and drones to collect real-time data, allowing for efficient decision-making without human intervention. Integrating AI and IoT in agriculture leads to better productivity and a more reliable supply chain. The introduction of Information Technology in agriculture enables monitoring and managing various factors affecting production. FIWARE, a technology-based tool, improves operational management processes in the agricultural industry and facilitates smart agriculture by allowing virtual factory simulations and impact

analysis. Numerous projects have been developed using the FIWARE framework for smart agriculture, making agriculture smarter with the help of AI, IoT, and FIWARE technology.

The vf-OS (virtual factory Operating System) is a European Project that aims to create an Open Operating System for the Factories of the Future (FoF). It includes a Virtual Factory System Kernel (vf-SK), a Virtual Factory Application Programming Interface (vf-API), and a Virtual Factory Middleware (vf-MW), integrating software resources with FIWARE Enablers for developing complex applications. Vf-OS supports interoperability, sharing data among various applications in the factory with different languages and models, and facilitates the implementation of FoF concepts in an IoT view by connecting resources, applications, sensors, and devices. The mentioned project targets an economical multi-sided market platform, enabling interactions between Software Developers, Manufacturing Users, ICT Providers, and Service Providers. Vf-OS acts as an intermediate between applications and devices, managing data sharing and visualization. It offers Enablers Framework (EF) to access functionalities, and new user requests that are executed using IoT protocols like REST or NGSI. The vf-OS system is designed to overcome the limitations of current industrial centralized systems by transforming them into a decentralized system, addressing complex plans, logistics systems, and control.

Smart farming is considered the current and future of agriculture, aiming to improve the quantity and quality of agricultural products while optimizing human labor. This concept harnesses modern technologies like the Internet of Things (IoT), artificial intelligence (AI), robotics, and drones to enhance farm management efficiency. By integrating these tools, smart farming enables farmers to monitor farm conditions and make strategic decisions based on real-time data.

Artificial intelligence technologies play a crucial role in the agricultural sector by enhancing the efficiency of traditional farming methods and addressing challenges faced by conventional farmers. Various AI-based instruments and technical devices have been developed to optimize different agricultural aspects, such as pesticide control, soil testing, irrigation, plant disease treatment, storage management, and weeding. AI also proves beneficial in mitigating environmental issues caused by adverse agricultural activities such as uncontrolled irrigation, excessive pesticide uses and water pollution.

The Internet of Things (IoT) are an essential component of smart farming, enabling applications to become “smarter” through sensor-actuator interaction. Capability of IoT’s to

efficiently collect data aids in understanding and monitoring of agricultural applications effectively. IoT sensor technologies are widely used in agriculture to improve soil quality and plant phenotyping, which leads to enhanced crop quality and growth, thereby increasing agricultural productivity. Farmers use IoT sensors to measure vital environmental factors like humidity and temperature and provides valuable insights for data-driven decisions. Various IoT applications in agriculture include disease detection, automated irrigation, intelligent greenhouse systems, and precision farming.

The fourth Industrial revolution, known as Industry 4.0, is a significant factor in controlling the industrial value chain. The proposed methodology combines FIWARE enablers with vf-OS functionalities to manage the entire fruit production chain efficiently. FIWARE enablers enable handling complex functions and creating lightweight applications, while vf-OS acts as a proxy between the application layer and generic enablers while providing an easy access to specific using designated protocols. This approach allows for handling application requests seamlessly across different scenarios, providing a range of services for small and medium-scale industries that integrate open-source tools.

The growing global demand for food underscores the Importance of building a smart system in agriculture. Just like other industries, the agriculture sector benefits from artificial intelligence and IoT by making systems more efficient and intelligent. Smart agriculture transforms traditional farming practices by addressing challenges related to climate conditions, soil quality, harvesting, and irrigation. It focuses on precision farming by improving crop quantity and quality through innovative agricultural resources. This report also emphasizes the significance of deep learning techniques in reshaping the industry by enabling predictive systems for plant disease, crop cultivation, and monitoring. The importance of developing smart agriculture systems is evident in today's world, paving the way for a more sustainable and productive agricultural future.

The concept of "smart cities" has emerged as a visionary approach to urban development, with a primary focus on environmental preservation, sustainability, and enhancing quality of life of residents. Numerous international organizations and governments have collaboratively initiated projects and initiatives to promote eco-friendly practices in urban areas globally.

The United Nations plays a pivotal role in promoting sustainable development, setting 17 global objectives where seven of which are directly related to environmental protection.

These goals address vital concerns such as ensuring access to clean water and sanitation, providing affordable and sustainable energy, developing sustainable cities and communities, promoting responsible consumption and production, acting on climate change, protecting marine life, and preserving terrestrial ecosystems. Participating nations have set a deadline of 2030 to achieve these objectives, driving concerted efforts towards a more sustainable future.

In the pursuit of sustainable urban development, the technology-based company HOPU has partnered with the municipality of Cartagena to create green zone innovations. Leveraging intelligent systems, they aim to devise innovative solutions that leverage technologies like Artificial Intelligence (AI), the Internet of Things (IoT), and Data-Quality to address real-world challenges and improve quality of life of residents. The focus is on aligning Cartagena's trajectory with the European Green Deal and Sustainable Development Goals, fostering environmental sustainability.

Cartagena has grappled with climate-induced crises, including water shortages. Effective planning and management of water resources are thus vital. Garden irrigation, a water-intensive municipal service essential for maintaining the urban environment, faces challenges. To adapt to climate change and sustainable energy, Cartagena prioritizes green spaces.

In this context, the integration of IoT systems becomes crucial for water resource management and risk mitigation. These systems effectively gather data and anticipate changing conditions, enhancing the management of public spaces. To realize their vision of a digitally transformed city, the Cartagena City Council incorporates various technologies, including AI and Big Data analysis. Intelligent irrigation systems have been implemented in green areas, leading to reduced water consumption and improved park maintenance.

Intelligent Irrigation Systems leverage multiple sensors to collect real-time data on soil moisture, temperature, humidity, and other environmental factors. This data helps to determine optimal watering schedules. IoT devices enable remote monitoring and control. AI algorithms analyze data to predict future watering needs, optimizing irrigation and conserving water.

By embracing AI, Big Data analysis, and other technologies, Cartagena demonstrates its commitment to environmental sustainability and resource conservation, paving the way for a more sustainable future. The integration of AI and IoT technologies in urban environments showcases their potential to optimize water usage, preserve resources, and improve overall

living conditions. Through such initiatives, cities like Cartagena are taking significant strides towards creating smart, sustainable urban spaces for their residents.

Football, with approximately 275 million players globally, holds the title of the world's most popular sport. Multiple leagues and tournaments, such as the FIFA World Cup, attract billions of viewers worldwide. This immense audience has led to a thriving economy in football, drawing interest from various fields, including game analysis, computer vision, and artificial intelligence.

Over the past decade, there has been an increasing demand for post-match analyses in football. Coaches rely on statistics to devise new strategies against opponents. Advancements in technology, such as automated tracking and object detection on the field have given rise to impressive technologies like VAR (Video Assistant Referee) and SAOT (Semi-automated off-side technology). The integration of artificial intelligence has significantly improved the accuracy of crucial aspects like ball possession, goal line detection, shot classification, and decision-making. This growing influence of AI in football analysis has elevated the sport's precision and performance on and off the field.

The paper concludes by explaining the integration of AI into various aspects of daily life which has led to numerous benefits for society, such as economic growth (Boutchaktchiev, 2017), (Boutchaktchiev, Forecasting Models for the House Price Index in Bulgaria, 2021) [1, 2] social development, improved security, and enhanced well-being. However, alongside acknowledging these advancements, researchers are increasingly focusing on the ethical implications of AI, particularly concerning fairness and decision-making. While important ethical guidelines have been established even though practical implementation remains a challenge.

Ethical questions related to AI revolve around issues such as clarity, security, privacy concerns, and data biases which can pose serious risks to society and users of AI systems. The complexity and autonomy of AI systems make it difficult to understand their decision-making processes and predict future decisions, raising the issue of accountability. Unlike traditional business environments, where unethical behaviors may often be attributed to human actions, AI's nature introduces a unique challenge. Some unethical outcomes in AI may arise not from intentional actions but by chance or uncontrollable factors. The "black box" problem further complicates the responsibility aspect of AI technologies. To fully harness the potential of AI while ensuring ethical practices, it is essential for researchers, policymakers, and organizations

to address these challenges proactively and implement transparent, fair, and accountable AI systems. Only by doing so can we strike a balance between reaping the benefits of AI's capabilities and safeguarding society's well-being.

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5 Introduction and Overview

5.1 Introduction

A smart system is a technology-based system capable of sensing, processing, and responding to data from its environment. The concept of smart systems was prevalent since the technological advancements where advancements are set to course for automated and efficient and error-free technology. For example, first ever thermostat prototype being was used to control the temperature of an oven by controlling the air intake with a mercury-based thermometer. This concept of having an automated system of temperature control continued to be extended to industries and eventually even made its way into the automation of homes. The idea was to automate various aspects of home like lighting, heating, plant irrigation, and the operation of other electronic devices. The goal was to not only automate this process, but also make them operate intelligently and optimally to save time and cost. In the 1970s home automation used AC wiring for communication between devices and control modules, but these systems were slow, error prone and unreliable. With the advent of wireless technology, and the internet things became faster and better.

Key Features of a Smart Systems:

- *Data-driven Approach:* Smart systems depend on huge amounts of data as their foundation. They collect, analyze, and process data from different sources, such as sensors, IoT devices, databases, and user interactions. This data is the basis for training models and making intelligent decisions.
- *Machine Learning:* Machine learning techniques play an important role in smart systems. By using algorithms and models, smart systems can learn from data, identify patterns, and make predictions or classifications. Deep learning, a subset of machine learning, employs neural networks to handle complex tasks like image recognition and natural language processing.
- *Intelligent systems:* Smart systems automate processes and tasks traditionally performed by humans resulting in streamlined operations and improved efficiency. They can handle repetitive tasks, analyzing of real-time data, and can adapt to changing

circumstances. This automation reduces human error, increases productivity, and frees up human resources for more complex endeavors.

- *Natural Language Processing (NLP)*: Smart systems equipped with NLP capabilities can understand, interpret, and respond to human language. They help in voice recognition, chatbots, language translation, sentiment analysis, and other language-related tasks.

5.1.1 Benefits of Smart Systems using AI:

- *Improved Decision-Making*: Smart systems can analyze vast amounts of data and extract valuable insights, enabling them to make informed decisions accurately. This capability helps organizations to optimize processes and reduce costs.
- *Enhanced Efficiency and Productivity*: By automating tasks and processes, smart systems increase efficiency and productivity. They can easily handle repetitive or time-consuming tasks, allowing human resources to focus on more complex and creative work, which in turn enhances output and streamlines operations.
- *Personalized User Experiences*: AI-powered smart systems provide personalized experiences tailored to individual users. By analyzing user data and preferences, these systems can deliver recommendations, content, and services, enhancing user satisfaction and engagement.
- *Scalability and Adaptability*: Smart systems can scale their capabilities as data volumes increase. With the ability to learn and adapt, they can handle diverse datasets and evolving business requirements. This scalability and adaptability make them valuable assets in dynamic and rapidly changing environments.

5.1.2 FIWARE-Based Use Cases

FIWARE-based solutions offer practical applications that enhance daily life, providing convenience, efficiency, and improved experiences. For example, smart home automation, enabling users to control and automate devices for increased comfort and energy savings.

Personal health and fitness solutions that connect wearable devices and fitness trackers to provide personalized health insights and promote an active lifestyle. Smart energy management allowing users to monitor and optimize energy consumption, reducing costs and supporting sustainability. Intelligent transportation systems that provide real-time information on public transport schedules, traffic conditions, and parking availability. Digital city services that offer convenient access to government services, citizen engagement platforms, and digital payment systems. Smart waste management that optimizes waste collection routes and minimizes environmental impact. Smart water consumption solutions that monitor usage patterns, detect leaks, and promote sustainable practices. Intelligent agriculture solutions that enable farmers to optimize crop production through monitoring and automation. Personalized retail experiences that optimize tailored offers and recommendations to enhance shopping experiences. These FIWARE-based use cases improve daily life by leveraging IoT, data analytics, and interoperability to make smarter choices, conserve resources and enhance the overall quality of life.

5.1.3 Smart Devices using AI

- *Smart Speakers*: Devices such as Amazon Echo (featuring Alexa), Google Home (with Google Assistant), or Apple HomePod (using Siri) integrate AI to comprehend voice commands, offer information, play music, manage smart home devices, and execute various tasks via natural language processing and machine learning.
- *Wearable Devices*: Fitness trackers and smartwatches often incorporate AI to monitor health-related data, analyze sleep patterns, track physical activities, provide personalized fitness recommendations, and offer real-time coaching or feedback to users.
- *Virtual Assistants*: AI-powered applications like Apple's Siri, Google Assistant, Microsoft's Cortana, and Amazon's Alexa utilize natural language processing, speech recognition, and machine learning to comprehend user commands, respond to questions, execute tasks, and offer information or recommendations.

- *Smart Cameras*: AI-powered cameras could detect and analyze objects, recognize faces, track movements, and perform video analytics for applications such as surveillance, facial recognition, and object detection.
- *Personalized Recommendation Systems*: Many online platforms, such as streaming services (Netflix, Spotify), e-commerce platforms (Amazon, Alibaba), and social media platforms (Facebook, Instagram) employ AI algorithms to analyze user preferences, behavior, and historical data to provide personalized recommendations for content, products, or connections.

5.1.4 SPAM Filtering

- *Rule-Based Filters*: Rule-based filters use predefined rules or patterns to identify and filter spam messages. These rules can include specific keywords, phrases, or characteristics commonly found in spam emails. Rule-based filters are effective at blocking known types of spam but may struggle with new or evolving spam techniques.
- *Bayesian Filters*: Bayesian filters use statistical analysis and machine learning algorithms to classify emails as spam or legitimate based on their content. The filter learns from a set of known spam and non-spam emails to determine the probability of an email being spam. Bayesian filters can adapt and improve their accuracy over time.
- *Content Analysis*: Content analysis involves examining the content of an email to detect spam patterns. This can include analyzing the text, HTML, and embedded links within an email. Content analysis looks for indicators such as excessive use of capital letters, misleading subject lines, suspicious URLs, or known spam keywords.
- *Blacklisting/Whitelisting*: Blacklisting involves maintaining a list of known spam sources or specific email addresses, domains, or IP addresses associated with spam. Emails from blacklisted sources are automatically blocked. Whitelisting, on the other hand, allows emails from trusted senders or domains to bypass spam filters.
- *Sender Reputation Analysis*: Sender reputation analysis assesses the trustworthiness of the email sender based on their past behavior. It considers factors such as the sender's domain reputation, IP reputation, and authentication records (e.g., SPF, DKIM,

DMARC). Emails from senders with poor reputation scores are more likely to be marked as spam.

- *Heuristics Analysis*: Heuristics analysis uses a set of predefined rules and algorithms to analyze various characteristics of an email, such as the header, content structure, and embedded elements. It assigns a spam score based on the presence of suspicious patterns or behaviors. The score determines whether the email is classified as spam.
- *Collaborative Filtering*: Collaborative filtering involves leveraging collective intelligence to identify spam. It compares the characteristics of incoming emails with patterns identified by a community of users. If multiple users report a particular email as spam, the filter can use this information to classify similar emails as spam for other users.
- *Machine Learning Approaches*: Machine learning techniques, such as supervised and unsupervised learning, can be applied to train spam filters. By providing a large dataset of labeled spam and non-spam emails, machine learning algorithms can learn patterns.

5.1.5 Face Recognition Using Modified Deep Learning Neural Network

Face recognition using modified deep learning neural networks can be applied in various products and systems to enable accurate and reliable identification of individuals. Here are some examples of products and applications that utilize face recognition with modified deep learning neural networks:

- *Facial Authentication Systems*: Many smartphones, tablets, and laptops incorporate facial authentication as a security feature. Revised deep learning neural networks train the device's facial recognition system to identify and authenticate the device owner accurately.
- *Access Control Systems*: Access control systems in buildings, offices, and high-security areas are incorporated with face recognition using modified deep-learning neural networks. This system captures and analyses facial features to grant or deny access based on pre-registered individuals.
- *Surveillance and Security Systems*: Face recognition is widely used in surveillance and security systems for real-time identification of individuals. These systems can be

deployed in airports, train stations, stadiums, and other public areas to enhance security and monitor potential threats.

- *Attendance Tracking Systems*: Face recognition can be employed in attendance tracking systems to automate attendance management in educational institutions or workplaces. By using modified deep-learning neural networks, this system can accurately identify and record the attendance of individuals.
- *Human Resource Management Systems*: Face recognition can be integrated into human resource management systems to streamline employee identification and management processes. It can assist in tasks such as employee time tracking, access control, and personnel management.
- *Customer Experience and Personalization*: Some businesses utilize face recognition technology to enhance customer experience and personalize interactions. For example, retail stores can analyze customer facial expressions to assess their engagement or satisfaction level and provide tailored recommendations.
- *Smart Home Systems*: Face recognition can be integrated into smart home systems to enable personalized automation. By recognizing specific individuals, the system can adjust settings such as lighting, temperature, and entertainment preferences based on individual profiles.

5.1.6 FIWARE in European Countries

5.1.7 AI in Aerospace

AI plays a significant role in the aerospace industry, driving advancements and improving various aspects. It enables the development of autonomous systems, such as unmanned aerial vehicles and autonomous spacecraft, by utilizing AI algorithms for navigation and decision-making. AI is used in flight control systems to enhance aircraft stability, optimize flight paths, and assist pilots. It supports predictive maintenance by analyzing sensor data to detect anomalies and predict component failures, improving aircraft safety and reducing downtime. AI also aids in air traffic management, optimizing routes, managing congestion,

and ensuring safe and efficient operations. In space exploration, AI assists in data analysis, spacecraft navigation, and decision-making, contributing to scientific discoveries and future mission planning.

5.2 Types of Smart Systems

Smart systems can be found in many different forms, from simple IoT devices to complex multi-component systems such as:

- *Smart homes*: These systems use sensors and actuators to control lighting, temperature, and security and can be remotely controlled via a smartphone or other device.
- *Smart cities*: These systems use sensors and actuators to monitor and control various aspects of urban infrastructure, such as traffic, lighting, and waste management.
- *Industrial automation systems*: These systems use sensors, actuators, and controllers to automate and optimize industrial processes such as manufacturing, agriculture, and energy management.
- *Self-driving cars*: They use sensors, such as cameras and lidar, to perceive the environment, and use machine learning algorithms to make decisions and control the car's movements.
- *Smart grid systems*: use sensors and actuators to monitor and control the flow of electricity in power grids, to optimize energy usage and reduce costs.
- *Smart healthcare systems*: use sensors, such as wearable devices and remote monitoring systems, to collect data on patients' health, and use machine learning algorithms to analyze this data and provide personalized care.

Smart systems are also expected to play an important role in the development of new technologies, such as 5G networks, edge computing, and blockchain, as well as in the deployment of new applications, such as virtual and augmented reality along with the integration of AI and edge computing.

Overall, smart systems are becoming increasingly prevalent in our daily lives and are expected to play an increasingly important role in many aspects of society and industry. They are designed to make decisions and to perform tasks with minimal human intervention, all the

while adapting to changing conditions and improving the capabilities over time through machine learning.

5.3 Aims of the Report

Overall, the aim of this report on smart systems is to provide a theoretical foundation, evaluate performance, explore the impact, share results, and contribute to the ongoing research and development of smart systems. The target audience for this report on smart systems is quite diverse, and can include researchers, academics, engineers, practitioners, policymakers, business leaders, and the public. This will offer individuals from various interest groups the information on smart systems that is most relevant to their needs.

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6 Methodologies Discovered

6.1.1 Overview of Methodologies

In this work we discuss various methodologies in smart systems, electronics, agriculture, and emotion recognition. Here's an overview of some of the methodologies worth studying and developing:

1. Digital Transformation in Enterprises: The impact of digital agility, networking capability, and Big Data Analytics (BDA) on modern businesses.
2. Human-Machine Interface for Smart Technologies: Addressing the challenges of AI-driven media personalization and recommendation.
3. Digitalization in Smart Workplaces: An exploration of smart office technologies and the factors influencing technology adoption.
4. Optimizing Agricultural Resources: The use of IoT and fuzzy logic in smart irrigation systems to conserve water and energy.
5. Advancements in Smart Agriculture: Investigating precision farming, remote sensing, BDA, and Machine Learning, particularly with the integration of IoT and UAVs.
6. Emotion Recognition in Various Applications: Covering the use of smart systems in emotion identification, including speech and visual emotion analysis, and wearable emotion detection.
7. Machine Learning in Healthcare: Utilizing machine learning to predict postpartum depression risk through pregnancy data analysis.
8. Facial Emotion Identification: A deep neural network-based system employing CNN-based feature extraction and SVM-based classification.
9. Ambient Intelligence (AmI): The integration of operational technology and AI methodologies for unobtrusive, flexible solutions.

10. Eldercare with IoT: Employing IoT devices to monitor the well-being and safety of elderly individuals.

6.1.2 Role of Python and AI: Methodologies

Python programming, along with its versatile libraries, and Raspberry Pi has led to a new era of smart systems, particularly in the field of emotion recognition. This synergy has opened new possibilities through Natural Language Processing (NLP) approaches, resulting in a significant shift with great impacts across various sectors.

Python's accessibility and numerous libraries allow developers to create complex Emotion Recognition systems. These systems use NLP to interpret textual and contextual signals to determine emotions across languages. This technology helps marketers and advertisers create emotive campaigns that boost brand engagement. In the healthcare industry, emotion-sensitive technologies can monitor the state of patients and provide them with better care by deciphering emotional nuances.

Emotion-aware systems that gauge student engagement are reshaping education by personalizing learning. Interactive entertainment that responds to users' emotions enhances immersion. Emotionally intelligent smart technologies identify potential hazards in public spaces and allow early interventions.

The whole concept depends on Raspberry Pi for cost-effective deployment of emotion-aware devices across various scenarios. Robots with emotion recognition could engage with people in a more socially aware form.

In conclusion, Python, along with its libraries, and Raspberry Pi have enabled smart system Emotion Recognition and opened new applications in marketing, healthcare, education, entertainment, public safety, and robotics. This synergy highlights technology's role in fostering a more empathic and responsive future across sectors.

6.1.3 FIWARE Technology in Smart Energy Systems and Renewable Energy Management: Methodologies.

This chapter covers smart energy systems, renewable energy management, machine learning models, and FIWARE technology. It emphasizes the impact of global warming and how energy is produced and used. The paper highlights the significance of FIWARE in creating standardized and reusable models for intelligent energy systems.

It addresses the evolution of energy systems from decentralized to centralized, distributed, and smart. These systems utilize modern technologies such as IoT, big data analytics, and cloud computing. The goal is to create a service-oriented architecture that allows easy integration of devices and enables customer interaction in the open energy market.

This study examines smart grid management of renewable energy. The approach uses automation, machine learning, and IoT data analysis to improve knowledge and decision-making. Decision Trees, Random Forests, Deep Learning, and Convolutional Neural Networks estimate grid stability and performance.

The FISMEP project uses FIWARE technology to build an intelligent energy platform. This study emphasizes the importance of standard interfaces in energy services, creating a multi-layered design that optimizes cloud data representation and interaction. The architectural design aims for scalability that may be altered based on demand and human participation in energy management.

Some research sources show FIWARE implementations in Santander, Valencia, Trento, Bari, Porto, and Lisbon. The document describes how they use FIWARE for energy, waste, and citizen interaction in smart cities.

This research advises creating FIWARE platforms to gather data, integrating renewable energy sources, and improving fault detection and prevention processes. It also highlights the potential benefits of integrating real-time meteorological data with machine learning to improve the efficiency of smart grids. Smart energy systems should prioritize scalability, adaptability, and open-source solutions to ensure sustainable and efficient energy management.

6.1.4 FIWARE-based smart Agriculture System using AI and IOT: Methodologies.

An important topic to discuss is smart agriculture using FIWARE, an open-source platform. FIWARE offers both generic and specific tools that aid in collecting, analyzing, and sharing data effectively. A European project introduced the vf-OS (virtual factory Operating System), which leverages software resources and FIWARE tools to create advanced applications that encourage data sharing and interoperability.

Furthermore, we can focus on higher precision in agriculture, in sub areas like disease detection in plants, and predicting crop yields. This highlights how artificial intelligence (AI), and deep learning can make farming more productive and environmentally friendly.

We should stress the importance of smart agriculture in meeting global food demands. AI, the Internet of Things (IoT), and FIWARE can revolutionize farming by improving disease detection, crop prediction, and other agricultural processes.

6.1.5 Intelligent Irrigation System Built-in Cartagena City Using FIWARE: Methodologies.

This section examines "smart cities," which encourage sustainability, environmental protection, and quality of life. Cartagena, in conjunction with HOPU (Human Oriented Products for Smart Cities and Industry) implement intelligent solutions that use AI, IoT, and data quality to address climate adaptation, water scarcity, and energy efficiency. These solutions are driven by IoT-based risk and water resource management, enhancing urban environments.

Implementing Intelligent Irrigation Systems is crucial. AI and machine learning enhance irrigation schedules using sensors to monitor soil moisture, temperature, and humidity. Data from sensors, weather forecasts, and evapotranspiration prevents overwatering and conserves water. These systems reduce water waste and maintain green environments.

The FIWARE IoT platform plays a vital role in Cartagena's integration of Smart Irrigation Systems. This platform integrates data sources and allows for Big Data, machine learning, and AI analysis. This technology-driven approach lowers costs, improves resource management, and contributes to a greener environment.

These technologies reduce water usage, CO₂ emissions, soil erosion, and pests. Compatibility and data integration improve cross-sectoral analysis and decision-making with FIWARE.

Future objectives include using Intelligent Irrigation Systems in agriculture and administration. Efficient agricultural systems save resources and increase crop production. Smart automation is vital for creating sustainable and thriving cities, but it's important to consider the advantages and disadvantages of each technology. To achieve effective approaches for smart and sustainable urban development, thorough research and proper implementation are necessary.

6.1.6 Smart Systems using Artificial Intelligence in Sports-Football: Methodologies.

This chapter focusses on AI integration methods in football. Football, with 275 million players, is popular and draws billions of viewers. Game analysis, computer vision, and AI are popular because the sport's large viewership drives its economy. AI has transformed post-match analysis, improving ball possession, goal line recognition, and decision-making.

