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AI and ML in IR4.0: A Short Review of Applications and Challenges

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ABSTRACT

Artificial intelligence and machine learning are essential for the development of IR4.0 due to their ability to analyse vast amounts of data, automate processes, and drive innovation across various sectors. These technologies enable intelligent decision-making, predictive analytics, and automation, leading to increased efficiency, productivity, and competitiveness in the digital age. In IR4.0, AI and ML power smart systems and connected devices, transforming industries. They facilitate the integration of digital, physical, and biological systems, enabling the creation of personalized medicine and medical diagnosis smart manufacturing, self-autonomous driving vehicles, smart cities, and smart home. Hence, this review aims to address the contribution of AI and ML in the development of medical diagnosis, smart manufacturing, smart cars, smart cities, and smart homes as well as to highlight the existing challenges faced by AI and ML in these fields. This review also showcases the relevant prospects of AI and ML applications in the fields mentioned.

1. INTRODUCTION

Industrial revolution is the industry word used to describe how technology has changed within a given time frame, particularly in the manufacturing and industrial sectors. The latest industrial revolution, known as "Industry 4.0," was first proposed in Germany in 2011. It emphasises automation through networked production and digitization. It advances the industrial revolution by creating "Smart Factories" through the use of cloud computing, cyber-physical systems, and IoT [1]. The four phases of the industrial revolution represent important developments in how societies arrange production, labour, and technology. The First Industrial Revolution (IR1.0), which began in the late 18th century, introduced mechanization driven by water and steam, resulting in the automation of manual labour and the establishment of factories. The Second Industrial Revolution (IR2.0) occurred in the late nineteenth and early twentieth centuries and was characterized by mass production made possible by electric power and the assembly line, changing manufacturing and transportation. The Third Industrial Revolution (IR3.0), often known as the Digital Revolution, began in the mid-twentieth century with the introduction of electronics, computers, and

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telecommunications, which enabled automation and the emergence of the internet. Finally, the Fourth Industrial Revolution (IR4.0), which began in the late twentieth century and continues today, is distinguished by the convergence of digital, physical, and biological technologies, blurring the distinctions between the physical, digital, and biological spheres, and ushering in a new era of connectivity, automation, and intelligence. Figure 1 shows the timeline for the four phases of industrialization along with the technological improvements that have been made over time.

Hence, among the technologies implemented, artificial intelligence (AI) and machine learning (ML) are key pillars of the Fourth Industrial Revolution (IR4.0). AI and machine learning (ML) are now used as catalysts for innovation and efficiency in a variety of industries. AI, which includes machine learning techniques, enables systems to learn from data, adapt, and make judgments independently, hence enabling process automation and resource management. AI and ML drive intelligent systems capable of processing massive volumes of data, extracting useful insights, and facilitating predictive analytics. From smart manufacturing and healthcare to finance and transportation, the incorporation of AI and ML technologies into IR4.0 transforms workflows, improves decision-making, and fosters unprecedented levels of connectivity and personalization. As IR4.0 progresses, AI and ML will remain critical transformational drivers, affecting the future of businesses and economies around the world.

In the field of healthcare, AI is a key component in improving efficiency and accuracy in the field of medical diagnosis. A great deal of medical data, including imaging scans and patient records, can be analysed by machine learning algorithms to find patterns and anomalies that may be difficult for human doctors to notice. This capacity not only expedites the diagnostic procedure but also aids in the early identification of illnesses, resulting in more efficient and timely treatment plans. On the other hand, in the field of smart manufacturing, AI and ML are revolutionising traditional production methods. These technologies enable manufacturing processes like workflow optimisation, quality assurance, and predictive maintenance. Smart cars with AI-powered systems are paving the way for autonomous driving and advanced driver assistance, which will improve traffic flow and safety. In smart homes, AI is used to create intelligent environments where devices can readily communicate with one another and adapt to user preferences, increasing convenience and reducing energy usage. Additionally, in the context of smart cities, AI and ML facilitate data-driven decision-making for traffic management, public services, and urban planning, all of which ultimately support more effective, sustainable, and liveable urban environments. Thus, this short review paper is intended to review the various applications of AI and ML in advancing IR4.0 in the field of medical diagnosis, smart manufacturing, self-driving autonomous vehicles, smart cities, development, and smart home facilities as well as to identify the challenges and prospects of AI and ML in these fields..