The methods examined are:

- *Performance Analysis*: AI uses player tracking data, game statistics, and video evidence to help coaches and analysts in player development, game design, and weakness identification.
- *Biomechanics and Player Tracking*: AI algorithms examine data from wearables and cameras to understand player movements, performance, and prevent injuries.
- *Video Analytics*: AI-powered computer vision algorithms automatically analyze game videos to improve the analysis match dynamics a.

- *Player Recruitment and Scouting*: AI algorithms analyze player data, recognize talent, and optimize scouting operations.
- *Referee Assistance*: VAR and other AI technologies help referees make crucial decisions during matches which in turn enhancing accuracy.
- *VAR - Video Assistant Referee*: AI assists referees in making decisions related to goals, penalty kicks, red cards, and mistaken identity decisions, improving fairness and accuracy.
- *Semi-Automated Offside Technology (SAOT)*: AI-powered sensors and cameras let officials make offside judgments swiftly and correctly.
- *Goal-Line Technology (GLT)*: High-speed cameras assess if the ball crosses the goal line, eliminating errors and improving fairness.

AI techniques can also predict match outcomes using previous data, assisting analysts, broadcasters, and betting organizations. AI improves audience engagement with personalized content, real-time analytics, and interactive experiences. AI-driven player selection forecasts, virtual reality fan experiences, and AI-integrated decision-making are the future of football. We can conclude that AI tools like VAR and SAOT have made football more interesting and accurate, while human judgment continues to maintain its competitiveness.

6.1.7 Smart Parking System: Methodologies.

Smart parking system use image processing to find parking gaps. Initially, image analysis is utilized to detect parking gaps. The parking lot is categorized based on training data, and SVM techniques are employed to enhance safety. The SVM further optimizes parking lot traffic by discovering the shortest and fastest paths. Python and CNNs are utilized to recognize parking spaces from camera images. This combined system notifies users of available parking spot.

6.1.8 Smart Systems in Aerospace: Methodologies.

This passage focusses on various application and methods of AI in aerospace industry. As the aerospace industry becomes more digitized, there is a growing focus on data science for improving aircraft product design, development, and operations. With the huge data generated by aircraft sensors, makes AI-driven Predictive Maintenance a promising aerospace strategy. The methods and applications are discussed below:

Aerospace: AI is used in autonomous systems for unmanned aerial vehicles and spacecraft. Flight control systems use AI to improve navigation and decision-making and it is also used for aircraft maintenance to monitor health of the aircraft and predict maintenance needs. AI is essential for air traffic control, aviation weather prediction, space research, satellite operations, and airline operations.

The design and development of aerospace products are complex processes that involve numerous standards, regulations, and factors to be considered. AI-powered digital twins and recommendation engines can help engineers and improve design and development quality and efficiency.

Smart Factory: Complex processes are automated and self-organized in a Smart Factory. This improves operational efficiency with AI-driven VR/AR, additive manufacturing, robotics, and data analytics.

Intelligent Inspection: AI and image recognition automate inspections after manufacturing, during operation, and maintenance. Drone-based aircraft surface inspections with augmented reality reduce inspection time and improve safety.

Predictive Maintenance: Using AI for predictive maintenance can enhance the operational success of aircraft and reduce maintenance costs. We should highlight the importance of data-driven diagnostics and hybrid solutions that use digital twins to predict Remaining Useful Life (RUL) and optimize maintenance schedules.

In summary, AI is advancing in aerospace manufacturing and maintenance. The aviation industry can utilize AI to enhance operational efficiency, safety, and cost-effectiveness.

6.1.9 Importance of Ethical Issues in smart system Development using AI with Focus on Algorithmic Bias: Methodologies.

The complexity and autonomy of AI decision-making raise ethical issues. While researchers aim to establish ethical principles, implementing them is challenging. AI's "black box" dilemma prevents comprehension and accountability for judgments. Transparency is an advantage, but issues like commercial confidentiality and complexity make it challenging.

Here, we must emphasize the need for AI systems to be clear and unbiased, especially in the criminal justice system. We should recognize the challenge of dealing with the "black box" problem in AI and the importance of regulating AI technologies. The goal is to make AI systems fair, accountable, and less biased, considering their growing influence on society.

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7 Role of Python and AI

Python is a widely used programming language in the field of smart systems due to its flexibility, readability, and powerful libraries and frameworks. Overall, Python plays a vital role in the development of smart systems by providing powerful tools for data processing and analysis, machine learning and artificial intelligence, IoT and networking, GUI development, and Emotion recognition. Python's popularity and wide range of libraries and frameworks make it an ideal choice for developing a wide range of smart systems.

7.1 Raspberry Pi

The Raspberry Pi, an affordable and compact single-board computer, was created by the Raspberry Pi Foundation in the UK. Its primary aim is to facilitate the teaching of fundamental computer science in developing nations and to offer an economical computing option for enthusiasts, developers, and professionals. This device features an integrated system on a chip (SoC) that combines a CPU, GPU, memory, and input/output (I/O) capabilities on a single board. The Raspberry Pi is available in various models, each differing in terms of processing power, memory, connectivity, and other specifications.

This versatile computer supports multiple operating systems, including Linux, Windows 10 IoT Core, among others. Its applications are diverse, ranging from home automation and media centers to robotics, internet of things (IoT) projects, and educational uses.

Raspberry Pi supports Python, making it a popular choice for developing Raspberry Pi projects due to its easy-to-learn nature. Raspberry Pi has GPIO pins that can interact with the physical world. It also has adept libraries like Adafruit and PySerial that are useful in reading sensor data and controlling actuators such as motors, lights, and relays.

Python also has several libraries such as PyQt, Tkinter, and Kivy that can be used to create graphical user interfaces (GUIs) for smart systems. These GUIs can be used to visualize data, control smart devices, and interact with users.

Raspberry Pi is an excellent platform for developing smart systems due to its flexibility, low cost, and availability of a broad range of software libraries and tools. It has enabled

developers, hobbyists, and educators to create innovative projects and solve complex problems using affordable computing resources which in turn have made the world of smart systems move forward at a rapid pace. And this platform is made even more adept when it's coupled with one of the most powerful languages in the world, python.

7.2 Artificial Intelligence and Emotion Recognition

With the availability of hardware and components involved in smart systems and IOT, we have unprecedented amounts of data that is being collected every second and ready to be repurposed into building even more advanced smart systems that can leverage the most revolutionary technology on the planet today, machine learning and artificial intelligence.

Smart systems often involve the collection and analysis of enormous amounts of data from sensors and other sources. Python has a wide range of libraries for data processing and analysis, such as NumPy, Pandas, and SciPy, which can be used to process and analyze data from smart sensors and other sources. Python is the primary language used in machine learning projects, including those on Raspberry Pi. TensorFlow with Keras are among the libraries for training machine learning models on Raspberry Pi. Python has enabled machine learning and artificial intelligence in a massive way. Day to day it is growing into one of the biggest tools in harnessing the power of this technology.

Emotion recognition in smart systems is the ability of a machine to detect, interpret, and respond to human emotions. It involves the use of artificial intelligence (AI), machine learning (ML), and other advanced technologies to analyze data from various sources such as facial expressions, tone of voice, and physiological signals. To implement emotion recognition technology, smart systems typically use techniques such as facial recognition, speech analysis, and physiological monitoring. These techniques are used to detect changes in facial expressions, voice tone, and body language, which can be used to infer emotions. The data is then analyzed using machine learning algorithms, which are trained to recognize specific emotional states.

One of the most common applications of emotion recognition in smart systems is in virtual assistants such as Siri and Alexa. These systems use natural language processing (NLP)

algorithms to understand spoken words and detect the emotional state of the user based on their tone of voice.

Other applications of emotion recognition in smart systems include:

- Marketing and advertising: Companies can use emotion recognition to analyze consumer behavior and tailor their advertising and marketing strategies accordingly.
- Healthcare: Emotion recognition can be used to monitor the emotional state of patients and provide them with personalized care.
- Education: Emotion recognition can help educators understand the emotional state of students and adapt their teaching methods to better engage and motivate them.
- Entertainment: Emotion recognition can enhance the user experience in video games, virtual reality (VR), and other forms of entertainment by creating more immersive and engaging experiences.
- Public Safety: Emotion recognition can be used to detect and respond to negative emotions in public places, such as airports, train stations, and shopping malls, allowing for early interventions, and preventing potential security issues.
- Robotics and autonomous systems: Emotion recognition can be used to make robots and autonomous systems more socially aware, such as detecting and responding to human emotions in social and domestic settings.

8 Literature Review

In this section we will discuss reports and will analyze peer reviewed articles exploring the topic of smartness, smart devices, and the role of different technologies, like Raspberry Pi and AI in the development and advancement of smart devices. This evolution has also given rise to emotion recognition technology. While this topic is the subject of a wide array of academic research today, the reliability and validity of this literature review were ensured by selecting literature with at least 30 prior citations.

To do justice to this topic it is paramount to understand the meaning behind the buzz words 'smartness' and 'smart systems' that are very popular in academic circles today but rarely explicitly defined. According to IGI-Global dictionary, 'Smartness' refers to "the awareness of people, technologies, and any combination of people interacting with each other and/or technologies, or technologies interacting with each other and/or with people (IGI, 2023) [3]. Whereas 'smart systems', as stated by IBM, refers to systems that "include sensing and intelligence that understands a situation. They will make predictive and adaptive data-driven decisions and perform smart actions. The cognitive intelligence of such systems is built on energy-efficient autonomous operation, closed-loop control, and communication functionalities" (IBM, 2023) [4].

Steven Alter (Alter, 2020) [5] argues that the careless usage of the term "smart" in modern times leads to questions about its meaning that extend beyond the immediate and impressive applications of Information Technology (IT). The term "smart" and its related concept of "smartness" must be contextualized for defining, evaluating, and devising smart systems. To establish the meaning of "smartness," certain examples regarding technically smart machines and systems and guidelines are necessary. Such an approach allows the development of a taxonomy matrix for smart capacities pertaining to four distinct categories such as:

Processing of information, internal regulation, real world efficacy, as well as attainment of knowledge. Every classification contains a range of competences that are classified centered around how smartness is defined, ranging from "not smart" to "somewhat smart" to "extremely smart". Thus, a multi-faceted view of smartness should be applied when devices and systems are described, analyzed, and designed (Alter, 2020) [5].

The development and enhancement of smart devices and systems have contributed to increased digitalization and digital transformation, which have numerous positive impacts on the daily lives of individuals and businesses. Peter C. Verhoef (Verhoef, et al., 2021) [6] wrote in the journal of business research, that digital transformation is of utmost importance but needs to be done in an efficient manner. Their objective was to reflect the phenomenon and literature surrounding digital transformation across multiple fields to promote comprehension and stimulate future research through strategic imperatives and a research agenda. To achieve this, they set three specific goals: (1) to identify external factors that have intensified the need for digital transformation, (2) to explore the strategic imperatives that arise from digital transformation in terms of necessary digital resources, structure of organizations, progressive strategies, and metrics, and (3) to propose a research agenda.

The drivers, stages, and requirements for digital transformation are described using a flow model. The drivers, stages, and requirements for digital transformation are described using a flow model. Starting with background information, the discussion delves into digital transformation in the context of peripheral factors. Reviewing literature from various disciplines outlines the different segments of digital transformation. This understanding of the phases allows for an exploration of strategic imperatives related to digital resources, organizational structure, growth strategies, key performance indicators (KPIs), and objectives.

The discussion provides timely insights into digital transformation and how it raises specific challenges for organizations. To successfully achieve digital transformation, an organization must possess digital agility, which involves the ability to integrate digital resources with other structural resources to innovate business practices. By constantly detecting and capitalizing on market opportunities, digital dexterity allows for the development of new goods, services, and business models that enhance customer value. In addition to digital agility, digital networking capability is necessary. This refers to the ability of a firm to match distinct users by digital means to answer their joint needs, which becomes increasingly important in digital settings. Another critical aspect to consider is the organization's big data analytics capability. During the digital transformation phase, the ability to acquire and analyze large amounts of data for decision-making is crucial due to high dependency on digital data. Aside from digital resources, it is important to address the organizational changes necessary to adapt to digital change, especially the requirement of flexible organizational structures. Based on the research, the digital transformation will be a pertinent and multidisciplinary area for

future research, considering the exponential innovation in digital technologies (Verhoef, et al., 2021) [6].

Iliev and Stanchev's paper (Iliev & Stanchev, Smart Services Using Voice and Images, 2021) [7] focus was on the key advancements in smart technologies that have contributed to the development of the smart ecosystem. The focus was on the automated extraction and analysis of digital media, using speech and images, and how these technologies have led to a range of practical systems for media personalization and recommendation. Furthermore, wide range of services in various fields that have directly benefited from these advances were also highlighted. These developments were designed being mindful of a human-machine interaction approach, providing various ways for humans and machines to interact with each other. In the past, such interactions were typically facilitated using standard interfaces, such as a mouse and keyboard, where responses had to be manually entered by users for subsequent analysis. It was suggested that, to streamline such interactions and enhance services, new approaches need to be researched, and developed. This will substantially improve services such as recommendation and personalization (Iliev & Stanchev, Smart Services Using Voice and Images, 2021) [7].

Similarly, Naty Angulo analyzed digitalization and its impact on smart workplaces. This research discusses the potential implications of Smart Offices on individuals and emphasizes the importance of learning about technologies, tools, and solutions to anticipate these changes. The author argues that the positive impacts of Smart Offices depend on the adoption and use of such technologies, and highlights the importance of Information, Connectivity and Automation as the most important elements of a Smart Working Environment. The paper explores some related work on the subject and describes some scenarios created as possible futures for Smart Offices. The author also discusses the unified theory of acceptance and use of technology (UTAUT) to support a quantitative study about IT adoption. The study shows that Effort Expectancy and Performance Expectancy, which were considered as the strongest predictors of Behavior Intention. Moreover, working experience acted as an important moderator in the relationship between Effort Expectancy and usage intention. Gender, age, and experience at work also affect the usage intention, with older women, newcomers to the workforce, and men showing the most concern about various aspects of Smart Offices. The author observes that although smart devices are utilized in the workplace, the complete smart office environment has not been fully established. The lack of

awareness and familiarity may be contributing to why most respondents are undecided about using these systems voluntarily. This paper offers suggestions for introducing new systems to be accepted that is better, by considering the role of genders, age, working experience, and willingness to use. Despite having a small sample size and low statistical power, the study is relevant in understanding the complex nature of interactions of workers with their workplace and the use of technology associated with it (Mejia, 2015).

Benyezza et al (Benyezza, Bouhedda, & Rebouh, 2021) [8] wrote a paper on smart irrigation system using fuzzy control technology and IoT to improve efficiency and reduce waste. This paper discusses the role of information and communication technologies (ICT) in traditional agriculture and agricultural development. A new irrigation strategy was proposed based on a zoning irrigation system that utilizes the Internet of Things (IoT) to optimize growth of plants and reduce use of water and improve utilization of energy. This system utilizes a Wireless Sensors Network (WSN) to collect information on real time environmental conditions, such as land moisture and temperature, and send them Raspberry Pi using radiofrequency (RF) communication. To process this information, a fuzzy logic controller (FLC) was used to control and to make rational decisions for the irrigation. An HMI developed by IBM was used to observe and manipulate the irrigation system remotely. This proposed system was tested in a real environment with tomato plants, and the results showed that the system reduced the water usage and the usage of energy significantly compared to other irrigation techniques. This paper explores the use of fuzzy logic (FL) in agriculture, which has helped farmers make informed decisions about their crops. Unlike the proportional–integral–derivative (PID) controller, FL does not require an exact estimation or model of the system, making it more attractive to researchers. Results show that FL is a more suitable controller for greenhouse irrigation.

Additionally, this paper discusses the implementation of the Internet of Things (IoT) in agriculture, such as a greenhouse farm supervision and automatic irrigation system that tracks plant water requirements, alerts the irrigation unit, and provides real-time farm information. An intelligent IoT irrigation management system has been proposed to minimize water consumption and reduce working time. A combination of K-Nearest Neighbor (KNN) and a classification machine learning algorithm has been proposed to analyze sensor data for soil water irrigation.

Finally, this paper discusses the use of wireless sensor networks (WSN) in agriculture, which has provided accurate resource management, irrigation optimization, and disease monitoring. A machine learning algorithm combined with a Wireless Sensor Network (WSN) has been suggested to predict soil moisture and enable effective irrigation decisions. Additionally, a monitoring and management system for potato crops has been proposed, utilizing low-power sensor nodes. To help farmers manage irrigation and improve water resource exploitation, a low-cost WSN-based decision support system and FL have been developed, along with a Smart Watering System (SWS) that uses a fuzzy approach and blockchain technology for enhanced security.

Overall, their paper presents a comprehensive overview of the use of ICT, FL, IoT, and WSN in modernizing traditional agriculture and agricultural development. The proposed zoning irrigation system based on IoT and FL with the use of WSN technology is a promising approach for minimizing water usage and energy consumption while maintaining ideal soil moisture conditions for plant growth (Benyezze, Bouhedda, & Rebouh, 2021).

Similarly, Boursianis et al. (Boursianis, et al., 2022) [9] discussed smart agriculture using IOT and UAV (unmanned ariel vehicles). In this paper, use of Internet of Things (IoT) and Unmanned Aerial Vehicles (UAVs) in the field of agriculture that has transformed conventional farming methods into a new age of accurate agriculture were discussed. The authors have conducted a survey of the latest research on these technologies in agriculture and have analyzed their applications in various situations, such as water management, use of fertilizers, pesticide usage, monitoring development of plantation and managing crop health. The authors have described the main principles of IoT, incorporating smart sensors, types of IoT sensors, arrangement and procedures implemented in farming, along with application of IoT. They have also presented UAV technology usage in innovative agricultural procedures and have analyzed the applications of UAVs in agriculture.

Furthermore, the authors have discussed how these technologies, along with Remote Sensing, Big Data Analytics (BDA) and Machine Learning (ML), can make new inroads in farming methods. Smart agricultural technology has introduced modern and innovative practices by enabling the monitoring of crops at a per-plant level. The use of WSNs, IoT sensors, and UAS, and ML processes, can establish an innovative methodology for precision farming leveraging the potential of agricultural crops. These key emerging technologies can

further improve crop yield, quality, reduce cost, and mitigate the ecological impact of conventional agriculture.

This paper has identified several challenges of precise water irrigation in two different farms, which contribute to the smart farming concept. The authors have proposed the utilization of 5G-IoT technology incorporated with energy harvesting and machine learning techniques to deliver a prototype end-to-end smart irrigation system.

Smart farming has still several agronomic aspects to be properly addressed. These include precise irrigation with salts minimization, efficient and rational fertilization, and pesticide utilization by drastically reducing pollution aquifer, adequate weed management, efficient management of crop diseases in the field, monitoring of crop growth on a plant basis by constructing efficient and precise 3D modeling algorithms, and the efficiency of the nutrients from roots to plants using non-intrusive techniques.

Overall, the authors concluded that the chief technologies that reinvent conventional agricultural procedures into an intelligent and precise procedure are IoT and UAV. The use of these technologies, along with Remote Sensing, BDA, and ML, can revolutionize traditional farming practices and lead to novel age of the agri-food industry (Boursianis, et al., 2022) [9].

J. G. Rana (Rana & Chate, 2016) [10] proposed a smart irrigation system using Raspberry Pi in 2016. This paper proposed the use of the Raspberry Pi microcontroller to create a smart irrigation system that can be controlled through a mobile application. The author has presented a detailed description of the system architecture, which includes various sensors and a real-time clock module to ensure precise watering of plants.

The research methodology employed in the paper involves the development of a prototype smart irrigation system using Raspberry Pi, soil moisture sensors, and a water pump. Rana described the programming aspects of the system, including the development of the mobile application using Python and Flask framework. Experimental setup was also discussed, which involved testing the system's performance under different conditions.

This paper presented the results of the experiments conducted, which demonstrated the effectiveness of the proposed system in regulating water usage for plants. The author has provided a detailed analysis of the system's performance in terms of water consumption and the impact of different weather conditions on plant growth.

Overall, this research paper presented a valuable contribution to the development of smart irrigation systems using Raspberry Pi microcontrollers. The results presented in the

paper were compelling and highlighted the potential of the proposed system to overcome the challenges of traditional irrigation methods (Rana & Chate, 2016) [10].

Similarly, Sanjana Prasad et al. [11] proposed a smart surveillance system using Raspberry Pi and infra-red sensors. This paper begins with an overview of the proposed system's architecture and design, which involves the use of PIR sensors to detect motion. Raspberry Pi was used to process the sensor data and trigger alerts when necessary. The authors have also described the software components of the system, which include the use of Python programming language and the OpenCV library for image processing.

The research methodology involves the development of a prototype surveillance system using the Raspberry Pi microcontroller, PIR sensors, and a camera module. The authors have provided a detailed description of the hardware and software components of the system, including the circuit diagram and the programming logic. The suggested security system for homes captures data and transmits it wirelessly to a mobile device via a web application using a 3G Dongle. Raspberry Pi manages the operation and monitoring of motion sensors and video cameras, allowing remote sensing and surveillance by streaming live video and storing it for future playback. The system's infrared sensor can even detect the number of people present in the area. Whenever motion is detected, the cameras immediately begin recording, and the Raspberry Pi sends an alert to the homeowner's smartphone, notifying them of a possible intrusion. This paper presents the results of the experiments conducted, which demonstrates the effectiveness of the proposed system in detecting motion and triggering alerts. The authors have also discussed the impact of different environmental factors on the system's performance and proposed possible solutions to overcome these limitations. The research paper presents a valuable contribution to the development of smart surveillance systems using Raspberry Pi and PIR sensors. The results presented in the paper are compelling and highlights the potential of the proposed system to overcome the limitations of traditional surveillance systems (Prasad, Mahalakshmi, John, Sunder, & Swathi, 2014) [11].

The use of IoT and its related technology for a smart health care system was proposed by Jaiswal et al. [12] in the paper published by IEEE. This paper presented a novel approach for developing an IoT-based framework for collecting patient data in a smart healthcare system using Raspberry Pi microcontrollers. This paper aimed to overcome the limitations of traditional healthcare systems, which are often inefficient and costly.

This paper begins with an overview of the proposed system's architecture and design, which involves the use of Raspberry Pi microcontrollers to collect and transmit patient data to a cloud-based server for storage and analysis. The authors have also described the software components of the system, which include the use of Python programming language and the ThingSpeak cloud platform for data storage and visualization.

The research methodology involved the development of a prototype healthcare system using the Raspberry Pi microcontroller and various sensors to collect patient data, including body temperature, heart rate, and blood pressure. The authors have provided a detailed description of the hardware and software components of the system, including the circuit diagram and the programming logic.

This paper presented the results of the experiments conducted, which demonstrated the effectiveness of the proposed system in collecting and transmitting patient data to a cloud-based server for storage and analysis. The authors have also discussed the system's potential applications in remote patient monitoring and telemedicine.

Overall, the research paper presented a valuable contribution to the development of smart healthcare systems using Raspberry Pi microcontrollers and cloud-based platforms. The results presented in the paper were compelling and highlighted the potential of the proposed system to overcome the limitations of traditional healthcare systems (Jaiswal, Sobhanayak, Mohanta, & Jena, 2017) [12].

Now, considering how these different technologies can be used in the field of emotion recognition and data sentiment analysis the research paper titled "Cross Corpus Multi-Lingual Speech Emotion Recognition Using Ensemble Learning" by Wishu Zehra et al. presented a fresh approach to literary multi-language dialogue/sentiment identification via joint learning methodologies. This paper focused to address the challenge of recognizing emotions from speech signals in a multi-lingual context by combining multiple classifiers to improve the recognition performance.

The authors argued that the accurate detection of emotions in robots has been a challenging task for researchers in recent years. With the increasing use of service robots, which interact with users from diverse cultural and linguistic backgrounds, conventional approaches to speech emotion recognition were no longer sufficient to provide efficient and emotional responses. Conventional methods for training and testing emotion classifiers rely on the same corpus for accuracy, but this approach cannot be easily applied in multilingual

environments, which is crucial for robots that operate worldwide. To tackle this challenge, the paper conducted a series of experiments that showcased the effectiveness of an ensemble learning approach using majority voting for cross-corpus multilingual speech emotion recognition systems. The study compared the performance of this novel approach with that of traditional machine learning algorithms.

Various machine learning algorithms have been effective in accurately categorizing emotions within the same corpus, but their performance declines when used on cross-corpus data. As a result, it was essential to find a way to apply machine learning algorithms for emotion detection to cross-corpus data. In this study, a dialogue-based sentiment identification method for machines which combines various audio features to identify emotions accurately in a corpus and cross-corpus data by employing ensemble learning techniques were suggested.

Experiments were conducted using literature in Urdu, English, German, and Italian. The experiments were conducted with Urdu as the central language comparing it to English, German, and Italian in various scenarios. The researchers investigated how combining classifiers, commonly used for dialogue sentiment identification, using a majority voting approach, enhances cross-lingual emotion recognition. This paper compares traditional machine learning practices, including decision trees, random forest (RF), and sequential minimal optimization (SMO), with an ensemble of these machine learning algorithms using majority voting. The collective learning technique efficiently improved emotion detection and provided precision on both singular and multi-lingual data compared to traditional ML methods.

Their findings suggested that the ensemble learning technique through majority voting is effective in handling sentiments in multiple languages as it allows machines to operate universally. The researchers found that various classifiers respond in a different manner to each language, arising the need for a universal classifier for any language. The collective learning method, that employed the three best used machine learning algorithms and employed a majority voting format which produced results that can compare all languages. These findings will contribute to the development of sentiment identification techniques for machines capable of engaging with global consumers while being sensitive to sentiment, a factor that significantly influences how robots interact with the world.

In the future, the researchers intend to further improve the ensemble using different ML algorithms. To make the study applicable to realistic situations, the researchers plan to research

diverse recorded audio databases in real situations. Furthermore, the writers intend to evaluate the effect of utilizing various ensemble techniques to achieve higher accuracy rates. Potential future challenging task for researchers would be to locate collections for several dialects and languages in real life environments since such collections are not easily accessible. Secondly, selecting algorithms that can cope with different languages in real time and recorded situations. Speech sentiment identification is one of the opportunities that arises from the shift from word-based to more intuitive control systems in human-robot interaction.

Overall, the research paper presented a valuable contribution to the field of speech emotion recognition in a multi-lingual context using ensemble learning techniques. The results presented in the paper were compelling and highlighted the potential of the proposed approach to improve the recognition performance in a multi-lingual context (Zehra, Javed, Jalil, Khan, & Gadekallu, 2021) [13].

Speech Emotion Detection (SED) is a field of research that focuses on detecting emotions in speech. Detecting emotions from speech can be used in various applications like designing robots that can interact with humans emotionally or assist people who have difficulty communicating their emotions. In the thesis work of (Sundarprasad, Speech Emotion Detection Using Machine Learning Techniques, Spring 2018) [14] explores various machine learning techniques that have been used for speech emotion detection. This paper reviews various machine learning techniques that have been used for SED. These techniques include Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees, and Artificial Neural Networks (ANN). This paper also explores various features that can be used to represent speech, such as Mel-Frequency Cepstral Coefficients (MFCCs), Linear Predictive Coding (LPC), and Gammatone Frequency Cepstral Coefficients (GFCCs). The performance of these techniques is evaluated using metrics like accuracy, precision, recall, and F1-score.

This paper highlights the importance of feature selection in SED. It suggested that MFCCs are the most effective features for SED. This paper also suggests that the choice of machine learning technique depends on the specific requirements of the application. SVM and ANN were found to be the most accurate techniques in this study. However, these techniques may not be the most appropriate for real-time applications due to their high computational complexity. The paper suggested that simpler techniques like KNN or Decision Trees may be more appropriate for real-time applications.

The results pointed out to the usage of different features and machine learning techniques in the substantial effect concerning the accuracy of SED. More specifically, SVM and ANN outperformed the other techniques in terms of accuracy. The use of MFCCs as features was seen as the most useful for SVM and ANN. This paper also found that the choice of emotion classification scheme can have a major affect concerning the performance of the system. The use of a two-class classification scheme (positive/negative) was observed to be more useful compared to a multi-class classification scheme (happy/sad/angry).

This paper concludes that machine learning techniques can be effectively used for SED. The choice of features and machine learning techniques can have a substantial influence on the correctness of a system. The paper suggests that the use of MFCCs and SVM or ANN can provide high accuracy for SED. However, the choice of technique should depend on the specific requirements of the application. This paper suggested that further research is needed to explore the use of simpler techniques for real-time applications (Sundarprasad, Speech Emotion Detection Using Machine Learning Techniques, Spring 2018) [14].

Along similar lines, Visual Emotion Recognition Using Deep Neural Networks were discussed by Alexander I. Iliev and Ameya Mote in their research (Iliev & Mote, Visual Emotion Recognition Using Deep Neural Networks, 2022) [15]. The focus was on the ability to recognize emotions is essential in human interactions, and it is equally important for machines to have this ability for a range of applications such as human-computer interactions, video analysis, and more. Visual emotion recognition is an area of research that aims to enable machines to recognize emotions from images and videos. Deep neural networks have shown remarkable results in image classification and have been applied in visual emotion recognition as well.

The authors proposed a framework for visual emotion recognition using deep neural networks. They used a publicly available dataset called the AffectNet dataset, which contains over 1 million facial images with labeled emotions. The dataset includes seven basic emotions: anger, disgust, fear, happiness, sadness, surprise, and neutral. The authors preprocessed the images by detecting faces, aligning, and cropping them to the required size. They also used data augmentation techniques to increase the size of the dataset. The authors used a deep neural network architecture called Inception V3, which showed excellent results in image classification tasks.

The proposed framework for visual emotion recognition using deep neural networks by Iliev and Mote has shown promising results. The authors achieved an accuracy of 60.16% for seven-class classification, which is comparable to state-of-the-art methods. Moreover, their framework performed better on a subset of the dataset containing images with subtle emotions, which indicates that the framework can recognize emotions even in challenging situations. The authors' decision to use a publicly available dataset is commendable, which makes their results reproducible, and other researchers can use the same dataset to evaluate their methods. However, the authors' evaluation is limited to the AffectNet dataset, and it would be interesting to see how their framework performs on other datasets. They also evaluated their framework on a subset of the dataset containing images with subtle emotions and achieved an accuracy of 33.78%, which is higher than the accuracy achieved by other methods on the same subset. The authors also conducted an ablation study to analyze the effect of different components of their framework on the overall accuracy. They found that data augmentation techniques and fine-tuning of the neural network played a crucial role in improving the accuracy of the framework.

Visual emotion recognition using deep neural networks is a challenging task, but Iliev and Mote's framework has shown promising results. Their results highlighted the potential of deep neural networks in visual emotion recognition, and their framework can be extended to other datasets and applications (Iliev & Mote, 2022) [15].

A. Revathi et al. [16] similarly explored emotion recognition using perceptual features and convolutional neural networks. The authors recognized that automatic emotion recognition systems can be helpful in numerous spheres like psychology, education, and human-computer interaction. In this research, the authors suggested a different method for sentiment identification from dialogue using emotive characteristics and Convolutional Neural Networks (CNNs).

The Berlin Emotional Speech database was used in this study, which consists of sentimental dialogue examples from 10 actors, each uttering 535 sentences in 7 different emotions. The authors extracted perceptual features such as pitch, loudness, and spectral centroid from the speech signals. Then, the features were normalized and fed into a CNN for emotion classification. The CNN architecture consisted of 5 layers, including a fully connected layer preceded by 2 convolutional layers and 2 max-pooling layers. The activation function of Rectified Linear Unit (ReLU) was used in the convolutional layers, and the output layer to

classify the emotions was achieved using softmax activation function. A stochastic gradient descent optimization algorithm was used to train the model.

The authors compared the performance of the proposed approach with two other machine learning algorithms: Support Vector Machines (SVM) and K-Nearest Neighbors (KNN). The proposed approach achieved an accuracy of 68.16%, which was higher than the accuracy of SVM and KNN. The F1 score of the proposed approach was also higher than SVM and KNN, indicating better precision and recall.

Furthermore, the author conducted an ablation study to evaluate the importance of each perceptual feature in emotion recognition. The results showed that pitch was the most important feature in emotion recognition, followed by spectral centroid and loudness.

The proposed approach for emotion recognition from speech using perceptual features and CNNs achieved higher accuracy and F1 score compared to traditional machine learning algorithms. The results also indicated the importance of pitch in emotion identification. The study contributed to the progression of automatic emotion recognition systems that have various applications like affective computing and virtual assistants. Future research could explore the use of other deep learning architectures and feature extraction techniques for emotion recognition from speech (Revathi, Nagakrishnan, Vishnu Vashista, Teja, & Sasikaladevi, 2020) [16].

Cross-cultural emotion recognition and comparison using convolutional neural networks were also considered in Alexander I. Iliev et al. in their 2020 journal article. The researchers aimed to investigate the accuracy of emotion recognition using convolutional neural networks (CNNs) across different cultures. They hypothesized that CNNs would perform differently when trained on emotions expressed by people from different cultures.

The study used a dataset of audio recordings of people from different cultures expressing six different emotions: anger, disgust, fear, happiness, neutral, and sadness. The dataset included recordings from participants from five different countries: India, Russia, the United States, China, and Colombia. The authors used a pre-trained CNN for emotion recognition, which was trained on a different dataset of English speech.

The authors found that the CNN performed well on recognizing emotions expressed by people from the United States and India, achieving accuracy rates of 80% and 73%, respectively. However, the CNN performed poorly on recognizing emotions expressed by

people from Russia, China, and Colombia, achieving accuracy rates of 50%, 58%, and 62%, respectively.

The authors also explored the differences in the acoustic features of emotions expressed by people from different cultures. It was found that there were significant differences in the pitch, loudness, and spectral features of emotions expressed by people from different cultures. These differences were more prominent in negative emotions, such as anger, fear, and disgust.

Overall, the study suggested that emotion recognition using CNNs may be culture-specific, and models trained on emotions expressed by people from one culture may not generalize well to emotions expressed by people from other cultures. The study also highlighted the importance of considering cultural differences in emotion expression when developing emotion recognition systems (Iliev, Mote, & Manoharan, 2020) [17].

The paper "Emotions detection on an ambient intelligent system using wearable devices" by (Costa, Rincon, Carrascos, Julian, & Novais, 2019) [18] presents a unique approach to detecting emotions using wearable devices in an ambient intelligent system. The proposed system consists of a set of wearable devices that measure physiological signals such as electrodermal activity, heart rate, and skin temperature to detect the user's emotional state. The collected data is then processed using machine learning algorithms to classify the user's emotions.

This paper introduced the Emotional Smart Wristband, which is integrated with the iGenda platform to detect emotional states of a group of individuals through the wristband and send the social emotion value to the iGenda. This project is especially beneficial for communities of elderly individuals, such as retirement homes, where creating a harmonious environment is crucial, and the resident population is growing. The iGenda provides a visual interface and an information center that receives emotional data from the wristband and strives to achieve a specific emotion, such as calm or excitement. The goal was to provide an affective system that can discreetly enhance the lifestyle of individuals.

Ambient Assisted Living (AAL) is a rapidly growing field that aims to aid elderly and disabled people. However, most AAL projects have a simple interaction with users with minimal effort and rely on automatisms and static user profiles. These projects failed to cater the complex human states and changes in emotional profiles. To address this issue, an adaptive system that perceives emotional changes is necessary.

The proposed concept involved an Emotional Smart Wristband (ESW) that communicates data to iGenda, allowing it to adapt task scheduling based on the user's emotional state. The ESW is crucial in Intelligent Virtual Environments for simulating different scenarios and observing varied outcomes from actual interactions. This document elaborately discusses the ESW's composition, along with the methods and architecture used to convert bio-signals into emotions employing the PAD model and neural networks. The goal is to develop a comprehensive Ambient Assisted Living (AAL) platform by integrating ESW and iGenda to collect emotional data, enhancing iGenda's understanding of the user.

The ESW platform captures and transmits time-stamped bio-signals from the user, which are then interpreted as current emotions. This platform serves two primary purposes: firstly, to synchronize with the iGenda platform, allowing iGenda to modify its operations based on the emotional changes of an individual or a group; secondly, to log user emotions and calibrate its reactions to various stimuli, ensuring an appropriate ESW response. Key advantages of this platform include a recommendation system via iGenda, which aids a demographic that is often overlooked, the use of inconspicuous sensing technology, and its adaptability for multiple applications.

In conclusion, the proposed system showed promising results in detecting emotions using wearable devices in an ambient intelligent system. The system has the potential to be used in various applications and the future work could involve expanding the dataset and incorporating more physiological signals to improve the accuracy of emotion detection (Costa, Rincon, Carrascos, Julian, & Novais, 2019) [18].

Similarly, (Moreira, Rodrigues, Kumar, Saleem, & Illin, 2019) [19] discuss postpartum depression prediction through pregnancy data analysis for emotion-aware smart systems. They state that postpartum depression is a major public health concern, affecting around 10-15% of women worldwide. This disorder can have serious consequences for both the mother and the child, including impaired maternal-infant bonding, decreased breastfeeding rates, and developmental delays in children. Timely identification and treatment of postpartum depression is crucial for preventing these negative outcomes. However, identifying women at risk for developing postpartum depression is challenging, as symptoms can be non-specific and vary widely in severity.

Recent advances in data analysis and machine learning techniques have enabled the development of emotion-aware smart systems capable of detecting and predicting mood

disorders. These systems utilized physiological and behavioral data to identify patterns and trends that may indicate the presence of a mood disorder. Pregnancy data, including physiological and behavioral data, may provide valuable insights into the risk of developing postpartum depression.

This study utilized a dataset of 100 pregnant women, collected over the course of their pregnancies. The dataset included physiological data, such as heart rate and skin conductance, as well as behavioral data, such as sleep patterns and physical activity. The women were also asked to complete questionnaires related to mood and depression at regular intervals throughout their pregnancies.

The dataset was analyzed using machine learning techniques to identify patterns and trends that may predict the onset of postpartum depression. A variety of models were explored, including logistic regression, support vector machines, and neural networks.

This study indicated that pregnancy data analysis may provide a valuable tool for predicting postpartum depression. By utilizing emotion-aware smart systems, healthcare professionals may be able to detect and intervene with women at risk of developing this condition before symptoms become severe. However, further research is needed to validate these findings and develop practical applications for these systems.

The results of this study suggested that these systems may be able to detect and alert healthcare professionals about women who are at risk of developing postpartum depression, allowing for timely interventions and support. However, further research is needed to validate these findings and develop practical applications for these systems (Moreira, Rodrigues, Kumar, Saleem, & Illin, 2019) [19].

Facial emotion recognition based on deep networks are discussed by (Salunke & Patil, 2017) [20]. The research focusses on automatic face emotion recognition and classification (FERC) systems that can provide a more objective and efficient way of assessing human emotional states. The existing FERC (Facial Expression Recognition Systems) suffer from various limitations, including low accuracy, dependence on specific feature extraction methods, and poor generalization across different individuals and facial expressions. In this paper, the authors propose a new approach for FERC based on deep neural networks.

This research proposed a FERC system consisting of two main stages: feature extraction and emotion classification. The feature extraction stage uses a deep convolutional neural network (CNN) to automatically learn discriminative features from raw face images.

The CNN architecture consists of multiple convolutional layers, pooling layers, and fully connected layers. The authors used the VGG-Face architecture, which is pre-trained on a large dataset of face images, for feature extraction.

In the emotion classification stage, the extracted features were fed into a support vector machine (SVM) classifier for recognizing six basic emotions (happy, sad, angry, disgust, fear, and surprise). The authors used the public AffectNet dataset for training and testing their FERC system. The dataset contained over 1 million annotated face images from diverse sources, which helps in improving the generalization performance of the FERC system.

The proposed FERC system based on deep neural networks showed promising results in recognizing and classifying facial emotions. The use of pre-trained CNNs for feature extraction allows the system to learn more general and discriminative features, which improves its performance on diverse datasets. The authors suggested that further research can be conducted to improve the FERC system's performance by exploring different deep network architectures and optimizing the SVM classifier.

Their proposed FERC system achieved an accuracy of 72.58% on the AffectNet dataset, which outperformed several state-of-the-art FERC systems. The system also showed good performance in recognizing emotions in real-time video streams. The authors conducted an extensive analysis of the learned features by the CNN and found that the deep network can automatically learn discriminative features related to facial expressions, such as eye and mouth movements.

In conclusion, the authors proposed a new approach for automatic face emotion recognition and classification based on deep neural networks. The proposed system achieved state-of-the-art performance on the AffectNet dataset and showed good performance in real-time video streams. The use of pre-trained CNNs for feature extraction and SVM classifier for emotion classification allows the system to learn more general and discriminative features. The proposed FERC system has potential applications in psychology, human-computer interaction, and marketing research (Salunke & Patil, 2017) [20].

Javier G. Rázuri et al [21] proposed an emotion recognition system that utilizes facial expression analysis in merged images, based on an artificial neural network, in their paper. In this paper, the authors proposed a new approach for automatic emotion recognition by analyzing merged images using an artificial neural network. The proposed method aims to recognize emotions accurately, even when the images contain multiple faces.

The proposed approach involves three main steps: face detection, face alignment, and emotion recognition. Firstly, the faces were detected using the Viola-Jones algorithm, which is a widely used technique for face detection. Next, the faces were aligned using facial landmarks to ensure that they are in a standardized position. Finally, the aligned faces are merged into a single image, and an artificial neural network is used for emotion recognition.

The authors used the Lucey P. et al. database [22] which contains 487 image sequences of 97 subjects displaying six different facial expressions: anger, disgust, fear, happiness, sadness, and surprise. The authors used a pre-processing step to extract the facial features and normalize the image data. They then used an artificial neural network with three hidden layers for emotion recognition.

The proposed approach achieved a recognition accuracy of 88.44%, which outperformed other state-of-the-art approaches on the same dataset. The authors also conducted experiments to evaluate the proposed approach's robustness to noise and illumination changes. The results showed that the approach was robust to both noise and illumination changes, with recognition accuracy of 87.26% and 86.92%, respectively.

In conclusion, the authors proposed a new approach for automatic emotion recognition through facial expression analysis in merged images based on an artificial neural network. The proposed approach achieved high recognition accuracy and was robust to noise and illumination changes. The proposed approach's ability to recognize emotions accurately, even in merged images with multiple faces, makes it a promising solution for emotion recognition in real-world applications (Rázuri, Sundgren, Rahmani, & Cardenas, 2013) [21].

Likewise, “Ambient Intelligence—the Next Step for Artificial Intelligence” by Carlos Ramos et al. [23] is an academic article that explores the concept of Ambient Intelligence (AmI) as the next step for Artificial Intelligence (AI). This article highlights the potential of AmI to enable a more natural and intuitive interaction between humans and machines, by integrating technology into everyday environments such as homes, offices, and public spaces.

The article begins by introducing the concept of AmI and its potential to transform the way we interact with technology. According to the author, AmI represents a paradigm shift in computing, where technology is no longer seen as a separate entity but rather as an integrated part of our environment. This means that technology is designed to be unobtrusive and intuitive, blending seamlessly into the background and adapting to the needs of the user.

The authors claimed that currently, some systems treat Ambient Intelligence (AmI) merely as a buzzword, incorporating only a limited amount of intelligence, while some researchers are concentrating solely on operational technologies such as sensors, actuators, communications, and ubiquitous computing without including AI. However, this low level of intelligence will eventually become a clear disadvantage. Achieving widespread acceptance of AmI requires a balanced combination of operational technologies and AI. AmI systems are inserted in diverse environments, such as homes, offices, museums, or even cars. They receive information, interact with users, perform reasoning, and order actions on the environment. To handle this complex environment, AmI systems use operational technologies and AI methods and techniques.

AI methods and techniques are vital in AmI environments, as they help accomplish important tasks such as interpreting the environment's state, representing the information and knowledge associated with the environment, and interacting intelligently with humans. For example, natural language processing and speech recognition are essential for interpreting language input from humans. Computer vision can identify traffic patterns, approaching vehicles, and even human gestures or facial expressions. Additionally, AI techniques such as Bayesian networks, fuzzy logic, and rough sets can handle incomplete and uncertain information.

AmI systems must also interact intelligently with humans, considering social and emotional factors such as context awareness, adapting to users and situations, and learning by observing users. Affective computing and social computing are important AI research areas that can help incorporate these capabilities into AmI systems.

The authors are adamant that AmI cannot be achieved without AI, making AmI environments a stimulating challenge for the AI community. The incorporation of AI methods and techniques, such as multiagent systems, case-based planning, fuzzy systems, logic programming, hidden Markov models, and ontologies, in various target environments, including hospitals, geriatric residences, homes, workplaces, cultural-heritage sites, and tourist attractions, is currently being explored (Ramos, Augusto, & Shapiro, 2008) [23].

IoT and facial emotion recognition can be very helpful in assisting people with special needs or the elderly. The aging population is increasing around the world, and with that, the need for elderly care is also increasing. As elderly people tend to have more health problems, living alone can be challenging and dangerous for them. Many elderly people prefer to live

independently, and for this, smart systems can be beneficial in ensuring their safety and well-being. The use of the Internet of Things (IoT) technology can be a solution for elderly people's monitoring and can help to ensure their comfort and safety. Sugamya, K. et al. [24] proposed a smart system for monitoring elderly people's comfort living using IoT, which will be discussed in detail in this report.

The system proposed in the paper consists of various sensors placed around the house to collect data related to the elderly person's behavior. The data collected by these sensors is sent to the IoT platform, where it is analyzed and processed. The processed data is used to detect any anomalies in the elderly person's behavior and to provide alerts to the caregiver or family members in case of an emergency.

The sensors used in the system include temperature sensors, humidity sensors, light sensors, motion sensors, and door sensors. The temperature and humidity sensors are used to monitor the temperature and humidity levels in the house. The lighting conditions in the house are detected using light sensors. The motion sensors are used to detect the movement of the elderly person. The opening and closing of doors are monitored using door sensors.

The data collected by these sensors is sent to the IoT platform using Wi-Fi or Bluetooth technology. The IoT platform consists of an analytics engine that analyzes the data collected by the sensors. The analytics engine uses machine learning algorithms to detect any anomalies in the elderly person's behavior. In case of an emergency, the system sends an alert to the caregiver or family members through a mobile application.

The proposed system aims to provide elderly individuals with enhanced security assistance by utilizing the internet of things. Among its key features is a smart doorbell which allows the elderly to remotely view visitors at their front door via their mobile device, thus eliminating the need for face-to-face communication. Authorized visitors are granted access to the premises, and their image is immediately captured and sent to the elderly individual's mobile device for notification. In the case of unauthorized visitors, the system prompts the elderly individual to decide whether to allow them entry. Additionally, the system offers the option to authorize the current visitor for future visits.

To achieve these objectives, the system employs a variety of cutting-edge technologies, including a Raspberry Pi which plays a critical role in its operation. Wireless monitoring of electrical appliances via an Android application is facilitated by an Arduino, further enhancing the system's capabilities. Furthermore, the system is designed to alert the elderly individual of

important daily activities such as mealtimes and medication schedules, ensuring they can maintain their comfort and well-being.

In conclusion, the proposed smart system for monitoring elderly people's comfort living using IoT technology can be beneficial for ensuring the safety and well-being of elderly people who prefer to live independently. The system can detect any anomalies in the elderly person's behavior and provide alerts to the caregiver or family members in case of an emergency. The system can also be used to monitor the temperature, humidity, and lighting conditions in the house, which can be beneficial for the elderly person's health (Sugamya, Pabboju, & Sathish, 2022) [24].

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9 Smart Energy Systems Using Machine Learning and PMU Measurements on FIWARE

9.1 Introduction

Energy has always been a source that we have used for centuries in one form or the other. From the early days of using fire as a light and heat source to fossil fuels to generate electricity. The alarming rise of ocean levels, unpredictable extreme weather and natural disasters are a concern. Global warming is an important issue that demands attention. Creating an efficient energy production and consumption model is crucial. It's not just the responsibility of energy infrastructure providers but also consumers to use energy wisely. That's why the new smart energy systems should empower consumers with the tools they need. FIWARE offers standardized, reusable, and easily deployable models to help design and implement these smart energy systems. Producing energy efficiently and delivering it to end-users are equally important. Energy has evolved, including renewable sources, batteries, electric vehicles, and rapid digitalization. Therefore, it is necessary to develop smart energy systems that tackles this upcoming issue. According to Zhou K. and Yang S (2016) [25], after the second industrial revolution, energy systems have been through four stages. These stages include decentralized systems, centralized systems, distributed systems, and, most recently, smart energy systems. Smart energy systems rely on innovative technologies like mobile applications, the Internet of Things (IoT), big data analytics (BDA), and cloud computing. Smart energy systems leverage cutting-edge technologies like automation, computers, smart devices, artificial intelligence, and the Internet of Things to swiftly adapt to fluctuating power demands. Their objective is to revolutionize the energy sector through a service-oriented approach that simplifies device connectivity. This approach delivers information, services, and helps to create an open energy market with active consumer engagement.

9.2.1 FIWARE

As depicted in Table 9.1, energy consumption has been rising rapidly and is projected to increase even more significantly. The significant thing to be noted is that not only the growing demand for energy but also the diverse range of energy technologies being introduced. In the past, we mainly relied on a handful of sources like coal-powered plants, nuclear plants, and dams. Nowadays, we have a broader spectrum of options, including wind, solar, and various other renewable energy systems. These systems need to work with each other seamlessly to optimize the energy supply to consumers. This is where FIWARE comes into play.

Table 9.1 Energy Consumption level

Energy Consumption levels in Data centers over different years (Avgerinou et al., 2017)		
Region	Year	Consumption (TWh)
EU	2001	18.3
	2005	41.3
	2007	56
	2010	72.5
	2020	104
US	2013	91
	2020	140
Global	2007	216
	2012	269

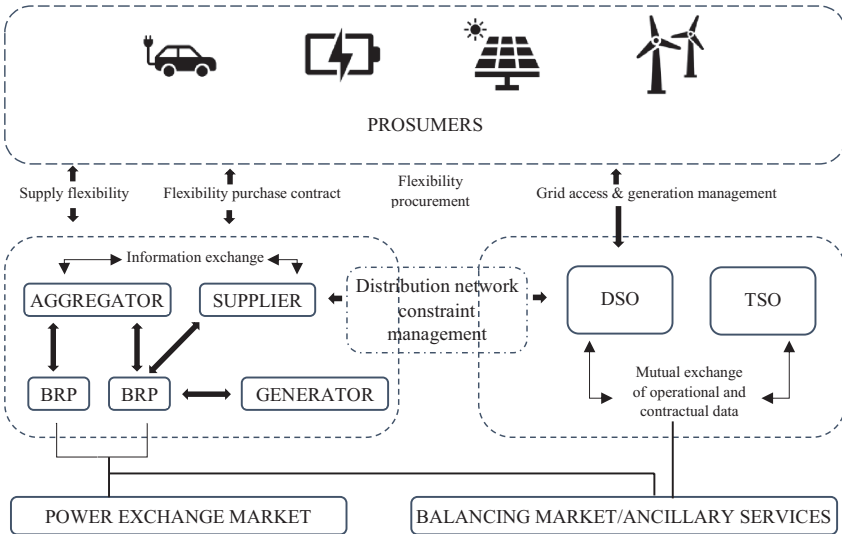


Figure 9.1 Possible market role relations (Energy, 2009) [26]

The flow chart above presents a very intuitive guide of a smart grid system (Energy, 2009) [26]. The grids interact with numerous systems. The primary objective is to create a grid that automates these interactions, which in turn gives the name “smart grid”. FIWARE provides data standards and is constantly creating new standards, such as the collaboration with ETSI which implemented FIWARE Context Broker. To ensure the fast, efficient, and reliable adoption of technology, it's essential to construct data platforms based on open standards.

9.2.2 Renewable Energy Management Using Smart Grid

The significance of a smart grid has been established, and the role of FIWARE in creating a cohesive system that operates in real time and takes automated actions has been introduced, aligning with the primary objective. The following paragraphs delves into the automation and application of machine learning within a smart grid.

According to United States Department of Energy (2009) (Energy, 2009) [26], there is a checklist of six items to build a smart grid; Participation of customers, accommodate different

generation and storage of energy, new products, markets and services to be launched, power quality at a level to meet a variety of needs, using minimum assets and efficient output, a quick action to resolve discrepancies and emergency situations. To implement big data and machine learning, valuable information is extracted from collected data. This information enhances understanding and provides insights into the issues. Subsequently, this knowledge is leveraged to make better decisions. Data from energy grids consists of mainly two types: temporal data, which encompasses consumption patterns, and geospatial data, including transmission locations, hospitals, roads, and infrastructure. This data is normally collected by IT systems but now with IOT (internet of things) smart buildings uses smart sensors and meters provide this information automatically.