2. MEDICAL DIAGNOSIS

AI and ML have transformed healthcare by increasing the efficiency and accuracy of medical diagnosis. These technologies use patient records, genetic data, and imaging to diagnose ailments, discover patterns, and predict risks, ultimately improving personalised treatment. The increasing prevalence of prescribing and taking medications has necessitated the development of medication reconciliation applications, which can improve patient outcomes by addressing issues such as incorrect diagnosis, excessive treatment, lower productivity, insufficient clinical data processing, and high costs and spending. Precision medicine, which combines multi-omics profiles with clinical, imaging, epidemiological, and demographic data, can improve traditional medicine by enabling early interventions for advanced diagnosis and personalised treatment plans [2]. Machine learning improves statistical approaches by recognizing patterns in data without making assumptions about the distribution of the data, allowing for more complicated tests and hypotheses, and improving model interpretation and generalizability across varied medical data types [3].

Supervised and unsupervised ML are two methodologies inspired by human learning as shown in Figure 2. Supervised learning includes training models with labelled data, whereas unsupervised learning focuses on discovering patterns in unannotated data, making it a safer and easier technique for formalising learning [4]. Semi-supervised learning is a hybrid framework that applies class labels and clusters to partially known data by mixing supervised and unsupervised approaches [4]. By improving accuracy, speed, and safety, AI has the potential to revolutionise healthcare. It has been utilised in medical radiography to develop clinical Linked Data Graphs (LDGs) that connect biomedical data banks and make them publicly available. This logic-based and reasoning-based method combination is predicted to produce considerable outcomes of various applications in the medical field [5]. Clinicians are focused on large-scale ML algorithms to discover novel medications quickly and cost-effectively utilizing supercomputers and ML capabilities for the diagnosis of diseases including cancer [5]. As ML is a branch of AI that allows machines to learn from examples, studying how models perform without human judgment, hence through automated systems, AI and ML are revolutionising the medical field by assisting in diagnosis, treatment, and outcome prediction. AI assists in laboratory tests, patient data collection, and medical discovery analysis. It can also identify and propose appropriate treatment plans to patients.

However, AI and ML's extensive use poses several challenges. One significant concern is the interpretability and transparency of AI-driven diagnostic models. Unlike traditional diagnostic approaches where human experts can explain their reasoning, AI algorithms often operate as "black boxes," making it challenging to understand how they arrive at their conclusions. Ensuring the reliability and trustworthiness of AI-based diagnostic systems is crucial to gaining acceptance from healthcare professionals and patients alike. Moreover, the integration of AI and ML into clinical workflows requires addressing regulatory and ethical considerations. Regulatory bodies must establish clear guidelines for the development, validation, and deployment of AI-based diagnostic tools to ensure patient safety and data privacy. Additionally, ethical concerns regarding the equitable distribution of healthcare resources, algorithmic bias, and the potential for automation to replace human judgment must be carefully addressed. Furthermore, the successful implementation of AI and ML in medical diagnosis depends on the availability of high-quality, diverse, and well-curated datasets. Data privacy regulations, interoperability issues between healthcare systems, and the need to protect sensitive patient information present significant hurdles in this regard.

Despite these challenges, the prospects of AI and ML in medical diagnosis remain promising. With continued research, collaboration between technologists and healthcare professionals, and a commitment to addressing ethical and regulatory concerns, AI and ML have the potential to transform medical diagnosis, leading to more accurate, efficient, and accessible healthcare services for patients worldwide.

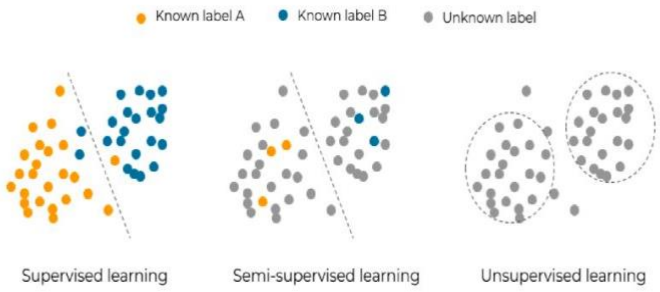

Fig. 1. Three classical learning frameworks in artificial intelligence: supervised, semi-supervised, and unsupervised learning [4].

3. SMART MANUFACTURING

AI and ML are used in intelligent manufacturing to improve quality assurance, supply chain management, production scheduling, and maintenance. These solutions reduce downtime, improve resource utilisation, and enable proactive decision-making. Real-time data analysis and continuous innovation provide a more flexible, responsive, and sustainable future in industrial production, improving operational efficiency and encouraging a more sustainable future. Manufacturing process planning, quality control, predictive maintenance, logistics, robots, support systems, machine learning training, process management and optimisation are significant areas of attention in a typical learning industry. As shown in Figure 2, ML includes reinforcement learning, supervised learning, and unsupervised learning, with supervised approaches accounting for most ML techniques [6].

Hence, in supervised approaches, the neural network model is the most implemented method as it mimics brain learning, whereas tree algorithms learn from objects. Unsupervised learning approaches such as principal component analysis and singular value decomposition can be used to minimise data dimensions, whereas Q-learning reinforcement learning enables optimal action. Industrial AI has enormous promise, but it must solve difficulties such as model selection, data processing, cyber security, fault tolerance, and network latency.

The integration of DL, ML, and AI in smart logistics for industrial organisations can be divided into five categories: predictive maintenance, production planning and control systems, decision support systems and man-machine interface, and operational process improvement [7]. Besides that, ML technologies also help industrial workers optimise processes by offering prescriptive analytics, allowing process optimisation and improvement. This subject, which integrates machine learning and process optimisation to create industrial analytics insights, is predicted to grow quickly over the next decade [8]. Besides that, deep reinforcement learning is being used to inform demand forecast models for modules and components as AI gains traction in semiconductor production. This method is effective in fault identification and categorization [9].

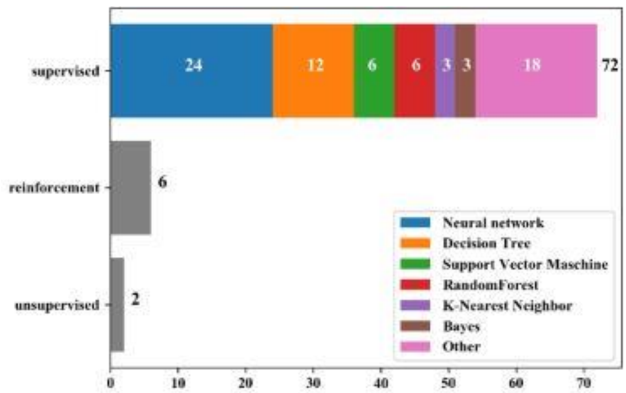

Fig. 2. Type of ML techniques [6].

AI and ML applications in smart manufacturing can significantly enhance ergonomics for workers as well by optimizing workflows, reducing physical strain, and mitigating safety risks [10]. Through AI-driven predictive analytics, systems can analyse historical data on worker movements, equipment usage, and environmental factors to identify potential ergonomic hazards and proactively suggest modifications to work processes or equipment layout [11-12]. ML algorithms can also analyse real-time data from sensors and wearable devices to detect signs of fatigue or repetitive stress injuries, prompting interventions such as rest breaks or ergonomic adjustments [13]. Additionally, AI-powered robotics and automation can handle repetitive or physically demanding tasks, freeing workers from strenuous activities and reducing the risk of musculoskeletal injuries [14]. By leveraging AI and ML technologies, smart manufacturing environments can create safer, more ergonomic workspaces that promote employee health, well-being, and productivity.