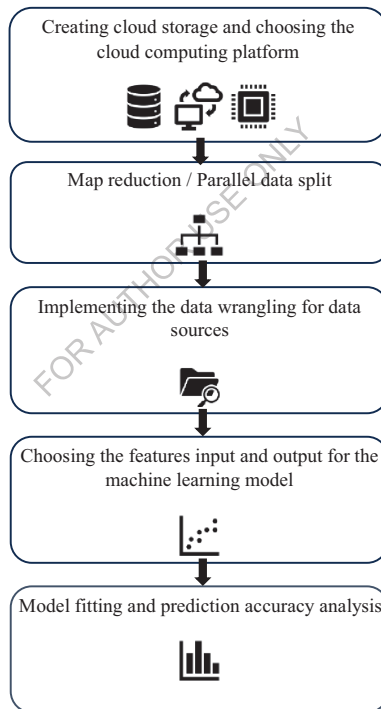


Figure 9.2 Implementation of big data and machine learning after data is collected (learning, 2023) [27]

The schematic provided above illustrates all the necessary steps. The following chapters will proceed to model fitting and the analysis of prediction accuracy to gain insights into the machine learning algorithms employed.

9.3 Model Fitting and Prediction Accuracy Analysis

Four machine learning models will be used for this: the Decision Tree Algorithm, Random Forest Algorithm, Deep Learning, and Convolution Neural Network. The Decision Tree Algorithm utilizes nodes that can be considered as leaves of a tree and branches to assess the model's accuracy of fitness. This classification model was mainly employed to determine the stability of the smart grid. The Random Forest is a more complex variation of the Decision Tree, consisting of various decision trees. The final solution is obtained by combining multiple decision trees, as illustrated in the figure below.

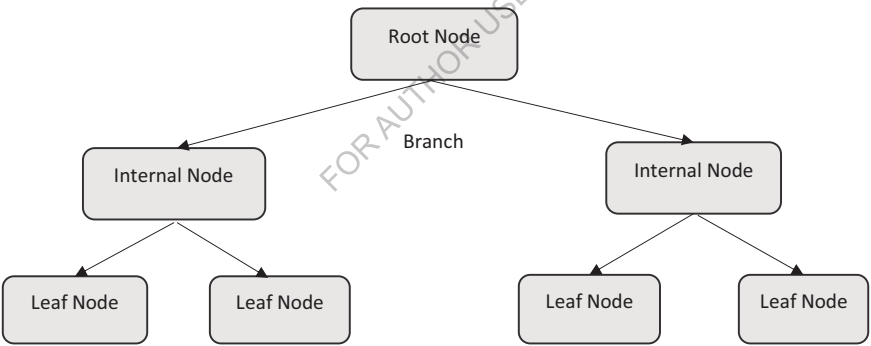


Figure 9.3 Reaching a decision after merging decision trees (Singh, 2019) [28]

Deep learning is a field inside machine learning which uses artificial neural networks to improve model learning and fitting of data. For smart grid system, the equation used to create the model is given by:

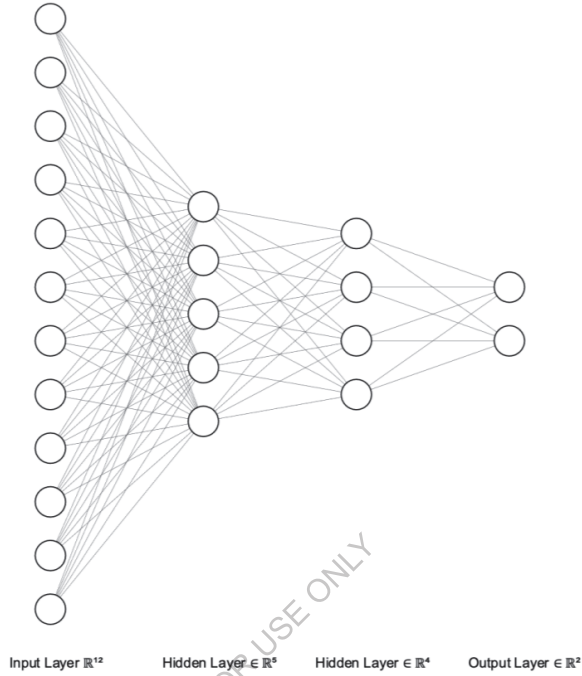


Figure 9.4 A typical Neural Network architecture with several Hidden Layers (Pramoditha, 2022)
[29]

In Figure 9.4 there is a typical neural network architecture shown. The input layer comprises 12 neurons, while the output layer contains 2 neurons. Between them, there are hidden layers. The first hidden layer consists of 5 neurons, and the second hidden layer has 4 neurons. An activation function, the sigmoid function, is employed. Convolutional networks utilize mathematical matrix convolution to extract features from input data in various applications, such as image processing, text analysis, and voice recognition. The convolution formula is used and is mentioned below:

$$net(i, j) = (x * w)[i, j] = \sum_m \sum_n x[m - n]w[i - m, j - n]$$

where: $\text{net}(i,j)$ = output for the next layer, x = input, w = kernel filter, $\otimes$ = operation of convolution.

9.4 Results and Discussion

The following Table 9.2 shows results of penalized learning model:

Table 9.2 Linear Regression results of a learning model (Leila Ziouche, 2020) [30]

x	Linear Regression result
1	0.036
2	0.031
3	0.024
4	0.022
5	0.022
6	0.022

Table 9.3 Results from applying Big Data Analysis (Leila Ziouche, 2020) [30]

Model Accuracy Applied on Big Data Analytics	
Machine Learning Model	Accuracy
Gradient Boost	96 %
Deep Learning	87 %
Random Forest	84 %
Decision Tree	78 %

Run time for the applied Big Data Analytics on decentralized smart grid system	
Machine Learning Model	Run Timing in Seconds
Gradient Boost	9
Deep Learning	4
Random Forest	10
Decision Tree	7

The results indicate a 96% accuracy and a running time of 9 seconds for the regression model. The data were split, with 70% used for training and 30% for testing. The Random Forest tree achieved an accuracy of 84%, while the Decision Tree model showed 78%. For the

classification model, the Convolutional Neural Network (CNN) achieved an 87% accuracy. It is evident that the regression model provided the best predictability for smart grid stability when using numerical values, and the CNN demonstrated the highest accuracy in quickly predicting smart grid stability for the classification model. This leads to the conclusion that regression and CNN can be effectively implemented for predicting the stability of more complex smart grids across the EU.

9.5 Rapid Data Growth and PMU

The exponential increase in the data over the last ten years brought challenges to storing the data, the scientist also resolved the issue of data storage with the help of big data technologies, high-performance computer storage capacities, and cloud computing. Advancements in digital signal processing and artificial intelligence (AI) unpacked most of the features of speech or voice, and videos by performing data extraction, cleaning, and transformation into different targets. A phasor Measurement Unit (PMU) is a device used to estimate the magnitude and phase angle between the voltage or current in the smart grid or systems (Standard, 2011) [31]. With the increase in the growth of the energy resources on the power grid, a better tracking and control system is required to efficiently monitor the power transformation.

9.6 FIWARE Technology

FIWARE's (Fireware, 2022) [32] mission is "building an open sustainable ecosystem around public, royalty-free and implementation-driven software platform standards that ease the development of new Smart Applications in multiple sectors". FIWARE is an open-source technology that is used for building smart system solutions in various domains for digital transformation. FIWARE held its position both in local and global markets. This technology facilitates the implementation of intelligent solutions in various domains, including smart cities, smart water management, smart agriculture, and smart energy systems. The FIWARE approach is distinctive because it is based on open standards and has a curated framework of open-source software platform components that can be assembled and combined with

components from other sources to create whole platforms. This approach facilitates faster, simpler, and cost-effective development of smart solutions. Government sectors, Private companies, and Research Institutions can build Smart Energy platform strategies using FIWARE.

FIWARE generic enablers are the set of general-purpose platform functions through APIs. These enablers help in the implementation of monitoring the systems for “self-sufficient” energy areas or the integration systems of various service providers with applications in the new market. For instance, the FINESCE smart energy platform brings together energy companies, research institutions, and universities from across Europe to create a marketplace for new “prosumers”. These generic enablers have various a range of functionalities such as cloud hosting, data and context management, application architecture, IoT service enablement, network and device interface, security, advanced middleware, and web-based user interfaces.

The FIWARE Context Broker Generic Enabler plays a central role in any smart solution. It's essential for managing and obtaining context information, enabling updates and access to context. This component must be integrated into any application or platform powered by FIWARE. Context information consists of attributes that describe items relevant to applications. This information can come from various sources using different interfaces and protocols. When designing applications, the focus should be on entities and their characteristics. It is interesting to observe that context producers and context consumers can have independent behaviors. In complex systems, some components are divided into producer and consumer roles to provide a global service:

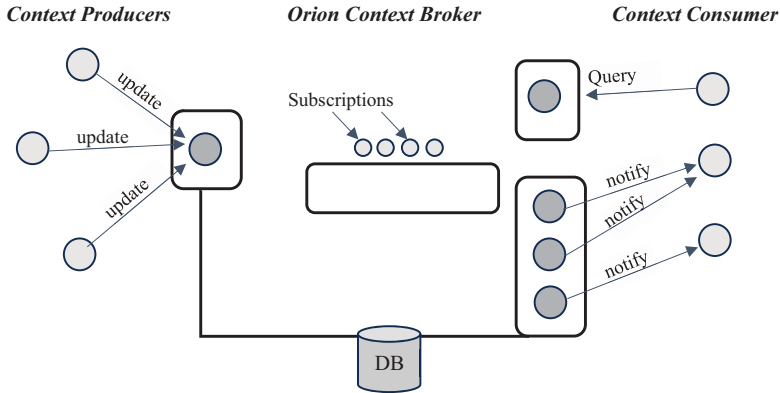


Figure 9.5 Orion context broker (standard, 2019) [33]

The key concept illustrated in Figure 9.5 is that context consumers receive updates when context information changes. Modifying the characteristics associated with a device's corresponding entity allows actions to be taken on the device. For example, in a smart meter application, there are two parts: the first part operates in the electricity meter board (context producers), and the second part is in authorized smartphones (context consumers), providing real-time metering data.

9.7 FISMEP Project

FISMEP, which stands for "FIWARE for Smart Energy Platform," isn't just about keeping up with the digital age but also adapting to the changing energy landscape, including renewable energy and decentralized system. This platform was built based on the concept derived from FI-PPP and improved a step further by establishing a new set of standard interfaces for energy services. To achieve this, a multi-layered architecture is employed, as illustrated in Figure 9.6. Layer 1, known as the field interface, is equipped with standard protocols and management capabilities to process raw data from various sensors and devices, transforming it into standardized data in the cloud. Layer 2 is formed by combining FIWARE-provided Generic Enablers (GEs) with a selection of FISMEP-created Domain-Specific

Enablers (DSEs). Layer 3, the open API, is an integral part of FIWARE and allows straightforward data access for other parties interested in utilizing the platform's capabilities. This architecture is groundbreaking in the energy sector and offers the potential for on-demand scalability.

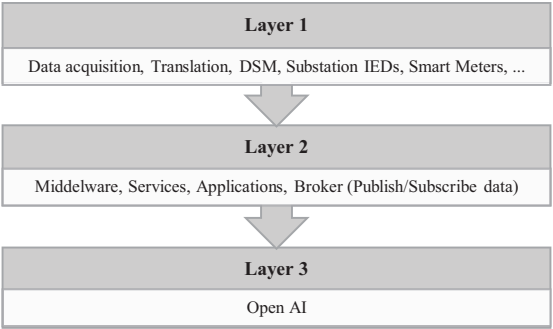


Figure 9.6 Cloud-based platform with three layers (Maliheh Haghgoo) [34]

This approach is a new concept in the energy sector and can adapt to growing demands as needed. An important aspect is the focus on connecting energy systems, energy grids, and end users. In this model, end users have an active role through a new home energy management system. This suggested architecture allows users to create and manage personal energy thresholds, schedule energy-consuming appliances, and assets, and plan energy consumption based on energy forecasts and personal goals to achieve more sustainable patterns of behavior.

9.8 FIWARE Implementation in European Countries

FIWARE has been implemented in several European countries to support the development of smart city initiatives and digital transformation projects. Here are a few examples of FIWARE implementations in European countries:

1. Spain:

- Santander: The city of Santander in Spain has been a pioneer in deploying FIWARE-based solutions. It has implemented various smart city projects, including smart

parking, waste management, environmental monitoring, and energy efficiency initiatives.

- Valencia: Valencia has adopted FIWARE to enhance its smart city infrastructure. The city has implemented solutions for smart mobility, energy management, water management, and citizen engagement.

2. Italy:

- Trento: The city of Trento in Italy has utilized FIWARE to develop smart solutions, including smart parking management, environmental monitoring, and smart mobility applications. These initiatives aim to improve the quality of life for residents and optimize city services.

- Bari: Bari has implemented FIWARE-based solutions for smart lighting, waste management, and mobility management. The city utilizes the platform to enhance urban sustainability and provide innovative services to its residents.

3. Portugal:

- Porto: Porto has implemented FIWARE to develop a smart city platform that integrates various urban services. This platform enables smart parking, waste management, energy efficiency, and public transportation management, among other initiatives.

- Lisbon: Lisbon has leveraged FIWARE to build a digital infrastructure that supports smart city projects. It includes applications for smart parking, water management, environmental monitoring, and citizen engagement.

4. Germany:

- Hamburg: Hamburg has adopted FIWARE to develop a smart city platform called “SmartCity.Hamburg.” This platform integrates data from various sources to create applications for managing energy, waste, and transportation.

- Berlin: Berlin has implemented FIWARE for its “Smart Sustainable Districts” project. The initiative focuses on energy-efficient buildings, renewable energy integration, and sustainable mobility solutions.

Overcoming faults in the power system is a significant challenge. The goal is to achieve the highest level of prevention, maximum scalability, and rapid analysis to improve efficiency and enhance customer service (H. H. Rad, 2018) [35]. The research team is focusing on the following areas:

1. Developing the FIWARE platform for collecting raw data from various measurement system operators, including Distribution System Operators and Transmission System Operators.
2. Managing the increasing volume of raw data generated by various units and simplifying data analysis using Big Data and Analytics techniques.
3. Integrating renewable energy sources into the power system on a large scale and utilizing Big Data Technologies to detect fault conditions efficiently (X. Liu, 2015) [36].

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10.1 Introduction

The agricultural sector is a vital component of the global economy and holds a prominent position in most nations (Katiyar, 2021) [37]. Agriculture is the fundamental factor essential for our survival (J. Mathew, 2022) [38]. The demand for quality and quantity of food increases tremendously with the rising population rate. Throughout history, the agricultural sector has been a significant source of employment. However, it is concerning that major portion of the global population still experiences malnutrition issues (Mahendra, 2022) [39]. This can be due to the various challenges faced by farmers such as climatic changes, unpredictable rains, controlling weeds, disease treatment, soil testing, efficient planting, and lack of suitable irrigation facilities (Mathushika, Smart Farming Using Artificial Intelligence, the Internet of Things, and Robotics: A Comprehensive Review, 2022) [40].

The continuous advancements in technology over the years have brought about significant changes in the field of agriculture. Traditional methods followed by farmers are not sufficient to meet the massive requirements. To meet the rising demands, the latest technologies and practices should be introduced in the field of agriculture. As smart systems are an emerging field in the current world, the agriculture sector could also be “smart”. As part of the technical development in the agricultural industry, artificial intelligence, and the Internet of Things (IoT) are promising elements to transform traditional cultivation into smart agriculture.

Smart agriculture refers to the latest advancement in the field of farming which includes IoT, machine learning, cloud computing, and artificial intelligence (Kutucu, 2022) [41]. Smart farming is based on the involvement of recent technologies in machinery, sensors, and equipment in agricultural systems (Vallakati, 2021) [42]. Smart farming depends on data transmission and storage of data in remote systems to combine and analyze data from various farms for better decision-making in the future. In the field of agriculture, the combination of artificial intelligence and IoT contributes to building an efficient smart agriculture system that enhances productivity. The Internet of Things (IoT) is an emerging field that has an impact on every industry by making the process smart (M. Jeyaselvi, IoT Based Smart Agriculture, 2022) [43]. IoT integrates the digital and physical worlds through actuators and sensors by extending

the internet in a balanced way. By combining IoT with AI, new strategies can be formed in the field of agriculture and help in remodeling the traditional approach with the latest innovations to overcome various challenges.

The evolution of Industry 4.0 has also led to a new form of agricultural enhancements. The use of technology in agriculture could improve agricultural production and supply chain which yield higher profits. Present day agriculture is being affected by a lot of factors like climate change, water scarcity, humidity, and excessive application of pesticides. This affects the entire production chain and the supply chain leading to an unreliable market. By introducing Information Technology in agriculture, these factors can be easily monitored and managed which can result in improved production rate. Many technologies have been emerging to enhance the agriculture industry. Even though numerous solutions have been found to overcome the agricultural problems as explained in (Corista, Description and performance of single hop wireless underground sensor nodes, 2018) [44], (Mirvakhabova, 2018) [45], most of them are expensive, copyrighted/ patented, and tough to install, maintained and integrated with external systems.

Collecting, processing, and analyzing real-time data with technology is known as smart farming. This approach maximizes outcomes and minimizes the wastage of water, fertilizers, and pesticides. It also helps in identifying diseases in the early stage to avoid mass infection. The invention of the Internet of Things (IoT) like IoT sensors, wearables, GPS services, robots and drones are used to get real-time data like pH, temperature, earth's moisture, or oxygen flow. These data are processed by the monitoring systems and necessary decisions can be taken without human intervention. FIWARE (Ferreira, Towards smart agriculture using FIWARE enablers, 2017) [46], (Corista, An IoT Agriculture System Using FIWARE, 2018) [47], (Firewire, 2022) [48] is an internet technology-based tool that improve the applications used to manage production chains. It also allows supply chains to use virtualization dynamically in operational management processes (Verdouw, 2015) [49]. Many projects have been developed using the FIWARE framework as in (Heideker et al., 2020) [50], (Heideker, 2020) [51] for the application in agricultural industry. With the recent technologies associated with industry 4.0, the myth of virtual factories has been made possible.

A Virtual factory is a digital representation of a real factory. In the virtual factory, regular operations of the factory are performed under simulation by the actors. This helps to predict and solve any malfunctioning of the devices and machines. Additionally, the impact of

analyzing any new service before implementation in a real factory is crucial. European Union under the Horizon 2020 programmer developed a global standard Virtual Factory Open Operating System. vf-OS along with its Software Development Kit offers numerous services for the Factories of the Future (FoF). This aims to serve as the standard system software for collaborative manufacturing and logistics processes, along with their associated resources and data (Ferreira, Towards smart agriculture using FIWARE enablers., 2017) [46]. This paper explains the FIWARE-based vf-OS system used in the agricultural production chain and summarizes the different techniques which make agriculture industry smarter with the help of artificial intelligence and IoT technology and the use of FIWARE.

10.2 FIWARE

FIWARE is a project created as part of FP7 (Seventh Framework Programmer) of the European Commission to develop future internet technology which could be employed in building smart applications, contributing to the technological competitiveness and growth of Europe (Corista, Description and performance of single hop wireless underground sensor nodes, 2018) [47]. This technology deals with various open-source resources and their functional building blocks are called Enablers which help to serve global or specific functions in several domains like manufacturing, agriculture, eHealth, irrigation, energy etc. The foremost features of them are reusability and interoperable interfaces. These Enablers are classified as Generic and Specific. Generic Enablers (GE) are deployed for a general purpose and domain-independent sector whereas Specific Enablers (SE) are engaged in industrial areas such as manufacturing, media, or agri-food. Through the combination of these enablers, a large volume of data is collected and analyzed efficiently. The information about the policy and characteristics of the various enablers can be found in (Catalogue, 2010) [52]. (Corista, Description and performance of single hop wireless underground sensor nodes, 2018) [47] explains about the Generic enablers used in this vf-OS platform belong to the IoT Services Enablement enablers (Protocol Adapter - MR CoAP and Backend Device Management -IDAS) and Data/Context Management enabler (Publish/Subscribe Context Broker Generic Enabler - Orion Context Broker and Short Time Historic (STH) – Comet) of the FIWARE.

vf-OS – virtual factory Operating System – is a European Project that aims to create an Open Operating System for the FoF with their application interface for the manufacturing industries (Johannes Tiusanen, 2013) [53]. vf-OS includes Virtual Factory System Kernel (vf-SK), a Virtual Factory Application Programming Interface (vf-API) and a Virtual Factory Middleware (vf-MW). It integrates software resources with FIWARE Enablers to develop complex applications. It supports interoperability by sharing data among the various applications employed in the factory which has different languages and models. It allows the implementation of FoF concepts in an IoT view by incorporating the resources and facilitating the connection with applications, sensors, and devices.

The target of the vf-OS project is to offer an economical multi-sided market platform by allowing interactions between different customer groups like software developers; manufacturing users; ICT providers and service providers (Ferreira, Towards smart agriculture using FIWARE enablers., 2017) [46]. Currently, centralized industrial systems face limitations due to their inability to handle complex plans, logistics systems, control, and adapt to changes effectively (Schuhmacher, 2016) [54]. The existing ICT technologies are transformed into a decentralized system which can overcome these current industrial limitations. Thus vf-OS plays an intermediate role between applications and devices. It also manages the visualization and data sharing among the physical devices.

vf-OS offers Enablers Framework (EF) which adheres to the same principles as a kernel and perform the required services for accessing the functionalities of Enablers. Users can perform the functionality directly from this framework. A new user request is executed using IoT protocols like Representational State Transfer (REST) or Next Generation Service Interfaces (NGSI) and forwarded to the preferred enablers to proxy communication components using analogous methods. Figure 10.1 shows the high-level system view of vf-OS.

In a regular fruit product chain, the fruits or vegetables are harvested and then they will be segregated either manually or mechanically based on factors like type, size, weight, and quality etc., Finally, they will be stored in carts and shipped to the buyers. The entire process involves several phases from cultivation to shipment before it is available for the end user.

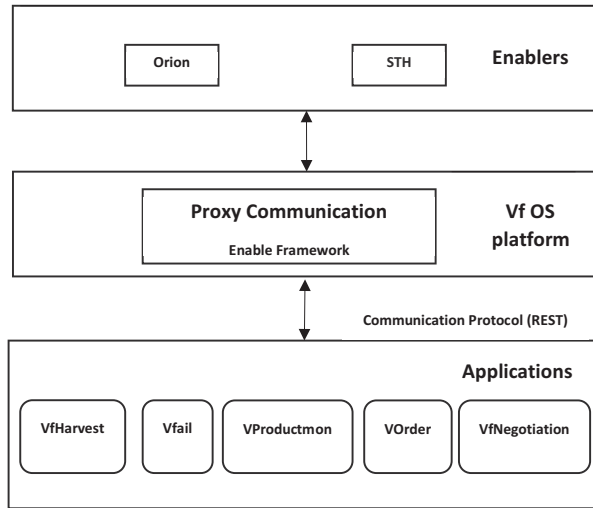


Figure 10.1 High-Level system view of vf-OS Agricultural Scenario (agriculture, 2010) [55]

In this proposed methodology, an application was developed that links the farmer and the buyer, where the buyer can buy a product based on buyer's desire and availability. This application allows both farmers and buyers to select the most suitable person to sell or buy from based on their individual needs and availability. Here, the entire cycle of fruit product chain will be monitored right from cultivation, harvest, packing, transportation, and delivery with the influence of advanced technologies. The entire process has been illustrated in Figure 10.1 and all the steps mentioned in the Figure 10.2 are detailed in Table 10.3.



Figure 10.2 Fruit Production Chain vAPPS for Agriculture industry (food production, 2010) [56]

10.3.1 vfHarvest

vfHarvest monitors agricultural activities using various sensors on the farm. It is currently in the implementation phase, requiring in-depth agricultural knowledge to install the necessary sensors as per specific needs (Corista, Description and performance of single hop wireless underground sensor nodes, 2018) [47]. vfHarvest currently provides simulated sensor data. These simulations are created by using the Extensible Messaging and Presence Protocol (XMPP) based wireless sensor representations. Applying XMPP on wireless sensors paves a way to share the collected data between the user and sensors linked in the system (Hornsby et al., 2009) [57]. Likewise, in this scenario also a realistic simulation of a farmer's cultivation with different sensors is achieved.

10.3.2 vFail

vFail also takes necessary action when new sensor data is collected and identifies the cause which helps the farmers to ensure higher fruit quality. The vApp checks whether the fruit harvest meets the expected quantity, whether it is measured accurately, and whether there are enough boxes available to pack the fruits (Corista, Description and performance of single hop wireless underground sensor nodes, 2018) [47].

10.3.3 vProductMon

vProductMon ensures that all the information from the sensors is received. Farmers can input context and corresponding rules into the system to manage quality checkpoints and ensure accurate quantity measurements. Farmers have the flexibility to create rules for specific contexts to evaluate situations. The system also maintains real-time communication with vFail, providing updates on context assessments. When needed, it shares information about fruit assessments with vfNegotiation.

10.3.4 vfNegotiation

vfNegotiation is a vApp used by sellers (farmers). A farmer can add or update new fruit stocks and define the quantity and price for each type (breed, size, color) of fruit. The buyer can find a seller who matches their needs. The farmer gets the details of the product availability from vProductMon and puts those on sale in vfNegotiation.

10.3.5 vOrder

Once the order has been placed the product will be shipped. vOrder connects the farmer, transport manager and buyer. Hence all three of them could get the status of the product during each phase until it is delivered. Data integration from the sensors inside the trucks enables a virtual representation of the truck. Once the truck is added under a farmer in the system, this helps the user to track and ensures successful delivery. It also provides a qualitative assessment of product transportation and delivery (Corista, Description and performance of single hop wireless underground sensor nodes, 2018) [47].

The agriculture scenario explained above uses four GEs which are namely, Orion Context Broker, STH, MRCoAP and IDAS respectively. The developed vApps integrate with GEs and offer a solution for a respective agriculture scenario. Here, the sensor or devices generates the data and Orion Context Broker acts as a data distributor. The data is later used by the vApps (Ferreira, Towards smart agriculture using FIWARE enablers., 2017) [46].

The Orion Context Broker assists in the formalization and comprehension of context rules and processes data collected from the sensors. In vProductMon Orion Context Broker formalizes rules and contexts. In vFail, it applies the rules to the data. In vfNegotiation, it describes and process the orders received from customers (buyers). In vOrder, it stores and processes the sensor data (Corista, Description and performance of single hop wireless underground sensor nodes, 2018) [47].

STH-Comet is engaged in storing and retrieving raw historic datasets stored in a repository. It performs the aggregation of information stored based on a specific time interval which helps to eliminate unwanted data. It offers competitive testing choices by providing its nodes and networks (Corista, Description and performance of single hop wireless underground

sensor nodes, 2018) [47]. vOrder merges all the sensor information and computes probabilistic metrics like average, variance, and standard deviation.

MRCoAP Enabler adheres to the CoAP communication protocol, which is used to connect low-powered devices like sensor nodes and actuators. These sensor nodes and actuators are responsible for gathering the data from the field (a place where it is installed) and passing the commands for the operation to be done. This MRCoAP Enabler is not required when the devices could communicate with internet protocols. IDAS Enabler manages the devices installed in the field. IDAS also plays a role as an interface between the Orion Context Broker Enabler and devices.

Each of the GEs is connected by the vf-OS proxy communication method as mentioned in Figure 10.1. To use an Enabler, each application first communicates with the vf-OS platform which offers access to the required GEs services. Based on the Enablers, the communication is done by different standard IoT protocols like NGSI and REST, thereby accomplishing an interoperable system.

10.4 Role of AI and IoT in Agriculture: Smart Farming

Smart farming is the future of agriculture (Katiyar, 2021) [37]. The purpose of smart farming is to improve the quantity and quality of products by optimizing human labor. It is a revolutionary concept that encompasses modern technologies such as IoT, artificial intelligence, robotics, and drones to yield efficient farm management. The benefit of integrating the latest tools is to monitor farm situations and take strategic actions accordingly (Katiyar, 2021) [37].

Artificial intelligence technologies are beneficial in the field of agriculture by improving the efficiency of conventional methods of farming and reducing the drawbacks handled by traditional farmers. There are several instruments and technical devices based on AI which are developed to optimize agricultural requirements. These technologies could lead to improved success rates in areas such as pesticide control, soil testing, irrigation management, plant disease treatment, storage management, weed control etc. (Mathushika, Smart Farming Using Artificial Intelligence, the Internet of Things, and Robotics: A Comprehensive Review, 2022) [40]. AI can also be useful in the field of agriculture to alleviate the environmental issues

caused due to adverse agricultural activities, such as uncontrolled irrigation, massive usage of pesticides, and water pollution. Figure 10.3 summarizes the latest technologies in the field of agriculture.

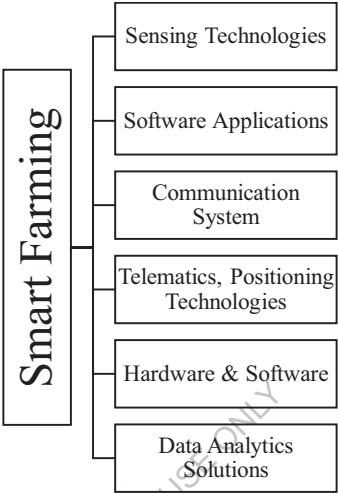


Figure 10.3 Latest technologies in agriculture (Katiyar, 2021) [37]

IoT plays a significant role in making this application “smarter” by utilizing sensor-actuator interaction (M. Jeyaselvi, IoT Based Smart Agriculture, 2022) [43]. One of the major benefits of IoT is its ability to efficiently collect data, allowing for a better understanding of various applications. IoT sensor technology offers better support, enabling farmers to map their fields for more effective monitoring (P. Abdul Hafeez, 2022) [58]. There is a wide range of areas in agriculture that depends on IoT sensor technologies for improving soil quality, and plant phenotyping. These sensor technologies enhance crop quality and plant growth which thereby improves the productivity of agriculture. Farmers can utilize sensors to measure crucial environmental factors such as humidity and temperature, which significantly impact agricultural output. There are different applications in agriculture utilizing IoT such as disease detection, automated irrigation, intelligent greenhouse system, precision farming, and so on. Figure 10.4 depicts how IoT technology is used in the field of agriculture (P. Abdul Hafeez, 2022) [58].

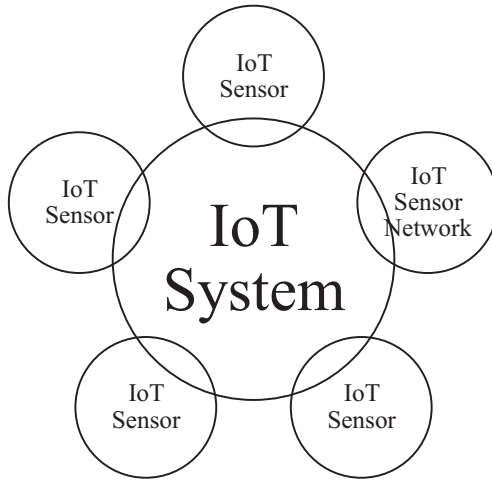


Figure 10.4 IoT technology used in agriculture (P. Abdul Hafeez, 2022) [58]

10.5 Applications of Smart Agriculture

Smart agriculture, using artificial intelligence, has a wide range of applications that helps farmers in improving productivity through crop monitoring, pest control, seed propagation, soil monitoring, reduction of manual labor, harvesting, resource optimization, storage, packaging, and nutrition supply management (Katiyar, 2021) [37]. The Internet of Things and Artificial intelligence could convert traditional farming methods into smart agriculture. Some of the applications of smart agriculture are explained below in detail.

10.5.1 Precision Agriculture

Precision agriculture is an effective agricultural process that attains high efficiency and productivity by integrating conventional agricultural technology with artificial intelligence and IoT (L. -B. Chen, 2022) [59]. It is convenient to mitigate the faults and produce an efficient agricultural system through these methods. Utilizing precision agriculture methods allows for

preparing the land for planting, optimizing crop placement, maximizing vegetation growth across the entire field, and detecting pests and diseases at an early stage with optimal use of time, resources, and inputs. In the agriculture industry, the four main aspects to consider are fertilizers, water management, pesticides, and ensuring high-quality produce (Rajamohan, 2022) [60]. Precision agriculture is the key element of automation around smart agriculture. Precision agriculture uses various sensors and software to enhance crop productivity. As the existing techniques couldn't satisfy the increase in the demand for food, agriculturists are currently relying on the latest innovative and cost-efficient systems. In (Rajamohan, 2022) [60], the authors focus on image-processing techniques by using geospatial images obtained through drones, robotics, and sensor technologies. Image processing acts as an efficient method to evaluate agricultural factors within a short period of time. Figure 10.5 represents the different steps involved in precision agriculture.

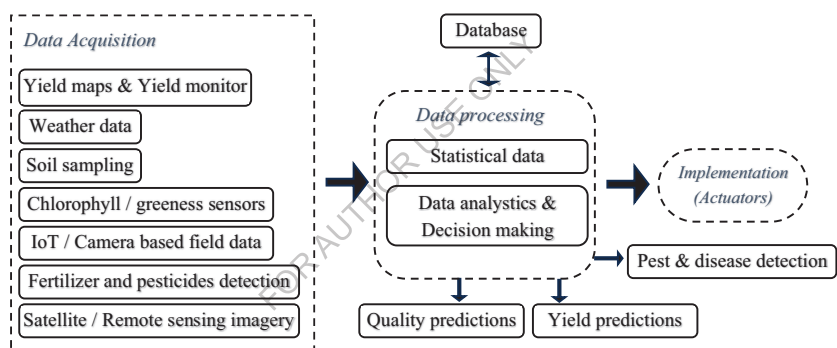


Figure 10.5 Steps involved in precision agriculture (Rajamohan, 2022) [60]

The authors in (Rajamohan, 2022) [60] have used various classifiers to classify the soil type and the accuracies of different algorithms are compared which is shown in Table 10.1. From the table, CNN gives a higher accuracy rate of 98.72% followed by 7-class SVM. The result also proves the significance of image processing techniques in the agriculture industry. In (L. -B. Chen, 2022) [59], an inspection system for detecting orchid growth in greenhouses was developed for precision agriculture. Apart from regulating the environmental conditions for orchid growth, the authors devised a self-supervised learning approach to distinguish different orchid types. This system aids in effective management tailored to the specific orchid

type. The system makes use of IoT technology which transfers the environmental information gathered by sensors to the administration management and cloud monitoring platform. The sensors import the images of the orchid’s growth status to the AI computing module to verify the growth status and sends back the information to the cloud monitoring system. For the classification purpose, the researchers have used ResNet-50 architecture, which resulted in an accuracy of 98.6%. Figure 10.6 depicts the overall training process as part of the self-supervised model.

Table 10.1. Accuracy comparison of various types of algorithms (Rajamohan, 2022) [60]

Classifier	Accuracy (%)
Linear Regression	84.9
Multi-class SVM	91.37
7-class SVM	95
CNN	98.72
ANN	90.32
Decision tree	94.3
Quadratic Regression	86
PCA	91
BPNN	89.7

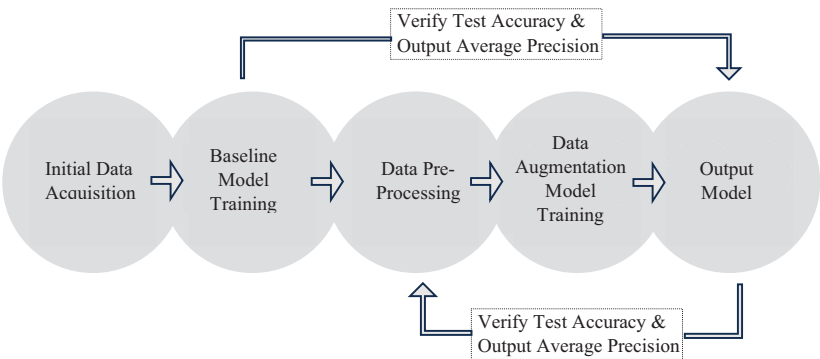


Figure 10.6 Overall training process of model (L. -B. Chen, 2022) [59]

10.5.2 Plant disease detection

Recent developments in computer vision have significantly improved the capabilities of detecting plant diseases, expanding the applications of computer vision in the field of smart agriculture. In (J. Thirunavukkarasu, 2022) [61], the authors have proposed an innovative approach that combines Variational Autoencoder (VAE) and Convolutional Neural Networks (CNN). This approach was used to detect the ‘Bacterial Spot’ of the plant using the images of leaves. This approach attained a test accuracy of 98.85%. In P. Qu et al. [62], the researchers developed a multi-layer intelligent greenhouse system with electrical and cloud systems along with a deep learning algorithm. They used the YOLOV4-Tiny-based deep learning algorithm to detect rose deficiency and other insect pests. This system provided a high degree of automation with a minimal cost and increased crop productivity. The authors (G, Gayathri, & N, 2022) [63] proposed a deep learning technique to classify different species of crops and used the Support Vector Machines (SVM) model to classify the healthy and unhealthy plants using the images of leaves and obtained an accuracy of 99.56%.

The researchers in (H. Abid, 2022) [64] created an autonomous system for detecting various types of pests using a deep learning technique. They used RetinaNet which is an object detector and remodified as PestinaNet for the detection of pests. The entire process of their system is illustrated in Figure 10.7. In (Yadhav, Senthilkumar, Jayanthi, & Kovilpillai, 2022) [65], the authors trained a CNN model to detect plant diseases and achieved an accuracy of 98.10%.

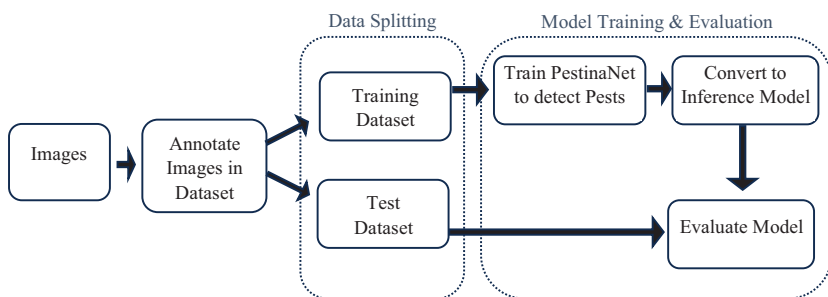


Figure 10.7 Flow diagram of PestinaNet system (H. Abid, 2022) [64]

10.5.3 Crop prediction

The prediction of different types of crops before cultivation is based on the historic data of climatic or weather conditions, previous crop yield, and soil conditions. In (T. Kavitha, 2022) [66], the researchers provided a solution for the farmers to make decisions easier to cultivate suitable crops based on the conditions mentioned above. To forecast crop outcomes, they employed the Random Forest (RF) algorithm and identified the appropriate fertilizer for enhancing crop productivity across various crop and soil types. The authors of (J. Mathew, Crop prediction and Plant Disease Detection using IoT and Machine learning, 2022) [67] used other factors such as rainfall and temperature to predict the type of crops using machine learning algorithms and IoT.

10.5.4 Towards Smart agriculture system using FIWARE

FIWARE is an open-source framework that accelerates the development of smart systems (FIWARE, 2022) [68]. FIWARE simplifies IoT by establishing data management standards, transforming Big Data into valuable insights, and maintaining data control. It plays a crucial role in expanding IoT platforms across various sectors, including Smart Cities, Smart Water, Smart AgriFood, and Smart Energy. (J. A. Barriga, 2022) [69].

FIWARE enables the development of a smart AgriFood system that is cost-efficient, user-friendly, and has interoperability (FIWARE, Smart Agrifood the New Revolution in Farming, 2022) [70]. One of the main advantages of FIWARE is its reusability. The major elements of FIWARE are enablers which consist of generic and specific enablers (Corista, Description and performance of single hop wireless underground sensor nodes, 2018) [47].

Generic Enablers (GE) are built for any general purpose and are not dependent on any domain area. Meanwhile, Specific Enablers (SE) are designed for industrial use such as in agri-food or manufacturing areas. The implementation of FIWARE is based on a different set of layers and consolidated elements such as (a) Interface to robotics, IoT, and third-party systems, (b) Core management (c) Context analysis, processing, and visualization (d) Data/API management (J. A. Barriga, 2022) [69]. There are several other tools that support each layer which comprises Context Broker, IoT Broker, and Complex Event processing. Orion Context

Broker is the core of FIWARE which is a generic enabler that consolidates information from sensors, drones, and other machines along with other information systems and smart solutions interoperability (FIWARE, Smart Agrifood the New Revolution in Farming, 2022) [70]. Figure 10.8 depicts the architecture for IoT-enabled smart agriculture solutions featured by FIWARE.

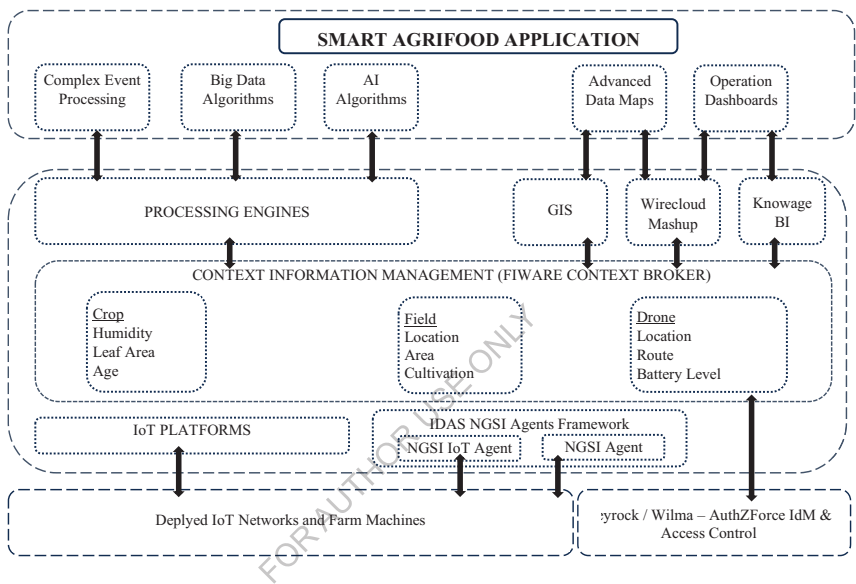


Figure 10.8 *FIWARE reference architecture for smart Agrifood (FIWARE, SMART AGRIFOOD THE NEW REVOLUTION IN FARMING, 2022) [70]*

The architecture of the Smart farm management system depends on the vision “system of systems” (FIWARE, Smart Agrifood the New Revolution in Farming, 2022) [70] which is illustrated in Figure 10.9.

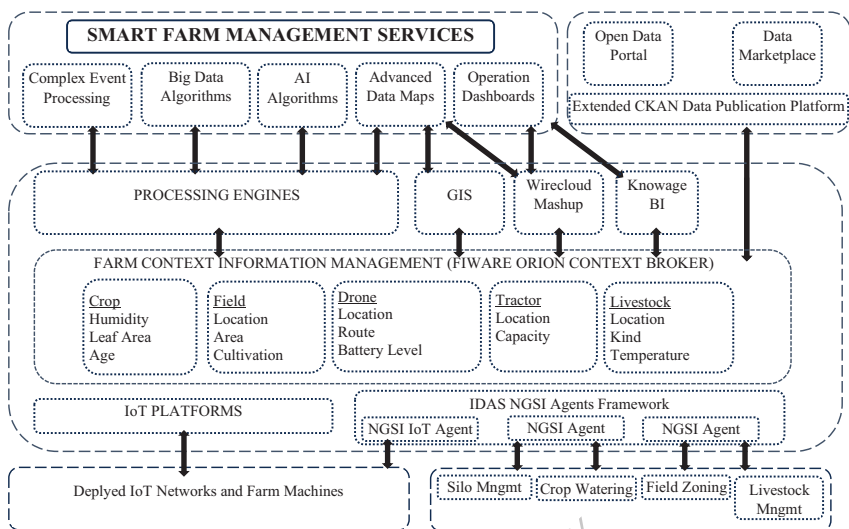


Figure 10.9 FIWARE reference architecture for smart management system (FIWARE, Smart Agrifood theNew Revolution in Farming, 2022) [70]

Table 10.2 Software Operating System vs vf-OS (CORDIS, 2016) [71]

Software Operating System	Virtual Factory Operating System (vf-OS)
Kernel	Virtual Factory System Kernel (vf-SK)
Processor, Memory, Internal Bus	Framework, Generic Enablers, Manufacturing Enablers
I/O	Virtual Factory Application Programming Interface (vf-API)
Interfaces, Peripherals, Device Drivers, APIs	Devices Drivers, APIs Connectors, Security & Data Access
File and Data handling	Virtual Factory Middleware (vf-MW)
Interfaces	Data Infrastructure Middleware, Data Storage, Data Harmonization, Data Analytics

Table 10.3 Agricultural Scenario Steps and Explanation (Laura Schmitt Olabisi, 2020) [72]

Steps	Explanation
1	Fruit harvest, controlled by IoT Devices
2	Fruit selection, separation (manually or automatically)
3	Farmer track of things (Amount and quality of fruit, faults and failures, spare boxes, etc.)
4	Buyer selection of a type of fruit, weight, and farmer
5	Placing order
6	Monitored transport to ensure successful delivery
7	Monitoring production and checking for failures

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11.1 Introduction

An innovative idea known as "smart cities" seeks to better manage urban areas while preserving the environment, enhancing sustainability, and improving the quality of life. The administrations and authorities also give top priority to urban development with a focus on tackling climate change. To accomplish this goal, several international organizations and governments have collaborated and have started numerous projects and initiatives that have encouraged cities to become more eco-friendly.

A new goal for sustainable development is set by the UN. They have established 17 global objectives, of which 7 were directly related to environmental protection. The environmental issues include concerns about clean water and sanitation, accessible and clean energy, sustainable cities and communities, responsible consumption and production, climate action, life below water, and life on land. The countries involved with this initiative have set a target deadline of 2030 for completing the task to accomplish those goals (Pedro Yepes, 2021) [73].

To maintain sustainable development, a technology-based company by the name of HOPU has attempted to create some green zone innovations in the city of Cartagena. The city of Cartagena, in partnership with a technology company called Human Oriented Products for Smart Cities and Industry (HOPU), is dedicated to embracing sustainability through smart systems. They aim to use advanced technologies to solve real-world problems and enhance the quality of life for their citizens. In their current initiatives, they are concentrating on developing innovations related to environmental sustainability using technologies such as AI, IoT, and data quality.(HOPU, 2021) [74]. These technologies are employed to support Cartagena in achieving the objectives of the European Green Deal and Sustainable Development Goals, leading the city towards an environmentally sustainable model.

The Municipality of Cartagena has experienced a severe climate crisis over the years, largely due to water shortages, with desalination being a major contributor. The requirement of effective planning of water resources became necessary. Garden irrigation is one of the municipal services that uses the most water, but it is also a vital service that is required for

protecting the urban environment. In Cartagena, the city's adaptation to climate change and sustainable energy is prioritized highly, with the top priority being green spaces.

In this context, the implementation of IoT systems is vital for managing water resources and mitigating risks. However, it's important to recognize that integrating these systems across various sections of Cartagena is essential for achieving optimal performance. These devices harness diverse data to go beyond mere irrigation control and predict changing conditions effectively. Essentially, they enable the use of new technologies to manage public spaces more efficiently.

As a result, the Cartagena City Council aims to transform the city digitally. This transformation will involve the integration of technologies such as AI, Big Data analysis, and others. To improve the management of available resources, intelligent irrigation systems have been deployed in the city's green areas. This has led to a reduction in excessive water usage and more efficient maintenance of public parks and gardens.

11.2 Technologies Used

Intelligent Irrigation Systems are advanced systems that make use of various technologies to perform their functions. They utilize a network of sensors to gather data about soil moisture, temperature, humidity levels, and other environmental factors. These sensors offer real-time information about soil conditions, enabling precise decisions on when and how much water to apply. Intelligent Irrigation Systems often use IoT devices such as weather stations, soil moisture sensors, and irrigation controllers that can be remotely controlled and monitored via a smartphone or computer. They also use weather forecasting technologies to predict upcoming weather conditions and adjust watering schedules accordingly. This helps to conserve water and prevent over-watering. Intelligent Irrigation Systems use machine learning and AI algorithms to analyze data from sensors and other sources and make predictions about future watering needs (Balaji & Ganapathy, 2022) [75]. After the development of the final product, users receive personalized irrigation recommendations based on weather data and their garden's specific soil characteristics.

The algorithms created for intelligent irrigation primarily rely on data from meteorological stations and evapotranspiration characteristics of the terrain. Water consumption is determined by combining this data with measurements from green spaces. This data forms the basis for intelligent irrigation programs, digital services, dashboards, and decision support tools, which incorporate Big Data, AI algorithms, and BI. It also includes data on weather predictions, such as rainfall and other weather conditions. This solution simplifies the process for garden and park administrators to gather, analyze, and assess environmental data. AI plays a vital role in automating decisions regarding watering schedules, the amount of water to be applied, and the choice of irrigation methods. This reduces the need for human intervention, saves time and resources, and ensures that plants receive the correct quantity of water. Such systems that use AI can be remotely monitored and controlled using mobile applications. This allows farmers to manage their irrigation system from anywhere, using real-time data and AI algorithms to make informed decisions about watering schedules. Moreover, by employing AI to optimize watering schedules, Intelligent Irrigation Systems can help conserve water by minimizing water wastage and ensuring that plants receive the right amount of water at the right times. This is especially significant in regions with limited water resources or frequent drought conditions.

11.3 Architecture

The Intelligent Irrigation System, based on IoT, installed in the parks and gardens of Cartagena, offers autonomous and real-time management of water resources by enabling control of the irrigation schedule and adaptability. The Cartagena city can effectively manage irrigation using this smart system's robust, integrated, and long-term solution, which is based on AI algorithms and accurate real-time data. By cutting back on excessive water use and significantly enhancing urban green spaces, the solution sets up a sustainable irrigation system to meet the needs of all parks and gardens.

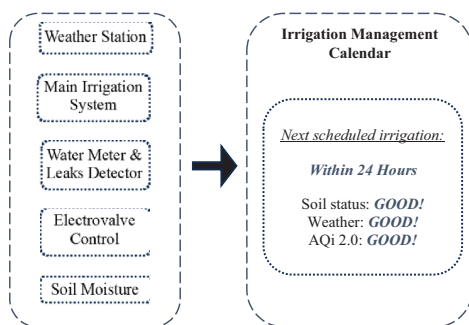


Figure 11.1 Irrigation System using Firware (Pedro Yepes, 2021) [73]

This system collects information and data from various sources to analyze and determine the required amount of data for a green area:

- Weather stations with sensors for evapotranspiration, ultra-violet radiation, humidity, wind, air temperature; and rains.
- Soil moisture sensors that continuously track electrical conductivity (EC), temperature, and humidity.
- A schedule to manage irrigation based on the types of soil, plants, etc.

One of the features of the Intelligent Irrigation System based on FIWARE IoT is a management interface that provides an excellent view and level of control over the installed irrigation components. This serves as a base and gives access to the system administrators regarding irrigation schedule as well as information on the following:

- Locations of multiple sensors
- Calendar scheduling
- Check alarms
- Leak detection in real time
- Water consumption along with its other features.

By enabling adequate water resource management in all the parks and gardens, Intelligent Irrigation System based on FIWARE IoT offers a solution. The FIWARE platform ecosystem is fully compatible with the irrigation scheduling calendars that control it. The Intelligent Irrigation System based on FIWARE IoT utilizes FIWARE technology because,

when combined with its standards-based context data management, it ensures complete compatibility and integration of data from both the internal Cartagena sensors and the external sensors. According to FIWARE smart data models, all the data collected during the monitoring process should be integrated into the smart city platform following a standardized framework that can be shared and combined with other data. The integration of multiple data sources allows for the creation of a data storage repository with data from various origins. This enables the city to employ analytical methods that leverage and enhance the integrated data within the platform using Big Data, machine learning, and artificial intelligence algorithms to extract valuable insights.

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Intelligent Irrigation Systems in parks and gardens operate by utilizing sensors and other technologies to optimize watering schedules and minimize water wastage. Here are the basic steps involved in how Intelligent Irrigation Systems work in parks and gardens:

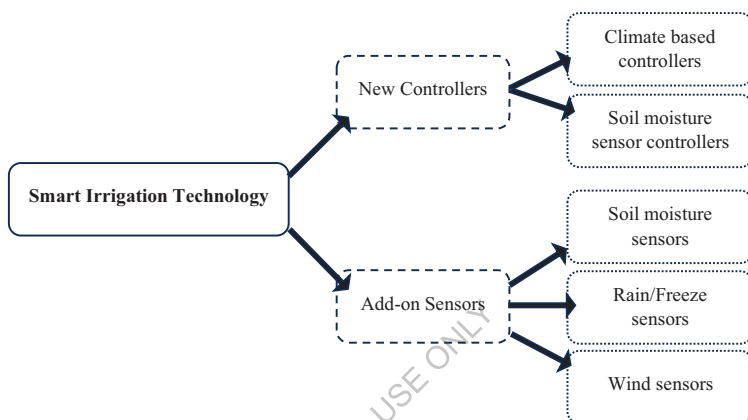


Figure 11.2 Overview of smart irrigation technology. Oklahoma State University (Malarie Gotcher, 2017) [76]

Intelligent Irrigation Systems uses various add-on sensors to retain data on moisture levels in soil, humidity, temperature, and other environmental factors. The collected data is then transmitted to a central controller, which analyzes the data and determines the amount and time to water. The central controller uses algorithms to analyze the data collected from the sensors and other sources to determine when to activate and deactivate the irrigation system (Frąckiewicz, 2023) [77].