However, several challenges must be overcome to fully realize the potential of AI and ML in smart manufacturing. One of the primary concerns is data security and privacy. Manufacturers must ensure that sensitive production data collected from various sources, including sensors, machines, and supply chains, is adequately protected from cyber threats and unauthorized access. Moreover, interoperability issues between different manufacturing systems and legacy equipment can hinder the seamless integration of AI and ML solutions into existing workflows. Manufacturers may need to invest in standardization efforts and interoperable technologies to overcome these barriers. Furthermore, the successful deployment of AI and ML in smart manufacturing requires a skilled workforce capable of developing, deploying, and maintaining these advanced technologies. Upskilling existing employees and attracting new talent with expertise in data science, machine learning, and AI is essential for driving innovation and maximizing the benefits of smart manufacturing initiatives. Additionally, ethical considerations surrounding the use of AI and ML in manufacturing, such as job displacement due to automation, algorithmic bias, and the impact on worker safety, must be carefully addressed. Manufacturers must prioritize ethical and responsible AI practices to ensure that these technologies benefit all stakeholders, including employees, customers, and society at large.

Despite these challenges, the prospects of AI and ML in smart manufacturing are considerable. With careful planning, investment in technology and talent, and a commitment to ethical principles, manufacturers can leverage AI and ML to transform their operations, drive sustainable growth, and maintain a competitive edge in the global marketplace.

4. SELF-DRIVING AUTONOMOUS VEHICLE

The incorporation of AI and ML in self-driving autonomous vehicles has transformed the automotive industry, allowing them to make quick navigation and obstacle avoidance decisions, adapt to complex environments, and enable more intelligent transportation in the future. AI is a field that analyses complicated data and operates autonomous vehicles, with subfields focusing on knowledge acquisition, learning, reasoning, natural language processing, trained perception, and object operation. The V-model approach for software development as shown in Figure 3 is often used in the automotive industry to connect stages of the development of safety-critical control systems. It employs a bottom-up method for testing and validation and a top-down approach for design, with iteration cycles and a lack of adherence to every phase [15]. Autonomous vehicles are a promising solution to increasing road accidents due to human error and traffic congestion. With hardcoded restrictions, these vehicles can function and make decisions without making mistakes, making them a safer and more comfortable option for reducing traffic congestion, preventing head-on collisions, and improving adherence to traffic laws [16].

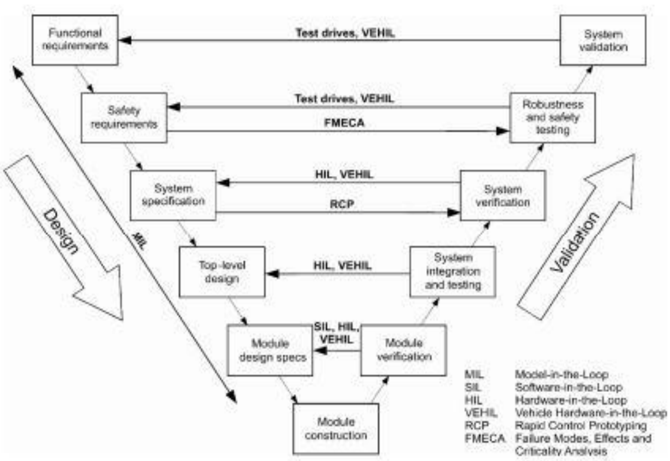

Fig. 3. The V-model approach for software development in the automotive industry [15].

Thus, autonomous vehicles have several societal benefits, including enhanced mobility, urban redevelopment, environmental preservation, and increased safety. However, these technologies are not without inherent hazards, which must be mitigated to fully realise their potential benefits. The Advanced Driver Assistance System (ADAS) collects real-time information about the driver's surroundings from in-car sensors, detecting static and moving objects. It recommends preventative measures such as adaptive cruise control, automated parking, lane-keeping assist, GPS navigation, and intelligent transportation services [17]. Although real-time autonomous driving hardware solutions are effective, their field test performance and cost remain a bottleneck for widespread commercial use. Hardware advancements are required to match the market's demand for AI applications in autonomous vehicle development while overcoming technological challenges [18].