By analyzing the data collected by the sensors, the system can determine the best time and amount of water to apply to the plants. This helps to prevent over-watering and under-watering, which can lead to minimum wastage of water and efficient damage control. Intelligent Irrigation Systems can also adjust watering schedules based on weather forecasts. For example, if rain is predicted, the system can delay watering to avoid wasting water.

Many Intelligent Irrigation Systems have also come with mobile applications that allow users to remotely monitor and control the system. This allows users to adjust watering schedules and check the status of the system from anywhere.

11.5 Advantages

The following advantages have resulted from the Intelligent Irrigation System based on FIWARE IoT implementation in the city of Cartagena:

- Automatic implementation of the irrigation calendar ensured that only the necessary resources were used for irrigation, effectively maintaining the gardens, and keeping the vegetation in top shape in green spaces. This has led to reduced water supply costs, prevention of soil erosion, and improved pest control, as it helps detect leaks and prevents excessive irrigation.
- Following the installation of the Intelligent Irrigation Systems based on FIWARE IoT, ground-level CO₂ emissions and water consumption have both decreased by up to 30%.

There has also been a significant decrease in the amount of chemicals that are filtered into groundwater and the coastline, including manures, fertilizers, insecticides, and herbicides.

11.6 Benefits Of Using FIWARE System

The system integrates datasets from the utility, social, and health sectors, providing a data-driven tool for data analysis, well-organized data collection, and urban planning, all supported by Artificial Intelligence (AI) which were leveraged by Cartagena city.

A further benefit of FIWARE was its improved capacity to comprehend sociology, urbanism, and a variety of other cross-sectoral aspects. This approach also offers indicators and conducts analyses to identify optimal solutions. Consequently, it contributes to improved health, a better climate, and a cleaner environment. Creating health-supportive environments necessitates strategic urban planning. Through their various networks, FIWARE has actively supported HOPU as a FIWARE-ready device, helping to grow their market (Open, 2020) [78].

Following the successful implementation of the Intelligent Irrigation System based on FIWARE IoT in Cartagena's green spaces and realizing its advantages, including enhanced real-time loss detection, HOPU's primary objective is to extend the system's implementation to governmental bodies, including local administrations. This has led to smarter urban transformations in areas where the process has not yet commenced.

It can be employed to establish irrigation systems that enhance resource efficiency, mitigate water wastage, and prevent crop losses caused by insufficient or excessive irrigation. Farmers can access, analyze, and validate data concerning various factors such as temperature, frost, rainfall, and wind. They can also obtain weather forecasts to update the irrigation schedule by correlating data with real-time weather conditions provided by monitoring stations.

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12 Smart Systems Using Artificial Intelligence in Sports - Football

12.1 Introduction

With around 275 million players worldwide, football is the most popular sport in the world (Connor, 2022) [79]. Multiple leagues are held throughout the year, such as Championships of every country, FIFA world cup, Champions League, and the Europa League. Football is watched by billions of people across the world, whether they are seated in the stadium or at home. The passion for the sport remains the same in every corner of Earth, with FIFA showcasing the world's best talents. The FIFA World Cup being the most-watched sporting event globally. FIFA estimates that over 5 billion people will be following the tournament. In the 2018 FIFA World Cup, an impressive 3.572 billion viewers tuned in to watch the pinnacle of world football, according to official broadcast coverage audience data [80].

This kind of enormous audience indeed generates a booming economy for the sport, which resulted in the potential of technology in many fields in the world of football, including game analysis, computer vision, and artificial intelligence. Over the past decade, post-match analyses have been more and more in demand. The team coaches required statistics to set up new strategies against the opponent. Automation of tracking and detecting objects on the field has made some fantastic technologies like VAR (Video Assistant Referee) and SAOT (Semi-automated off-side technology) possible. Ever since AI become a part of this sport, the accuracy of the facts such as ball possession, goal line detection, shot classification, the accuracy of decisions, etc., has increased (The future is now: FIFA bringing performance analytics to a whole new level, 2021) [81].

12.2 Artificial Intelligence in Football

- **Performance Analysis:** AI is used to examine a wide range of data, such as player tracking information, game statistics, and video evidence. Machine learning algorithms may find patterns, evaluate player performance, and offer coaches and analysts useful

information. Systems based on artificial intelligence can aid in player development, game strategy, and team strength and weakness analysis.

- **Biomechanics and player tracking:** Artificial intelligence (AI) algorithms can evaluate player tracking data from wearables and cameras to offer in-depth insights into player movement, physical performance, and injury prevention. Utilizing this information can help to reduce the risk of injuries, track player load, and improve training regimens.
- **Video Analytics-** AI-powered computer vision algorithms can automatically analyze video of games and practice sessions through a process called video analytics.
- **Player Recruitment and Scouting:** AI algorithms can assist in player recruitment and scouting by analyzing player data and identifying talent. By examining various performance metrics and characteristics, AI systems can help clubs discover promising players who may have gone unnoticed, making the scouting process more efficient and comprehensive.
- **Match Predictions and Game Simulation:** AI models can analyze historical match data and player performance to make predictions about upcoming matches. These predictions can be used by analysts, broadcasters, and betting companies to provide insights or inform their decision-making processes. Additionally, AI-powered game simulations can be used to simulate different scenarios and predict potential outcomes.
- **Fan Engagement and Experience:** AI technologies can enhance fan engagement by providing personalized content, real-time statistics, and interactive experiences. AI-powered chatbots and virtual assistants can interact with fans, answer questions, and provide updates. Furthermore, AI algorithms can analyze social media data to understand fan sentiment and preferences, helping clubs and organizations tailor their marketing and engagement strategies.
- **Referee Assistance:** AI technology, such as video assistant referee (VAR) systems, can be used to support referees in making critical decisions during matches. VAR systems use AI algorithms to analyze video footage and provide referees with additional information or alerts for potential fouls, offside calls, or handballs.

12.2.1 VAR – Video Assistant Referee

VARs possess the capability to oversee the main referee's application in accordance with the standard rules of football. The objective is to enhance fairness and support the official referee's decision-making process in the following scenarios:

- Goals
- Penalty kicks
- Straight red card incidents and
- Mistaken identity when awarding a card.

During a game, the team assistant referees constantly screen video captured by multiple cameras and analyze the stadium's sensors (Tsokwa, 2019) [82]. To rectify any mistakes made by the main referee in uncertain circumstances, the match official has the option to either take the VAR team's input to decide or examine the video footage on monitors placed alongside the field. Since the implementation of VAR, the precision of these decisions has improved, rising from 93% to 98.9%. (Frąckiewicz, 2023) [77].

12.2.2 SAOT – Semi-Automated Offside Technology

The FIFA authorization has announced that SAOT will be used at the FIFA World Cup 2022 in Qatar (Semi-automated off-side technology to be used at FIFA World Cup 2022, 2022) [83]. The SAOT system will offer a support tool for the video match officials and the on-field officials to help them make faster and more accurate off-side decisions during a live game. The official match ball, "AI Rihla Pro" by Adidas, uses an Internal Measurement Unit (IMU) sensor, which is positioned in the center (inside) of the ball. The sensor sends ball data 500 times per second to the video operation team, allowing them to note the precise detection of the kick point. The stadiums are well-fitted with 12 different tracking cameras to track the ball and 29 data points of each player 50 times per second (Semi-automated off-side technology to be used at FIFA World Cup 2022, 2022) [83]. The 29 data points represent the player's limbs that are relevant to make an off-side call. By combining the ball and limb data and applying AI, the SAOT system alerts the match officials, who further investigate the video and forward the call

to the official referee. This has helped the official team to make more accurate off-side decisions in a shorter period.

12.2.3 Goal-Line Technology

Goal-Line Technology (GLT) was first implemented in 2014 and is a technical means of determining whether the whole ball has crossed the goal line or not (P. Shah, 2014) [84]. The system uses 14 Hawk-Eye high-speed cameras mounted under the stadium roof, automatically tracking the ball once it enters the range (Technology, 2022) [85], (R. Psiu, 2014) [86]. The information is sent to the video operation team within one second. It ensures that the signals are transmitted only to the official referee with a vibration in the watch, which indicates a goal. GLT has proven to be more and more valuable with time, making the game even more exciting.

12.3 Limitation of Artificial Intelligence in Sports

Hight cost:

The supporting hi-tech gadgets that incorporate diverse set of AI technologies in football, tennis and other very popular sports are costly as they need a lot of maintenance and improvement to fulfill higher level of sophistication in the assigned tasks. Every year the rules change, and thus, on-field technologies need frequent updates.

Increased dependency on machines

With technology's incremental usage and involvement, people tend to become more dependent on smart technologies delivered through various handheld devices. If this continues, not only football but all sports globally will become more and more dependent on AI smart technologies. This is becoming a controversial issue with many mainstream sport fans and supporting organizations. This is why the advancement of AI technologies must be regulated by the organizations in charge. The European Union is taking the lead on that realm.

12.4 Future Scope of Artificial Intelligence in Football

12.4.1 Possible 11 Prediction

An AI can be trained with big data that contains the performance data of all the registered players in a team. The physical and tactical abilities of each player will determine if he/she/they are to be selected in the playing 11 or not, depending on the difficulty level of the upcoming match.

12.4.2 Fan Experience

Virtual Reality (VR) can be provided to the fans in the stadium, which will automatically track the ball and the players. This will enhance the overall experience as it will be possible to zoom in and out as per personal choice. The live stats of the game, such as ball possession, number of shots, each player's performance, off-side line, wind direction, instant replay, and much more.

13 Smart Parking Systems

13.1 Introduction

In this paper, the parking smart system is explained, starting with the utilization of image processing to detect gaps in the parking lot (Al-Kharusi, 2014) [87]. Then, the classification of the parking is discussed using training data (Gandhi, 2016) [88]. Subsequently, the use of the (SVM) function to enhance safety (T. Lin, 2017) [89] is illustrated. Finally, the process of identifying an available parking space and determining the route to it is presented using Python code and accompanying graphs.

13.2 Classifying Parking System Using Image Processing

The process begins by selecting a camera, either a webcam or an IP camera (Internet Protocol Camera), capable of transmitting images to a Neural Network System. The system analyzes each image from the video feed to determine if it contains a parking gap or an available parking space. When using a webcam, it is typically connected to a computer, which then relays information to a remote server. An IP camera can directly transmit data to remote machines. While both options are connected to parking lot objects, an IP camera tends to be more expensive. To validate the effectiveness of the solution, an implementation team might initially opt for a webcam. Once the project is approved and established, it may become apparent that an IP camera is a more suitable long-term choice. A webcam is more cost-effective for the initial stages of the parking system project. The initial step involves measuring the distance between the cars to identify available parking spaces. Once the trained data is available, the next step is to resize the trained data (image) before employing the neural network to detect the parking spaces within the parking lot and assess the parking lot's occupancy rate. Following that, the machine learning module is applied to the trained data. If the module functions effectively, it should be tested on random images sent from a random function. It's important to note that some of these images may not be actual images. Now that the parking system has been trained to distinguish a full parking lot from a parking lot with

available space, once an available parking lot has been found, an SVM (Support vector machine) takes over to enhance the working of the parking system.

13.2.1 Adding An SVM Function

Some smart parking system uses SVM function, especially in big parking lots, to help the drivers to find the right and shortest path for the parking space inside the parking lot. This will help save time for the drivers and enhance safety, especially when multiple drivers are using the parking lot simultaneously. The SVM function evaluates three main criteria to determine the parking space inside the parking lot: the shortest trip, the fastest trip, and the traffic.

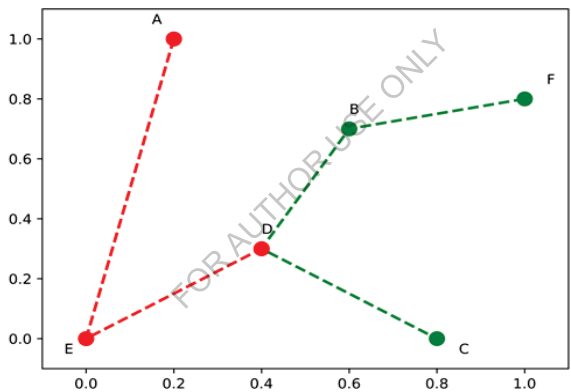


Figure 13.1 SVM function to find shortest path (Sepehr Valipour) [90]

This image shows how the SVM function is used to find the shortest path inside the parking lot, and then suggest the ideal path that the car driver can use (which in green color) to reach the parking space.

14 Smart Systems in Aerospace

14.1 Introduction

Recent exploratory studies have shown that aerospace industry could generate close to 100 million terabytes of data per year towards end of this decade because of digitalization across different industries (within aerospace). With the advent of technology in the data storage and processing, aerospace manufacturers are now looking into the potential of the Data Science in optimizing the design, development, production, of aerospace products and processes. Additionally, airline operators are looking to improve operational reliability, driving down maintenance costs and increase in operational safety (see Figure 14.1).

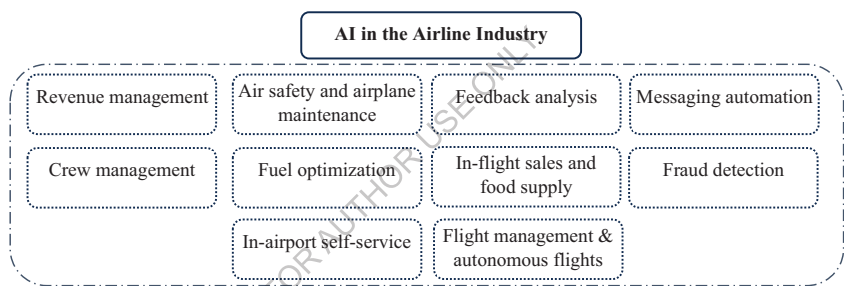


Figure 14.1 AI Use Cases in Airline industry (10 Ways Airlines Use Artificial Intelligence and Data Science to Improve Operations, 2021) [91]

For this purpose, a large-scale effort is on-going in the aviation industry to adopt the AI/ML technology, due to which Predictive Maintenance, powered by AI, is quickly becoming the most important strategy across Aerospace. As newer Aircrafts are being equipped with more sensors, machine learning based Diagnostics and Prognostics techniques are becoming increasingly popular compared to conventional approaches in developing Predictive Maintenance solutions (Partha ADHIKARI) [92].

Autonomous Systems: AI facilitates the creation of autonomous aerospace systems like unmanned aerial vehicles (UAVs) and autonomous spacecraft. These systems benefit from the real-time decision-making, navigation, and environment-adaptation capabilities of AI algorithms.

Flight Control Systems: AI is incorporated into flight control systems to increase pilot aid, boost flight path optimization, and improve aircraft stability. AI systems can examine flight data, anticipate future problems, and offer the best control inputs.

Aircraft Maintenance and Predictive Analytics: AI is employed to monitor aircraft health, detect anomalies, and predict maintenance needs. Machine learning algorithms can analyze sensor data, maintenance records, and historical data to identify patterns and predict component failures, reducing unplanned downtime and improving maintenance efficiency.

Air Traffic Management: AI plays a crucial role in air traffic management systems, enabling efficient route planning, congestion management, and collision avoidance. AI algorithms optimize flight trajectories, predict airspace congestion, and help air traffic controllers make informed decisions.

Weather Prediction and Optimization: AI is used in weather prediction models for aviation, aiding in more accurate forecasting of weather conditions along flight routes. This helps pilots and airlines optimize flight paths, minimize fuel consumption, and enhance safety.

Space Exploration: AI supports space exploration missions by assisting in data analysis, spacecraft navigation, and decision-making. AI algorithms can process vast amounts of data from space probes and satellites, helping scientists discover new insights and plan future missions.

Satellite Operations: AI is employed in satellite operations for tasks such as orbit control, data processing, and communication optimization. AI algorithms can autonomously control satellite functions, manage data transmission, and perform on-board data analysis.

Airline Operations and Customer Service: AI-powered systems are used in airline operations and customer service to improve efficiency and enhance the passenger experience. AI chatbots provide automated customer support, AI algorithms optimize flight scheduling and crew assignment, and AI systems analyze customer data for personalized services.

14.2.1 Product Design and Development

Aerospace industry being safety critical industry, designing a simple component is associated with immense complexity. A designer must account for many requirements from certification authorities, customers, and the organization itself. The designer must also consider the previous relevant designs, novel designs, lessons learnt, novel ways of manufacturing, selection of supply chain (capability and capacity based on previous interactions), overall cost and quality etc.

Additionally, development engineers must design optimum verification and validation strategies against all the requirements, that involves bench testing or flight testing, assessments, assist designers such that they comply to all the requirements, reporting and certification. An aerospace product contains thousands of such parts with varied complexity and each such part has multiple standards and combinations, which makes aerospace product design and development one of the most complex, time-taking, and expensive projects.

This complexity and the non-linear combination of work factors could be handled instead through a digital virtual assistant and / or a digital twin, powered by artificial intelligence (AI), which leverages real-time data and makes recommendations to the engineer. This recommendation engine could complete tasks much quicker with higher first-time quality (see Figure 14.2).

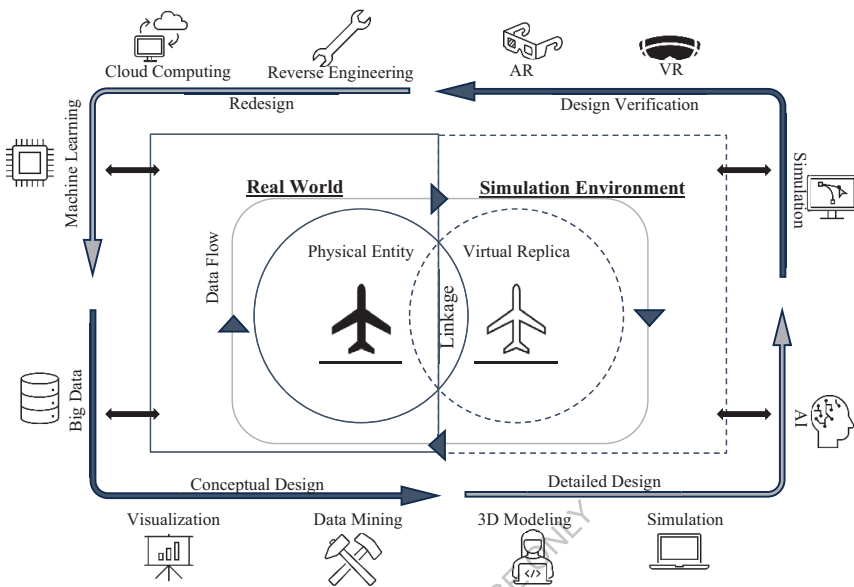


Figure 14.2 Design and Development Lifecycle Schematic (Partha ADHIKARI) [92]

In addition, using the digital twin, the assembly process can be simulated on a computer to validate the design-to-build process through augmented reality, reinforced by predictive analytics. This could expose a new way of implementing customer-driven design changes by understanding the quality, cost, supplier choices and available inventory implications before building the product.

14.2.2 Smart Factory

A factory (manufacturing or logistic) has numerous complex process that involves humans and machines to work seamlessly to achieve desired result. The next evolution of these factories is called a Smart Factory, where most of the repetitive complex processes are automated and self-organized.

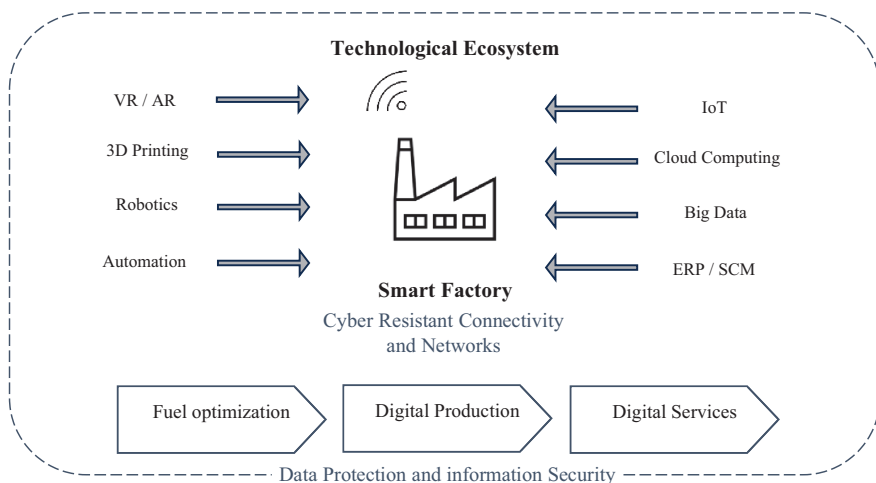


Figure 14.3 Smart Factory Infographic (Adobe Stock, 2023) [93]

This is possible using novel and advanced technologies powered by AI such as Virtual or Augmented Reality (VR/AR), automated additive manufacturing, robotics, image recognition etc. Site-level and business-wide data analytics will further enhance the level of operational effectiveness and insights across the industry.

For example, at Pratt and Whitney's Singapore based Maintenance (Whitney, 2023) [94], Repair and Overhaul (MRO) organization, fully automated ultrasonic measurement and inspection of blade aerofoil wall thickness has been implemented. This produces fast and reliable inspections, helping to free up inspector hours to perform more critical visual inspection tasks (inspection) [95].

14.2.3 Intelligent Inspection

Inspecting a component/system after manufacturing, operation or maintenance is a tedious and time-taking task, which requires highly skilled technicians. Therefore, this visual inspection process can be automated using the image recognition technology.

One of the examples of this technology is Airbus’s Drone and Augmented Reality inspections (inspection) [95]. This technique uses drones equipped with high-definition cameras and a three-dimensional (3D) Augmented Reality (AR) LASER-Imaging Detection and Ranging (LIDAR) technologies, to digitally paint the path around the aircraft and conducts a fly-around inspections taking videos/images. This data is then processed by an application powered by AI to determine the condition of the aircraft surface and propose corrective actions (inspection) [95]. This reduces inspection time and effort, whilst guaranteeing quality and adherence to airworthiness standards and improves safety if the technicians.

14.2.4 Predictive Maintenance

Aircraft operators and OEMs worldwide are encountering significant challenges in improving their ability to meet specified Mission Success Rate (MSR) and Operational Support Cost targets due to unscheduled maintenance, which leads to operational interruptions (OI). Key contributors to OI include the lack of advanced warning of failure events, high fault isolation and troubleshooting overhead, and the absence of integrated and optimized planning for fleet, maintenance, and logistics. So, Predictive maintenance and related technologies are generally seen as potential strategies to address these problems (see Figure 14.4) (Partha ADHIKARI) [92].

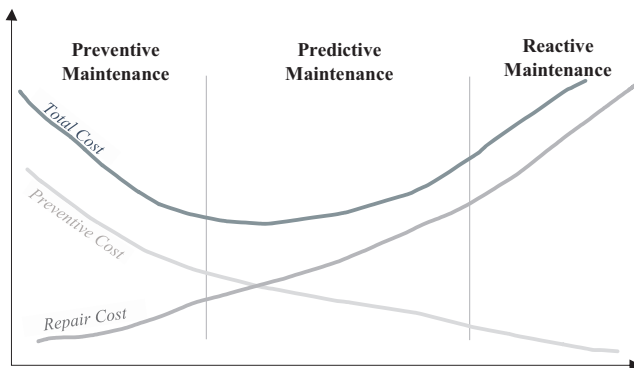


Figure 14.4 Total Costs Associated with Maintenance Actions (The MathWorks, 2023) [96]

As newer Aircrafts are being equipped with more sensors and systems like real-time health monitoring. Machine Learning based Diagnostics and Prognostics techniques are becoming increasingly popular compared to conventional approaches in developing Predictive Maintenance solutions (see Figure 14.5) (Hyunseong Lee a, 2020) [97].

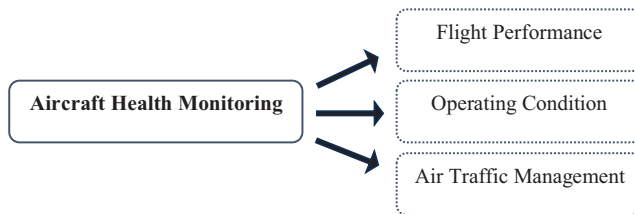


Figure 14.5 Real-Time Aircraft Health Monitoring (Hyunseong Lee a, 2020) [97]

Predictive maintenance provides an integrated solution of assessing present & future health of complete system and derives planning of operation, maintenance, and logistics. With the rapid growth of technologies such as Internet of Things (IoT), AI and Big Data technology, predictive maintenance is becoming smarter day-by-day. Thus, Data-driven and hybrid diagnostics and prognostics solutions are becoming more popular (Partha ADHIKARI) [92]. Aircraft manufacturers (OEMs) collect data from airlines on both scheduled and unscheduled maintenance to assist in their efforts to improve maintenance processes and operational efficiency. This data is then used to develop methodologies to predict potential failure (i.e. Remaining Useful Life (RUL)) that may lead to disruption (The MathWorks, 2023) [96].

Additionally, use of modern techniques such as Digital Twin to predict RUL is under development. Use of Digital Twins reduces the need to rely on probability-based techniques to determine when an engine might need maintenance or repair. Digital Twins are precise virtual copy of the real-world product, which will continuously learn and update itself using real-time data from EHM system. They can also factor in historical data from prior usage.

15 Importance of Ethical Issues in Smart System Development Using AI With Focus on Algorithmic Bias

15.1 Introduction

AI has become a part of daily life and plays a tremendous role in decision making for many businesses and organizations. The development and proper utilization of AI technologies have indeed led to numerous benefits for our society, including improved medical diagnosis and detection, advancements in facial recognition, the emergence of self-driving cars, more effective disaster, and risk management, and much more. These advancements have contributed to economic growth, social development, enhanced security and safety practices, and an overall improvement in human well-being (Siau, 2020) [98].

Alongside pointing out the benefits and great advancements of AI, the researchers started to pay their attention to the ethical issues of AI with a great focus. To identify and determine unfairness in the decision-making process and proposing the implementation of some practices and improvements in such area (Lagioia, 2022) [99]. Ethical guidelines have been extensively researched, yet in many cases, practical implementations of these principles remain inadequately addressed. Many ethical questions related to AI revolve around topics such as the absence of simple explanation, security, and privacy concerns, as well as the historical evidence of data biases in AI model analyses. These issues pose serious risks for the society and users of the systems and thus must be considered and addressed (Siau, 2020) [98].

The complexity of the AI systems and the developing autonomy of their decision-making process are the factors that have been considered since the infancy of the research on the ethical issues in AI. Since AI systems are complex in nature, designers and users of those systems are often faced with the difficulty of determining how and why the system has reached a particular decision, as well as predict its future decisions. The autonomy of the system in the decision making refers to its ability to come to decisions without supervision or approval from the human side (Brendel AB, 2021) [100].

It is important to note that in traditional business or manufacturing environments, ethical issues often arise from the design of systems or processes. Consequently, the causes of unethical behaviors can be attributed to the people involved in the processes, as well as factors

such as negligence, personal biases, and societal biases, among others. However, considering the nature of AI it is evident that some unethical behaviors may not be related the design or intentional actions but by chance or by causes that are hardly controllable in practice (Brendel AB, 2021) [100]. Furthermore, all automation technologies, including AI, must grapple with the well-known "black box" problem, which raises issues of responsibility (Coeckelbergh, 2020) [101].

15.2 AI's "Black Box" Problem

The well-known AI's "Black Box" problem is directly related to the characteristics of most of the AI systems such as lack of transparency and interpretability. Due to the nature of AI, the decisions or predictions made by it cannot be explained in the same sense as human reasoning or the functionality of other ICT systems. The creator or designer of the AI system understands how it works in general, the expected range of output values, its intended purpose, and benefits. However, explaining a particular decision in a specific case may not be feasible, and this is exactly what causes problems of transparency, interpretability, and accountability of AI.

Transparency has been covered by many researchers focused on ethical issues of AI. This is indeed one of the prominent issues. Resolving this matter would significantly enhance the proper use of AI. The importance of the transparency issue can also be extended by its connection to question of accountability [102]. Another point to consider is that commercial confidentiality may contribute to the issue, since disclosing valuable information about the system and its functionality would hinder the competitive advantage of a business and contradict the confidentiality laws (Coeckelbergh, 2020) [101, 102]. While this might be one of the main obstacles for the development of further solutions to tackle the opacity of AI. It is important to understand that transparency does not necessarily imply revealing the code or the exact architecture of the system. The main goal of revealing the system's decision-making process to the relevant stakeholders and regulators without revealing critical confidential information. Thus, the primary focus of the research should be in determining the ways to reveal the "black box" to an extent, which reveals the explanation of the decision without disclosing any important confidential information. This brings us to another question - what

kind of explanation is required and what exact information it should contain? (Coeckelbergh, 2020) [101].

The lack of transparency of AI systems contributes directly to the prevailing issues of bias and discrimination due to the difficulty of tracing their sources.

15.3 Algorithmic Bias

The concerns about Artificial Intelligence systems exacerbating existing biases in society and potentially creating new ones have grown particularly following the exposure of numerous controversial cases related to these issues (Stahl, 2021) [102]. Bias plays a detrimental role in our society since it implies unfair and unjust treatment of individuals and groups/communities (Coeckelbergh, 2020) [101].

Algorithmic bias can be defined in the way proposed by Wooldridge (2021): “The possibility that AI systems will exhibit bias when making decisions, either as a result of being trained on biased data sets or because of poorly designed software” (Wooldridge, 2021) [103]. Such definition already pinpoints the ways bias can originate in AI systems, which can occur at various stages of technology development, from design to application. Bias can emerge during the selection stage of the data set that will be used for the model, in the training dataset itself, during the stage of developing and optimizing the machine learning model, as well as in the process of making decisions based on the received results.

Furthermore, considering that our society and everyone are naturally prone to bias might, intentionally or unintentionally act on it. The sources of bias and discrimination in AI also encompass the human behavior: from the biases imbedded in the AI’s designer (or group of designers) to the whole society (Coeckelbergh, 2020) [101], (Wooldridge, 2021) [103].

Political philosopher Michael Sandel, Anne T. and Robert M. Bass Professor of Government stated that “*Part of the appeal of algorithmic decision-making is that it seems to offer an objective way of overcoming human subjectivity, bias, and prejudice..*”, “*But we are discovering that many of the algorithms that decide who should get parole, for example, or who should be presented with employment opportunities or housing ... replicate and embed the biases that already exist in our society*” (Pazzanese, 2020) [104].

This statement represents the major ethical concern for the misuse of AI: machine learning algorithms can preserve, support, and amplify the already existing biases and can be seen from a significant number of cases brought to the public attention and under scrupulous scrutiny. For instance, the most prominent of such cases are usually related to racial and gender biases. AI systems used in the recruitment screening process might inadvertently favor male candidates over females, or algorithms employed in judicial systems to assess the likelihood of convicted individuals reoffending could exhibit bias. These examples illustrate the potential repercussions of algorithmic bias within the technology landscape (Stahl, 2021) [102].

Bias is indeed easily replicated in AI, if we consider that the data used for the model plays one of the paramount roles in establishing success and performance of the system. And a great amount of the data is fed from open sources and the World Wide Web, which might have already been impaired with some sort of bias. Another potential cause of bias is the establishment of the connection between the input and output through correlation and not causation (Coeckelbergh, 2020) [101]. An example of such case would be an algorithm suggesting or predicting, a person is likely to commit a crime based on the criminal history of his/her parent. Here we may see possible correlation and it might even be accurate or foretelling to a certain degree. However, if a decision regarding whether an individual should receive a harsher treatment or punishment is influenced by such a correlation, one could argue that such a decision is unjust and discriminatory, especially if there is no actual causation involved (the person actually having a record of committing a crime) (Coeckelbergh, 2020) [101]. The number of scholars and organizations are raising concerns on this account since AI has been extensively used without proper assessment and regulation by various judicial authorities (e.g., in predictive policing and criminal probation) (Stahl, 2021) [102]. The growing trust and dependence on these systems will unquestionably magnify the issues and repercussions stemming from the incorrect or biased predictions of AI algorithms. The consequences may result in denying basic freedoms to groups of individuals or limiting access to primary resources: for example, preventing a person from getting a job or loan or extending the duration of a prison sentence without a justified cause.

When speaking about the causes of bias, we cannot ignore the issue of diversity precisely the lack of AI in the field. It is a known fact that the foundation of the IT and AI disciplines was set by men and after a certain period the situation started to change with more female scientists and researchers contributing to the fields (Wooldridge, 2021) [103]. This, however, does not eradicate or diminish the effects of the homogeneity or gendered bias of the historical data used in the early machine learning models, and which might still be used for new research and developments.

The fact that the early days of the discipline were primarily influenced by one gender is a historical fact that cannot be altered. However, taking proactive measures to foster diversity in workplaces and the field is crucial for bringing about positive change and addressing algorithmic bias. Unfortunately, current statistics, while indicating some progress compared to the mid-20th century when AI was first recognized as a scientific discipline, still reveal a significant gender gap among AI specialists. Numerous reports indicate that we need proactive steps to enhance the process of diversification: for example, men still prevail among the job applicants with more than 70% of the total number of applications (Hagendorff, 2020) [105]. Another report published by “AI Now Institute” in 2019, mainly focused on diversity issues in AI, shows the disheartening statistics: more than 80% of professors in the AI field are men and the percentage of female AI research at Facebook and Google are 15% and 10% respectively (West, 2019) [106].

While lack of diversity might not seem like a crucial problem at a first glance, but it does in fact instill other issues and has direct correlation with arithmetic bias. When systems are designed and tested from a single gender point of view, there is a high chance of such systems being prone to bias, deliberately or unconsciously discarding the attributes which are more important or relevant to another gender. The situation might deteriorate even further considering that such biases in most cases go unnoticed, again due to the absence of criticism from the group comprising only the minority.

To showcase and emphasize the significance and adverse effects of negligently designed and insufficiently regulated systems, further focus is necessary on three prominent cases of evident bias incorporated into the AI systems.

15.5 High Profile Cases with Focus on Issue of Bias in Ai

15.5.1 Amazon Recruiting Tool Biased Towards Female Candidates

Possibly the most discussed case of automated applicants screening process associated with bias is the case of Amazon's recruiting system, which was found to exhibit gender discrimination against female candidates. This system was introduced in 2014 with the purpose of facilitating the hiring process for Amazon but later discovered to favor male candidates over females. The reports revealed that the AI screening tool had been trained on the data set from the hiring cases of the past 10 years which was not diverse enough and included mostly male applicants. This resulted in a situation where any resume containing terms such as "women's college" or any similar combinations involving the word "women's" received low rankings and penalties from the system. Consequently, the machine learning model learned to favor male candidates, making it clear that the system was not gender-neutral (News, 2018) [107], (Dastin, 2018) [108].

After some attempts to adjust the algorithm and resolve the issue the project was eventually shut down. However, this case continues to serve as one of the most illustrative examples of gender-biased AI technology, highlighting the vital importance of addressing concerns surrounding these flawed systems. It emphasizes the potential consequences of deploying such technologies on a broader scale without rigorous oversight from unbiased and impartial experts in the field.

15.5.2 COMPAS and the Loomis Case

COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) and Loomis controversy serves as an exemplary case revealing some ethical concerns of AI in the judicial systems. This has been cited more frequently than any other case in the scientific papers and books touching on the topics of AI ethics. The machine learning system employed in this instance is one of the examples of "Recidivism risk algorithms." These risk assessment

tools are often utilized by judges when determining sentencing for suspects being sent to jails or prisons.

This case gained its popularity partially due to the attention drawn to ProPublica's "Machine Bias" report criticizing the system after conducting a thorough and extensive study on the data of 11,757 defendants in Broward County, Florida, who were analyzed and assessed by COMPAS in 2013 and 2014. The investigation focused on the comparison between the predicted recidivism risk rates assigned by the system and the actual rates of the defendants within the period of two years, which was meant to show the accuracy of the predictions made for various racially segregated groups (black, white, Native American, Asian and Hispanic) (Lagioia, 2022) [99].

Based on the information revealed by the study, ProPublica criticized the system and pointed out the insufficient accuracy of its results: the individuals who were flagged as high risk did not in fact reoffend, and, on the contrary, the defendants who were considered low and medium risks committed crimes again. The accuracy scores calculated by ProPublica were 61% for the correct predictions of recidivism overall and 20% of the correctly predicted violent recidivism.

Another, even more disturbing concern raised by the ProPublica investigation was the evidence of the racial bias embedded in the predictive system. The study revealed that black defendants were on average more likely to be incorrectly classified as high risk than white defendants (with 45% as opposed to 23%), and at the same time white defendants were more likely to misclassified as medium or low risk (48% as against 28%).

The results of the study allowed ProPublica to raise questions and important concerns for the usage of such systems and put much trust in them. The assessment tool was widely used in the judicial systems of the United States and its output factor - risk scores of recidivisms - may significantly affect the decision made by the judge who relies on such a tool (Mesa, 2021) [109]. The lack of explain ability and transparency of the system is what prompted Eric Loomis, who was sentenced to 6 years of imprisonment and 5 years of extended supervision, to appeal the judge's decision since the harshness of the decision was influenced by the risk score based on COMPAS assessment. If the system had indeed integrated some biases and there is a reason to believe that it discriminates against groups of people or based on ethnicity, the question of the fairness of such decisions is of utmost importance (Lagioia, 2022) [99].

15.5.3 Facial Recognition Systems Used by The Police in the UK

The usage of facial recognition systems without consent from the public has raised a great number of concerns from individuals and organizations. The UK is one of the countries that has been using facial recognition surveillance by its police departments and is often mentioned in the news and headlines due to the controversies and disagreement from the public on this regard. Live facial recognition systems were set up in England (London) and Wales and are currently officially used by five forces in the UK. Various organizations, such as Big Brother Watch and Electronic Frontier Foundation, advocate for and demand to ban the usage of such systems.

According to London's Metropolitan Police website, "*Live Facial Recognition is not a ubiquitous tool that uses lots of CCTV cameras from across London to track every person's movement. It is a carefully deployed overt policing tactic to help locate a limited number of people the police need to find to keep London safe*" (Mesa, 2021) [109]. This department also assures that the systems are continuously tested on the presence of bias in the algorithm, and it facilitates further improvements and fairness of its performance.

Still, the evidence from the conducted studies and growing concerns in the public questions whether such systems can be deployed in other areas of the world. According to Big Brother Watch's information, the facial recognition technology used by Met Police in London misidentified individuals with 87% rate of inaccuracy in the period of 2016 to 2022 which resulted in roughly 3,000+ people being incorrectly identified by the police (Watch, 2023) [110].

The use of facial recognition technologies has been a subject of some legal cases that eventually resulted in the ban of the AI technology in certain areas and cities, as well as in three states in UK. In 2020, the UK Court of Appeal ruled that facial biometrics used by South Wales Police were unlawful. This decision was made due to the lack of evidence demonstrating that the technology was bias-free and the absence of clear guidance on the usage of such technology. (Burt, 2022) [111]. This shows the disheartening tendency of the AI tools being used way before their proper assessment and regulation, which occurs only after attention to the misuse of such tools is brought to the public and relevant authorities within judicial systems.

16 Transfer Learning

16.1 Background

Deep Learning:

Deep learning is an area of machine learning that focuses on modelling and solving complicated problems using artificial neural networks with numerous layers (Deep Neural Network (DNN)). Its ability to automatically learn and extract hierarchical patterns from data has given it enormous importance in a variety of disciplines. Deep learning has had a substantial impact in several domains, including Computer Vision, Natural Language Processing (NLP), Speech Recognition, Healthcare, Recommendation Systems, Finance, Autonomous Systems, Gaming, Scientific Research, Manufacturing, among many others.

However, training the DNNs poses its own challenges such as:

- *Vanishing and Exploding Gradients:* In deep networks, gradients can become too small (vanishing) or too large (exploding) during backpropagation, making training difficult. Techniques like weight initialization and gradient clipping help mitigate these issues.
- *Overfitting:* Deep networks are prone to overfitting, where the model learns noise in the training data. Regularization methods, dropout, and more data can help combat overfitting.
- *Data Availability:* Deep learning models require large amounts of labelled data for effective training, which might not always be available in all domains.
- *Computation and Memory Resources:* Training deep networks demands significant computational power and memory, making them inaccessible to many researchers and applications.
- *Hyperparameter Tuning:* Finding the right hyperparameters for a deep network can be a time-consuming and trial-and-error process.
- *Interpretability:* Deep learning models are often considered "black boxes," making it challenging to understand their decision-making processes, especially in critical applications like healthcare.

The first neural network, the perceptron (1957), functioned as a binary classifier but had drawbacks. In the 1980s, multi-layer perceptron (MLPs) cleared the path for deep learning by managing non-linear interactions. Backpropagation (1986) pioneered efficient training by using gradient descent. Convolutional Neural Networks (CNNs), which were developed in the late 1990s and became popular in the 2010s, revolutionized computer vision. Recurrent Neural Networks (RNNs) first appeared in the 1980s, and they are now widely used in NLP and time series analysis. The vanishing gradient problem was solved using Long Short-Term Memory (LSTM) Networks. Modern NLP is based on Transformers (2017) and self-attention. GPT-3 (2020), a huge transformer, exhibits deep learning's ability to generate and comprehend meaningful language.

16.2 Introduction to Transfer Learning

A machine learning technique called transfer learning involves adapting a model created for one job to perform on another related activity. It makes better use of a model trained in one domain by utilizing knowledge from another. This method can assist get over the limits of having too little training data, which makes it especially useful when you have a tiny dataset for the intended task.

The notion that people can apply what they have learned from their past experiences to new, related tasks serves as the inspiration for transfer learning. For example, if a person is good at riding bicycle, it is then simpler for that person to pick up motorcycling. Like this, pre-trained Machine Learning (ML) models can be made adaptable to another similar purpose.

Pre-trained models are crucial to the transfer learning process. Usually, these models are trained for a particular task—like speech recognition, natural language processing, or image classification—on vast, varied datasets. The generalized characteristics and representations of these models can be used for a variety of related tasks.

Fine-tuning is frequently required when applying knowledge from a previously trained model to a novel problem. A pre-trained model is fine-tuned when it is made to fit the

requirements of the intended task. Usually, this entails changing a few or creating new layers for the model.

The goal of domain adaptation strategies is to change the model's representations to close the gap between the two domains.

Transfer Learning has numerous advantages such as its ability to train effectively with smaller datasets for the target task. Convergence is also faster due to working on smaller datasets and pre-trained / base model that has already learned general features. Transfer learning often leads to better generalization and performance on the target task compared to training from scratch. In addition, Transfer learning can be applied to various domains, such as computer vision, natural language processing, and speech recognition.

However, transfer learning is not preferable if the source and target domains differ significantly, which reduces / impairs model's ability to infer accurately in any of the domains. Additionally, transfer learning can only work with labelled data for the target task if pre-trained model was trained on labelled data.

Transfer learning is a powerful machine learning technique that may be used in a wide range of applications especially in the field of Artificial Intelligence. It is useful in situations where using knowledge from a related task can greatly increase model performance while requiring less data and computer resources. It is extensively used in computer vision for tasks such as image classification, object recognition, and segmentation, where pre-trained models such as VGG, ResNet, and Inception are fine-tuned for specific purposes. Models such as BERT and GPT-3 are used in natural language processing for text classification, named entity recognition, and language production.

In healthcare, transfer learning is critical for medical image analysis and clinical natural language processing. It is also required in fields such as autonomous driving, recommendation systems, anomaly detection, robotics, finance, gaming, astronomy, and environmental monitoring. Its choice is determined by the availability of pre-trained models and data, making it useful in domains with limited data. Success is dependent on task similarity as well as the selection of the appropriate pre-trained model and adaptation approach.

In conclusion, transfer learning is a potent machine learning technique that enables models to use information from one domain to enhance performance on tasks that are similar.

It can drastically cut down on the time and resources needed to train models from scratch and has a wide range of applications. In any field of application, the preference for transfer learning frequently hinges on the availability of datasets and models that have already been trained. Transfer learning is especially beneficial in domains where there is a dearth of significant labelled data or where it would be computationally expensive to start from scratch. It is imperative to select an appropriate pre-trained model and adaptation technique since the efficacy of transfer learning is contingent upon the degree of similarity between the source and target tasks.

16.3 Transfer Learning Techniques

There are several transfer learning techniques, each suited to different scenarios. Typically, there are 2 main types of Transfer Learning:

- **Feature extraction:**
 - A pre-trained model, often a deep neural network, is used and the final layers responsible for task-specific predictions are eliminated.
 - The model's final component, known as the feature extractor, is employed to extract relevant features from the input data. These characteristics are then fed into a new, task-specific classifier or model.
 - Feature extraction is especially effective when you have a little dataset since it harnesses the knowledge contained in the lower layers of the pre-trained model.

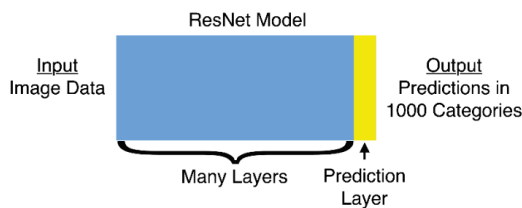


Figure 16.1: Feature Extraction in ResNet (Source: Kaggle)

- **Fine-tuning**: In certain circumstances, it is preferable to adjust the pre-trained model, to the new dataset. This is typically practiced when a dataset is sizeable, and the target task is extremely comparable to the source task. In these circumstances, the model's layers can all be trained for the new task.
- **Domain Adaptation**: Domain adaptation deals with distinctions between the source and target domains. Its goal is to improve the pre-trained model's performance in the target domain. Adversarial training, distribution alignment, and domain-specific fine-tuning are examples of techniques.
- **Multi-Task Learning**: A model is trained on numerous tasks at the same time in multi-task learning. This method enables the model to learn shared representations that are beneficial to all tasks. Frequently used when you have several linked activities but just a limited amount of data for each.
- **Zero-Shot Learning**: Training a model to recognize classes or concepts it has never seen before. To generalize to unknown classes, it uses attributes, textual descriptions, or other auxiliary information.
- **One-Shot Learning**: A model learns to recognize new classes with very few examples, sometimes just one or a few examples per class. Siamese networks and metric learning are common approaches.
- **Semi-Supervised Learning**: To increase model performance, a little amount of labelled data is merged with a large amount of unlabeled data in semi-supervised learning. This method strikes a balance between data efficiency and model performance.
- **Knowledge Distillation**: Training a smaller, more computationally efficient model (student) to mimic the predictions of a bigger model (teacher). This strategy shrinks the model while maintaining performance.
- **Pre-trained Embeddings**: Word embeddings in NLP, such as Word2Vec, GloVe, and FastText, capture semantic meaning and can be used as features in a variety of downstream tasks.

The choice of transfer learning technique depends on factors such as the size of the dataset, the similarity between the source and target tasks, the computational resources available, and the specific problems. Each technique has its own advantages and trade-offs,

and selecting the right one is crucial for achieving optimal results in building transfer learning application.

16.4 ResNet50: An Overview

CNNs (Convolutional Neural Networks):

CNNs are a type of deep neural network that is specifically developed for picture and grid-like data problems. They are distinguished by their capacity to learn spatial hierarchies of features from input, making them extremely useful for tasks such as picture classification, object identification, and image segmentation. CNNs scan and extract local patterns using convolutional layers, pooling layers to minimize spatial dimensionality, and fully connected layers for high-level reasoning, as shown in Figure 16.1. Their architecture can vary in the number of layers used and is based on visual processing in the human brain and has proven to be extremely effective in a variety of computer vision tasks.

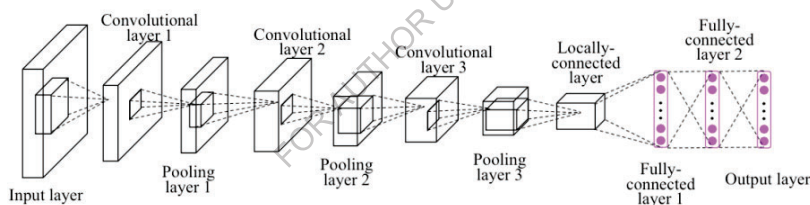


Figure 16.1: CNN Blocks and Layers (Source: ScienceDirect)

ResNet50:

ResNet50 is a deep CNN architecture developed in 2015 by Microsoft Research. Kaiming He et al. introduced ResNet50 in their publication "Deep Residual Learning for Image Recognition" and won the ImageNet Large Scale Visual Recognition Challenge, indicating a considerable improvement in image classification accuracy. ResNet50 has since become a core architecture for a variety of computer vision tasks. ResNet50, which stands for Residual Network with 50 layers, (48 convolution layers, 1 MaxPool layer, and 1 Average Pool layer), is a variant of the ResNet architecture.

Keras ResNet50

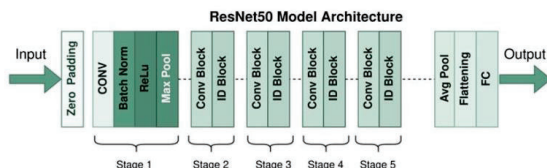


Figure 16.2: Keras ResNet50 [115]

ResNet50 was created to address the issue of vanishing/exploding gradients that occur when deep CNNs are employed to recognize low, medium, and high-level features in images. To solve this issue, the ResNet50 architecture employs shortcut connections that execute identity mappings. In other words, they allow the network to learn the difference between the input and the desired output. The shortcut connections explicitly allow the layers to fit a residual mapping and the non-linear layers to fit another mapping $f(x)=h(x)-x$, transforming the original mapping into $h(x)=f(x)+x$. This method enables the training and performance of ultra-deep neural networks.

Transfer learning is a strategy that includes starting a new task with a pre-trained model. ResNet50 is a popular choice for transfer learning because it is a deep CNN architecture has following attributes:

- **Pre-Trained Model**: Over 14 million photos and 1000 object categories are included in the ImageNet dataset. ResNet50's pre-training on this dataset enables it to learn a diverse variety of features that can be used for transfer learning in other image recognition tasks. The pre-trained ResNet50 model can be fine-tuned on a new dataset with fewer images and categories. Because the model does not need to be trained from scratch, this method can save time and computational resources.
- **Depth**: ResNet50 is a deep network with 50 layers, and deeper networks often capture more complex features, which can be advantageous for a wide range of tasks.
- **Skip Connections**: ResNet50's residual connections allow for efficient deep network training. This is particularly relevant in transfer learning, when adapting a previously trained model to a new task may necessitate training extra layers.

- **Availability:** Pre-trained ResNet50 models are widely available in popular deep learning frameworks such as Keras/TensorFlow and PyTorch, making it simple for practitioners to use them as a foundation for transfer learning.
- **Community and Resources:** The success of ResNet50 has resulted in a large community of support, resources, and pre-trained models fine-tuned for specific applications, which simplifies the transfer learning process.

16.5 Transfer Learning with ResNet50

As discussed in Section **Error! Reference source not found.**, ResNet50 knowledge can be transferred to a target job using multiple techniques. The pre-trained model is utilized to begin the new task, and the model's weights are updated to fit the new dataset. For this report, the pre-trained model has been used as feature extractor in current model that feeds the output to a bespoke classifier (i.e., fully connected layers). The steps involved are discussed next.

16.5.1 Pre-trained ResNet50 Model Selection:

Most of the pretrained models are readily available in deep learning frameworks such as TensorFlow/Keras or PyTorch. For the purposes of this report, we have selected the ResNet50 model, which has been pre-trained on a source task (i.e., the ImageNet database) using Keras, as depicted in the code below:

```
import tensorflow as tf

print(tf.__version__) # 2.14.0
num_classes = 4
my_model = tf.keras.Sequential()
my_model.add(tf.keras.applications.resnet50.ResNet50(include_top=False, input_shape=(256, 256, 3), pooling='avg',
                                                    weights='imagenet'))
my_model.add(tf.keras.layers.Flatten())
my_model.add(tf.keras.layers.Dense(units=512, activation='relu'))
my_model.add(tf.keras.layers.Dense(units=128, activation='relu'))
my_model.add(tf.keras.layers.Dense(num_classes, activation='softmax'))
my_model.layers[0].trainable = False
for layer in my_model.layers:
    print(layer.trainable)
opt_adam = tf.keras.optimizers.Adam(learning_rate=0.0001)
my_model.compile(optimizer=opt_adam, loss=tf.losses.SparseCategoricalCrossentropy(), metrics=['accuracy'])
print(my_model.summary())
```

- The code uses TensorFlow (tf) to create a neural network model. tf version 2.14.0 is used for the purpose of this report.
- The number of classes are set to 4, as this model is designed for a classification task with four classes.
- A new sequential model named 'my_model' is created using `tf.keras.Sequential()`.
- The ResNet50 model from TensorFlow-Keras's applications module is added to 'my_model'.
 - the top layer (fully connected/dense/neural network layers) is excluded using '`include_top = False`'. This is because the pre-trained model is intended to be used as a 'Feature Extractor' and therefore, a bespoke classifier needs to be added on top of it. In this case, a new dense layer with softmax activation function needs to be added to the model, which will have several neurons equal to the number of classes in the current classification task.