However, significant challenges remain for the application of AI and ML in self-driving autonomous vehicles. Ensuring the safety and reliability of autonomous vehicles is paramount, requiring rigorous testing and validation of AI systems to handle a wide range of real-world scenarios. Regulatory hurdles, including liability, insurance, and compliance with existing traffic laws, pose significant challenges to the widespread adoption of autonomous technology. Ethical dilemmas surrounding the prioritization of passenger safety versus the safety of other road users in unavoidable collision scenarios must also be addressed. Data security and privacy concerns are paramount, as autonomous vehicles generate vast amounts of data vulnerable to cybersecurity threats. Moreover, public perception and acceptance of autonomous vehicles remain key hurdles, with concerns about safety, job displacement, and loss of control over the driving experience needing to be addressed to ensure widespread adoption. Overall, while the prospects of AI and ML in self-driving autonomous vehicle applications are promising, addressing these challenges is essential to realizing the full benefits and ensuring the safe and responsible integration of autonomous vehicles into our transportation infrastructure.

5. SMART CITY DEVELOPMENT

AI and machine learning are transforming urban planning by improving traffic management, public safety, resource allocation, and environmental programmes. These technologies aid in the automation of decision-making processes, the extraction of insights from massive datasets, and the analysis of data. This blend of efficiency, creativity, and sustainability promotes urban environments that are sensitive to residents' needs and adapt to changing urban dynamics. In a smart city, information, and communication technology (ICT) is critical for managing data analysis, communication, and implementing complicated plans, assuring safe and seamless operation through effective utilisation. Smart cities, IoT, blockchain, UAVs, AI, ML, and DRL-based techniques are still in their infancy, but their implementation in various applications will almost certainly lead to future opportunities, as shown in Figure 4 and Figure 5 [19].

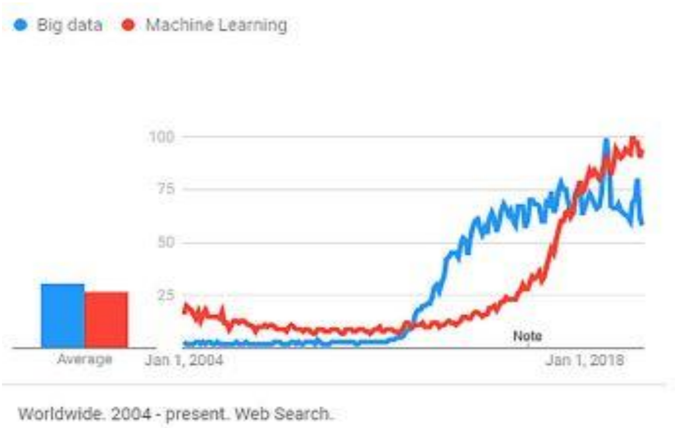

Fig. 4. An era of Big Data and ML from 2004 to January 2020 [19].

Fig. 5. The popularity of the smart city concept and big data over the given period particularly after 2012 [19].

Intelligent Transportation Systems (ITS) are critical for smart cities, but their full potential requires low-latency analytical tools and accurate data. AI and ML are critical for tracking and estimating real-time circulation data. Reliable monitoring and management systems are required for processing vast amounts of data at the vehicle level. Deep Learning approaches can improve the quality of ITS data [20]. In addition, in for testing or simulation of microgrid connection for electricity distribution in smart cities, it also implements AI and ML to enhance the microgrid connectivity via a microgrid model. A microgrid model involves renewable energy sources, storage, various power-consuming entities, and a grid link. It replicates microgrids based on real-world data on consumption, local generation, and external influences, providing minimum configurations for residential, neighbourhood, and campus/community simulations. It specifies minimum settings for household simulations, neighbourhood simulations, and campus or community simulations.