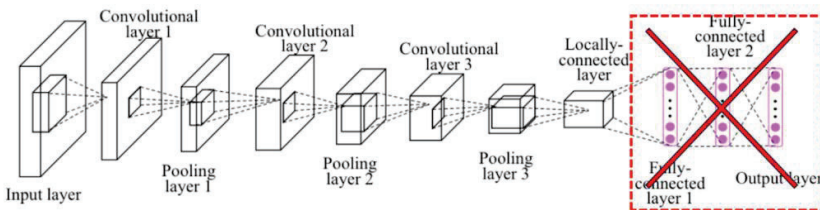


Figure 16.4: 'include_top = False' depiction

- Additionally, if `'include_top=False'`, the `'input_shape'` parameter must also be specified when creating the model, which should match the shape of the new input data.
 - the pooling parameter is set to `'avg'`, which means that the global average pooling operation is applied to the output of the last convolutional layer of the ResNet50 model.
 - the weights parameter is set to `'imagenet'`, which means that the pre-trained weights on the ImageNet dataset are loaded into the model (for convolution layer only).
-
- The trainability of the first layer (ResNet) of the model to be non-trainable (`trainable = False`), which means the weights of the ResNet layer are frozen and won't be updated during training. This is common in transfer learning to preserve pre-trained knowledge.
 - Input and hidden Dense layers with `'ReLU'` and output Dense layer with a `'softmax'` activation function is added to `my_model` after the ResNet50 base model. This layer is used to make predictions and classify data into the specified number of classes (4 in this case).
 - `my_model` is then compiled using `'Adam'` optimizer, `'SparseCategoricalCrossentropy()'` loss function (4 different classes, not requiring one-hot encoding)
 - Finally, a summary of `my_model`, which provides information about the layers, output shapes, and the total number of parameters in the model is printed, as shown next in the code snippet. The trainability of the ResNet layer is set to false, as can be seen in the summary shown next:

```
False
True
True
True
True
Model: "sequential"

-----
Layer (type)                Output Shape                Param #
-----
resnet50 (Functional)       (None, 2048)                23587712
flatten (Flatten)           (None, 2048)                 0
dense (Dense)                (None, 512)                 1049088
dense_1 (Dense)              (None, 128)                 65664
dense_2 (Dense)              (None, 4)                   516
-----
Total params: 24702980 (94.23 MB)
Trainable params: 1115268 (4.25 MB)
Non-trainable params: 23587712 (89.98 MB)
-----
None
```

16.5.2 Data Preparation:

The image data for the purpose of this report has been downloaded from Kaggle ([Brain Tumor MRI classification V2 | Kaggle](#)). The dataset contains a total of 7023 images, with training split of 5712 and testing split of 1311 images. The image classified into 4 classes. A snippet is shown in Figure 16.5.

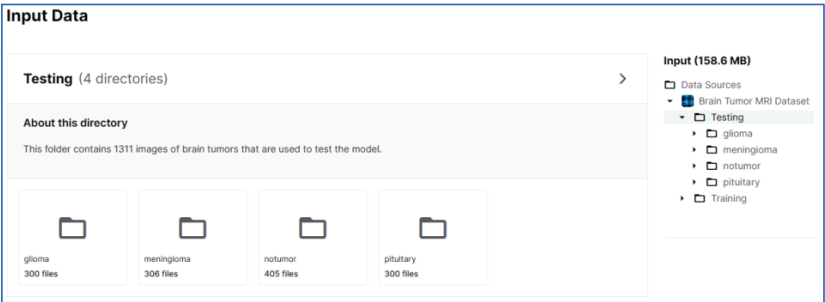


Figure 16.5: Input Data from Kaggle

As the ResNet50 ([tf.keras.applications.resnet50.ResNet50](#)) expects the input data to be pre-processed using [tf.keras.applications.resnet50.preprocess_input](#).

As shown in the code snippet below:

```
# Prepare and load the data
datadir_train = "E:\\1. All_Notes\\4. Thesis\\Masters\\transfer_learning\\Data_brain_tumor\\Training"
datadir_val = "E:\\1. All_Notes\\4. Thesis\\Masters\\transfer_learning\\Data_brain_tumor\\Testing"

preprocess_input = tf.keras.applications.resnet50.preprocess_input
img_generator = tf.keras.preprocessing.image.ImageDataGenerator
data_generator = img_generator(preprocessing_function=preprocess_input)

train_generator = data_generator.flow_from_directory(
    directory=datadir_train,
    target_size=(256, 256),
    batch_size=32,
    class_mode='sparse',
    color_mode='rgb')
print(train_generator.class_indices)

validation_generator = data_generator.flow_from_directory(
    directory=datadir_val,
    target_size=(256, 256),
    batch_size=3,
    class_mode='sparse',
    color_mode='rgb')
print(validation_generator.class_indices)
```

- two ImageDataGenerator objects using TensorFlow's Keras API are created. The first object is created with the `preprocessing_function` parameter set to `tf.keras.applications.resnet50.preprocess_input`, which is a function that preprocesses a tensor or Numpy array encoding a batch of images. This function scales the pixel values of the input image to be between -1 and 1, which is required by the ResNet50 model.
- The `train_generator` object is created using the `flow_from_directory()` method, which generates batches of tensor image data with real-time data augmentation. The `directory` parameter specifies the path to the training data directory, and the `target_size` parameter specifies the size of the input images. The `batch_size` parameter specifies the number of samples in each batch, and the `class_mode` parameter is set to 'sparse', which means that the labels are encoded as integers.

- The `validation_generator` object is created in a similar way, but with different parameters. It generates batches of validation data from a separate directory specified by the `directory` parameter.
- The `color_mode` parameter is set to `'rgb'`, which means that the input images are expected to have 3 color channels. Even though, the input images are greyscale images, they are passed as `rgb` since Resnet50 was trained with RGB images and expects 4D inputs(`num_images`, `pixel_h`, `pixel_w`, 3 color channels).
- The `class_indices` attribute of each generator object returns a dictionary mapping class names to class indices, this is done to ensure that the labels are correctly perceived by the model.

The processed and batched inputs are visualized using code, both shown in

Figure 16.6.



Figure 16.6: Visualization of Inputs

16.5.3 Training and Validation

The next step is to train the model on new data. The code as shown below trains a Keras model using the `fit()` method.

- The `train_generator` and `validation_generator` objects are used as input data for the model.
- The `steps_per_epoch` parameter is set to `STEP_SIZE_TRAIN`, which is the number of batches in the training set.
- The `validation_steps` parameter is set to `STEP_SIZE_VALID`, which is the number of batches in the validation set.
- The `epochs` parameter is set to 10, which means that the model will be trained for 10 epochs.

The `fit()` method trains the model for a fixed number of epochs (iterations on a dataset). For each epoch, it iterates over the training data in batches, computes the loss and gradients, and updates the model weights. After each epoch, it evaluates the model on the validation data, as shown below.

The `hist` variable stores a history object that contains information about the training process, such as the loss and accuracy at each epoch (see the result from the code execution below):

```
STEP_SIZE_TRAIN = train_generator.n//train_generator.batch_size
STEP_SIZE_VALID = validation_generator.n//validation_generator.batch_size

hist = my_model.fit(
    train_generator,
    steps_per_epoch=STEP_SIZE_TRAIN,
    validation_data=validation_generator,
    validation_steps=STEP_SIZE_VALID,
    epochs=10)

my_model.save("E:\\1. All_Notes\\4. Thesis\\Masters\\transfer_learning\\my_model\\brain_tumor_renet50.h5")
```

```

Epoch 1/10
178/178 [=====] - 231s 1s/step - loss: 0.4072 - accuracy: 0.8528 - val_loss: 0.2997 - val_accuracy: 0.8909
Epoch 2/10
178/178 [=====] - 233s 1s/step - loss: 0.1997 - accuracy: 0.9324 - val_loss: 0.2442 - val_accuracy: 0.9138
Epoch 3/10
178/178 [=====] - 239s 1s/step - loss: 0.1621 - accuracy: 0.9415 - val_loss: 0.3590 - val_accuracy: 0.8902
Epoch 4/10
178/178 [=====] - 231s 1s/step - loss: 0.1213 - accuracy: 0.9595 - val_loss: 0.1791 - val_accuracy: 0.9283
Epoch 5/10
178/178 [=====] - 237s 1s/step - loss: 0.0889 - accuracy: 0.9724 - val_loss: 0.1537 - val_accuracy: 0.9474
Epoch 6/10
178/178 [=====] - 239s 1s/step - loss: 0.0733 - accuracy: 0.9764 - val_loss: 0.1292 - val_accuracy: 0.9489
Epoch 7/10
9/178 [>.....] - ETA: 2:54 - loss: 0.0618 - accuracy: 0.9861

```

16.5.4 Results

The model achieved ~97 % val_accuracy as shown in Figure 16.7:

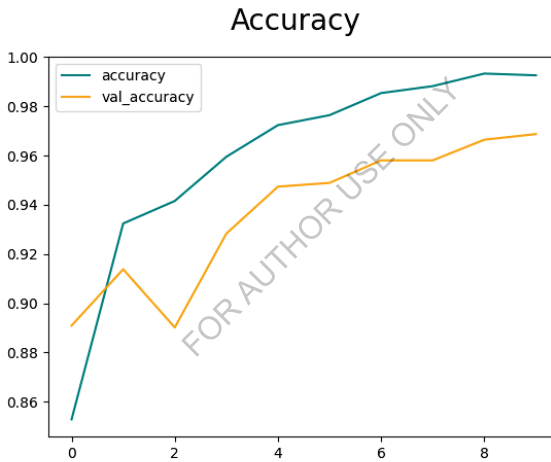


Figure 16.7: Validation Accuracy

The reduction in val_loss is shown in Figure 16.8:

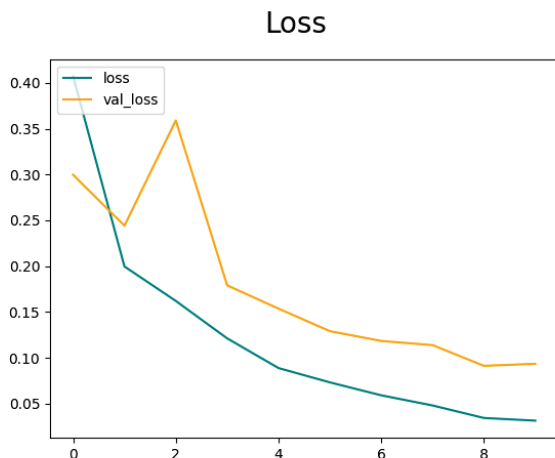


Figure 16.8: Validation Loss

16.6 Applications of ResNet50 Transfer Learning

ResNet50 transfer learning, which is based on the knowledge of a pre-trained ResNet50 model, finds varied real-world applications across fields. It excels in image categorization in the domain of computer vision, allowing the identification of objects, animals, and scenes. Its versatility extends to object detection, enabling self-driving and surveillance systems by detecting and classifying things in photos and videos. The influence of ResNet50 extends to the healthcare sector, where it aids in medical image processing, detecting diseases from X-rays and scans, and therefore improving early disease diagnosis. It also contributes to natural language processing by supplying image embeddings for NLP models, effectively combining text and image analysis.

Furthermore, ResNet50 is a valuable tool in gaming for character and object recognition, improves quality control in manufacturing, aids in agriculture by monitoring crops and livestock, transforms retail and e-commerce with visual product search, and contributes to

the object recognition of autonomous vehicles. It is a prominent actor in online content filtering and plays an important role in environmental monitoring by analyzing satellite imagery, allowing for the tracking of environmental changes and wildlife populations. ResNet50's adaptability in high-level feature extraction elevates it above picture classification to a critical force in defining the AI landscape across a wide range of real-world scenarios.

16.7 Challenges and Considerations

16.7.1 Challenges in Transfer Learning:

While transfer learning is an effective strategy, it is not without its drawbacks. One key issue is "domain shift," which occurs when the source and target domains differ significantly. When transferring knowledge, these inequalities might lead to a loss of performance. Another issue is "overfitting," which occurs when the model gets too customized to the source job and becomes less adaptive to the target task. When the target dataset is tiny or dissimilar, overfitting occurs, causing the model to memorize the source data rather than learning generalized features.

16.7.2 Best Practices for Addressing Challenges:

Several best practices should be addressed to mitigate these difficulties. For starters, "domain adaptation" strategies can help bridge domain shifts by matching the distributions of source and target data, allowing for improved knowledge transfer. Second, "fine-tuning" is essential when dealing with overfitting. Fine-tune the top layers of the pre-trained model while freezing the bottom layers, allowing the model to adapt to the new goal without forgetting the source task. Another approach for combating overfitting is data augmentation, which artificially increases the size of the target dataset, making the model more resistant. Overfitting can also be avoided using "regularization techniques" such as dropout and weight decay.

16.7.3 Challenges in Transfer Learning:

It is critical to select a suitable pre-trained model. The similarity between the source and target tasks should inform the decision. If the tasks are closely related, utilizing a pre-trained model from the same domain as the source task is preferable. If the tasks differ greatly, choosing a model that has been pre-trained on a larger dataset, such as ImageNet, is a good place to start. Furthermore, the architecture of the pre-trained model should correspond to the task requirements. For example, employing a pre-trained ResNet for picture classification is more appropriate than using a model developed for language problems. Finally, examine the model's depth and computing requirements; a deeper model may offer more accuracy but requires more resources, making it critical to strike a balance between accuracy and practicality. Finally, selecting the correct pre-trained model is critical for successful transfer learning since it shapes the model's ability to adapt and learn effectively in a new context.

16.8 Future Directions

Transfer learning is a fast-expanding area of study with the potential to transform machine learning. Emerging transfer learning trends involve the creation of new algorithms and approaches for transferring knowledge from one area to another. Transfer learning is also being investigated by researchers in new disciplines such as natural language processing and computer vision.

Deep learning and transfer learning technique advancements are predicted to have a substantial impact on the field of machine learning. The creation of new algorithms that can learn from unstructured data, such as photographs and text, is one potential advancement. Deep reinforcement learning could be used to train models that can learn from experience, which is another possible development.

Transfer learning is projected to have a substantial future impact in a variety of fields, including healthcare, finance, and education. Transfer learning can be applied in healthcare to create models that predict disease outcomes and discover novel treatments. Transfer learning

can be applied in finance to create models that anticipate stock values and identify market patterns. Transfer learning can be used in education to create models that tailor learning experiences for students based on their unique needs and talents.

16.9 Conclusion

Transfer learning is a machine learning technique that involves transferring knowledge from one domain to another. ResNet50 is a popular deep learning model that can be used for transfer learning. Transfer learning has many applications, including image classification, natural language processing, and speech recognition. It has several advantages, such as reducing the amount of labeled data required for training, improving the accuracy of models, and reducing training time. However, there are also challenges associated with transfer learning, such as selecting the appropriate source domain and dealing with domain shift. Advancements in transfer learning include the development of new algorithms and techniques that can be used to transfer knowledge more effectively. The future of transfer learning is promising, with potential applications in healthcare, finance, and education.

17 Contributions of this Work

Role of Python and AI:

The programming language Python, along with its libraries and the extensive global community support. The combination of python with Raspberry Pi offers a powerful system for advancing the development and deployment of AI and smart systems. One such example can be the development of an emotion recognition system utilizing AI logic implemented on Raspberry Pi using Python packages.

Smart Energy Systems using Machine Learning and PMU Measurements on FIWARE:

We outlined the evolution of energy systems through stages such as decentralized, centralized, distributed, and, recently, smart energy systems. These systems leverage innovative technologies like IoT, big data analytics, and cloud computing. The goal was to create a service-based architecture that supports plug-and-play connection devices and active consumer participation in the open energy market.

The FIWARE technology was introduced as a solution to challenges faced in smart energy systems. It addresses the lack of IoT standards, integration issues, data security, and limited usability of applications. FIWARE provides data standards and tools to effectively design and implement smart energy systems.

FIWARE-based smart Agriculture System using AI and IOT:

Challenges faced by farmers, including climatic changes, disease control, and inadequate irrigation facilities were acknowledged, which lead to the need for innovative solutions. Smart farming's potential was explored, encompassing data transmission, remote storage, and analysis for informed decision-making. The integration of AI and IoT in agriculture was emphasized to address these challenges. The emergence of Industry 4.0 is noted as a catalyst for agricultural enhancements, offering improved production, supply chain management, and market reliability.

The work underscores the importance of smart agriculture in meeting the growing global food demand. The integration of AI, IoT and FIWARE was highlighted as a transformative approach that can make agriculture more efficient and intelligent. The benefits

of AI and IoT in disease detection, crop prediction, and other aspects of farming are reiterated, emphasizing their role in reshaping the industry.

Intelligent Irrigation System Built-in Cartagena City Using FIWARE:

The implementation of Intelligent Irrigation Systems. These systems prevent over-watering and conserve water resources by analyzing sensor data, weather forecasts, and evapotranspiration. Such systems contribute to the sustainable management of water, decrease water wastage, and maintain green spaces. The FIWARE IoT platform facilitates the integration of Intelligent Irrigation Systems in Cartagena. This technology-driven approach reduces costs, improves resource management, and promotes a healthier environment.

The advantages of these systems include reduced water consumption, lowered CO₂ emissions, prevention of soil erosion, and controlled pest populations. Expanding the use of Intelligent Irrigation Systems in administrative bodies and farming contexts. Such systems can contribute to efficient agricultural practices, conserving resources and improving crop yields.

Smart Systems using Artificial Intelligence in Sports-Football:

This application has revolutionized post-match analysis, enhancing accuracy in areas such as ball possession, goal line detection, and decision-making. AI technologies like VAR and SAOT have made the sport more exciting and accurate, and the unpredictable nature of human presence keeps football dynamic and competitive.

Smart Parking System:

We highlighted the significance of machine learning techniques in transforming parking systems into efficient, automated, and environmentally friendly solutions.

Smart Systems in Aerospace:

This work delves into the current AI applications in the aerospace industry, focusing on enhancing safety through airplane health monitoring, predictive maintenance, efficiency improvement, and the development of the Smart Factory concept.

Importance of Ethical Issues in smart system Development using AI with Focus on Algorithmic Bias:

The book also emphasizes the importance of transparency, neutrality, and unbiased models to prevent bias and discrimination, safeguarding against the exacerbation of societal biases.

18 Conclusions

In conclusion, it is crucial to look back to the world of smart systems and the transformative FIWARE framework that's been our focus. This journey has shown how these technologies touch many parts of our lives. From healthcare to farming, cities to airplanes etc.

The technology of Emotion Recognition was reviewed, and we saw how it allows smart systems to be more responsive and intuitive to human emotions. This technology has a wide range of applications and is used to improve human-computer interactions, healthcare, marketing, public safety, robotics, and autonomous systems, to mention some fields and it is rapidly advancing with the contemporary developments. Furthermore, it is not the only one escalating; it is the whole of the AI spectrum that is building up, Machine Learning, IoT, Industry 4.0, Smart Systems and even frameworks like FIWARE, that allow each aspect to be interconnected.

Next, we focused on the smart grid application focusing on the main aim and goals to be achieved. An overview of the entire process was given, and then detailed explanation with prediction algorithms and machine learning models were discussed. The FISMEP platform is introduced to address some of the challenges, like standardization of protocols, integration of services and scalability were also discussed. Few examples of current FIWARE uses in different European cities were also mentioned.

One of the cities discussed in this book was Cartagena. This work showcased how FIWARE, and smart systems help the management of resources and development of the city. The primary focus was on the significance of sustainable water use and the developed Intelligent Irrigation Solution. This solution contributes to cost reduction, improved management, and the creation of a healthier and more aesthetically better landscape.

The discussion continued with the current fourth industrial revolution, known as "Industry 4.0," representing the new phase of controlling the industrial value chain. In the proposed methodology, FIWARE enablers were used together with vf-OS functionalities to control the entire fruit production chain. The FIWARE enablers provided the feasibility of handling complex functions to create a light application. vf-OS acted as a proxy between the application layer and GEs, by providing access to respective GEs using specific protocols.

Thus, it provides ease of handling any application request by matching it to the respective enablers irrespective of the scenarios. For the small or medium-scale industries that integrate the open-source tools enablers, vf-OS provides a range of services for the networked factory of the future. This enables manufacturing industries to develop and integrate better and build more intelligent manufacturing and logistics processes at a very low cost. The growing demand for food all over the world makes it important to find solutions to build a smart system in the field of agriculture.

In addition to city irrigation, the analysis explored the agricultural sector where, like other industries, AI plays a crucial role in simplifying and enhancing systems through integration with the Internet of Things, Industry 4.0, and virtual factories. These technologies play a huge role in confronting the challenges faced due to climatic conditions, soil quality, harvesting, and irrigation. Smart agriculture is based on precise farming and improved crop quantity and quality by enhancing agricultural resources through recent innovations. This report describes how artificial intelligence and IoT benefit the agricultural industry. The current research in smart agriculture, its applications, and the use of FIWARE for developing a smart agriculture system were also discussed. The study showed that deep learning techniques play a significant role in reshaping the industry by building systems that make it easier to predict plant disease, crop predictions for cultivation, and other monitoring systems. The basis of a country is that of its production capacity and its ability to help sustain its masses. Such sustainability can be achieved only when there is a smart automation of its day-to-day essential activities out of which smart irrigation is the most essential. With the help of an Intelligent Irrigation System, the quality of the entire lifecycle of a crop can be improvised which will have a result of less wastage and more yield. Thereby, it shows the importance of developing a smart agriculture system in today's world.

Another industry that fully benefits from these solutions is the aviation industry. Ever since the first commercial flight took place in Florida in 1914, global commercial aviation has grown by leaps and bounds, and recent rapid growth has presented a huge challenge for industry players and consumers alike to ensure safety, reliability, profitability, and development. Developing, producing, and maintaining a modern commercial airplane are mammoth tasks and involve thousands of parts, processes, and personnel to work cooperatively and, more importantly, money. For example, it takes roughly 10 to 15 billion dollars in the

development/certification of a clean sheet commercial airplane and billions more in ramping up production, training, and deployment. Maintenance and operating the aircraft is equally expensive and risky. Therefore, the role of AI in the aviation industry will only grow in the future, especially in the fields of Manufacturing and Maintenance.

The sports industry is another industry focused in research of AI systems (Ignatova, 2021), (Ignatova, Affirming wellness culture through innovative methodology related to Blaze-pod trainer system, 2023), (Ignatova & Iliev, Benchmarking for Development of Speed and Power Characteristics, 2022) [112, 113, 114]. The future of sports lies in the hands of technology, and there is no doubt that current usage has positively affected the sport despite some controversies. Decision-making has become more factual and less based on emotions, making the game less biased. AI is not only used inside the stadium, but it also serves several purposes outside. Many teams have been using automated techniques to gather live data and improve their strategies according to the game plan of their opponents. Multiple television broadcasting channels also use AI to increase the accuracy of ball tracking. Bettors worldwide use prediction models to improve their chances of winning a pot.

A few other AI technologies have been a part of this industry for years but are not mentioned in this paper. Without a doubt, AI technologies like VAR and SAOT have made the sport even more exciting to watch from a fan's perspective. But it is vital to understand the human presence in the sport always makes it unpredictable and even more fascinating. As long as there are surprises in the sport, the industry will never die, and it will keep improving with time, making it more competitive and dynamic.

The paper not only mentioned big industries but also highlighted projects like the smart parking systems described in the text. This smart system project described how drivers can use the parking lot without human intervention. Smart parking is a very good example of how machine learning can be used to find practical solutions for a daily problem issue. Smart parking systems not only solve parking problem issues for drivers but also help save time and money, reduce stress, and can have a real impact on reducing pollution and traffic congestion. The article explained how machine learning techniques are used to analyze the parking lots and then extract trained data to make further processing to find if there are available parking spaces inside the parking lot or if it is full without any places. The smart parking system could

be enhanced by adding smart detection for the objects inside the parking lot and distinguishing the vehicles from other types of objects inside the parking lot.

Finally, the paper raised ethical questions about using certain AI technologies. They have only recently started to appear in the spotlight, and the seriousness and importance of such issues and concerns should not be neglected. The cases of algorithmic bias in AI systems mentioned earlier demonstrate the potential and real damage and consequences caused by the utilization of faulty models. Therefore, a great number of researchers and advocates propose ways of regulating the systems and contemplate the approaches that can be used to combat or mitigate the fallouts coming from the fact that AI systems are not transparent, easily prone to bias, they still lack diversity in both the datasets used and the designers of the algorithms.

Regarding algorithmic bias, we can see that AI often exacerbates the already existing societal and personal biases. Some researchers might argue that the issue is not of concern for the programmers or designers of the systems since it simply reflects the state of the world by adjusting the code to favor minorities or individuals suffering from bias would not be a fair practice to the other groups. However, a more popular outlook still focuses on minimizing the bias rather than shifting the blame from the AI systems creators to the whole society.

Still, it is extremely challenging to find definitive answers to how a particular AI technology works and comes to a certain decision. This paper also raised questions about who should be responsible and accountable for the mistakes or discriminative behaviors of such technologies and how to regulate the use of systems that play a significant role in deciding individuals' future based on predictive models (News, 2018) [107].

It seems important and reasonable to focus future research on revealing the “black box” of AI algorithms to bring more transparency and determine the hidden pitfalls negatively affecting many systems. However, as of today, this research is still in its infancy stage, and we might need to establish rigid regulations and guidelines first.

After all, it must be acknowledged that in a world of change, where there are more and more billions of people living on Earth, a planet that must be maintained hospitable with its limited resources, in a moment where we have to be more mindful than ever of the resources we use, in a time of already Climate Emergency, it is only with the further development and

implementation of intelligent solutions like the ones disclosed in the paper that we could, in any case, try to improve our quality of life further.

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