Besides that, AI and ML applications in smart cities can significantly improve energy harvesting from renewable sources by optimizing energy generation, storage, and distribution systems. These technologies enable predictive analytics to forecast energy demand and supply and optimize the operation of renewable energy sources such as solar panels, wind turbines, hydroelectric generators, and other alternative green energy [21-22] based on weather forecasts, energy consumption patterns, and grid conditions. ML algorithms can analyse historical data to identify optimal locations for renewable energy installations and adjust their configurations for maximum efficiency. An energy management system is crucial for renewable energy because it optimizes the utilization, storage, and distribution of renewable resources, ensuring efficient and reliable energy supply while minimizing waste and maximizing sustainability [23-25]. AI-driven energy management systems can optimize the storage and distribution of renewable energy by dynamically adjusting battery storage systems, grid connections, and demand response programs based on real-time conditions. Additionally, AI-powered smart grids can intelligently balance supply and demand, manage energy flows, and integrate distributed energy resources into the grid more effectively. By leveraging AI and ML technologies, smart cities can enhance the utilization of renewable energy sources, reduce reliance on fossil fuels, and promote sustainability and resilience in energy systems.

In addition, AI and ML applications in smart cities enhance education and learning experiences for students in classrooms and laboratories by personalizing instruction, facilitating real-time feedback, and enabling immersive learning experiences. AI-powered adaptive learning platforms analyse students' learning styles, preferences, and performance data to tailor educational content and activities to their individual needs, promoting engagement and understanding. ML algorithms can assess students' progress and provide personalized recommendations for further study or intervention, helping educators identify areas for improvement and adjust teaching strategies accordingly. Additionally, AI-driven virtual reality (VR) and augmented reality (AR) technologies create immersive learning environments in classrooms and laboratories, allowing students to explore complex concepts, conduct experiments, and simulate real-world scenarios, enhancing their understanding and retention of knowledge [26]. Students who conduct experiments and simulate real-world scenarios are proven to gain practical experience, deepen their understanding of theoretical concepts, and develop critical thinking and problem-solving skills essential for their academic and professional success [27]. By leveraging AI and ML technologies, smart cities revolutionize education by providing dynamic, interactive, and personalized learning experiences that empower students to achieve their full potential.

While AI has many advantages for various smart city services, it also presents several difficulties. Due to differences in data organisation among jurisdictions, AI technology confronts issues in data gathering and exchange, notably in criminal justice. Ethical problems arise as well, necessitating the development of a computational ethics framework for AI decision-making [28]. Due to AI algorithms being less adaptive and requiring careful design to avoid unexpected behaviour and societal difficulties, overcoming these issues is critical for effective AI applications. Another significant challenge is data privacy and security. Smart city systems collect vast amounts of personal and sensitive data, raising concerns about data breaches, surveillance, and potential misuse of information. Ensuring robust data protection measures and adhering to privacy regulations are essential to maintaining public trust and confidence in smart city initiatives. Moreover, interoperability and standardization issues pose challenges to the integration of diverse AI and ML technologies across different city systems and infrastructures. Ensuring compatibility and seamless communication between various sensors, devices, and platforms is crucial for the effectiveness and scalability of smart city solutions. Furthermore, ethical considerations surrounding algorithmic bias, transparency, and accountability must be addressed to mitigate potential discrimination and ensure fairness in decision-making processes. Additionally, addressing digital literacy and access disparities is essential to ensure that all residents can benefit from smart city technologies and services.

Regardless of these challenges, the prospects of AI and ML in smart city applications are promising. With careful planning, collaboration between stakeholders, and a commitment to ethical and responsible deployment, AI and ML have the potential to transform cities into more efficient, sustainable, and liveable environments for all residents.

6. SMART HOME FACILITY

The utilization of Internet of Things (IoT) sensors plays a crucial role in enabling automation, monitoring, and control within smart homes; however, they also consume energy, leading to concerns about energy efficiency and environmental sustainability. An IoT sensor is a small electronic device equipped with sensors and connectivity capabilities that collects data from the physical environment and transmits it to other devices or systems over the internet [29]. The proliferation of IoT devices in modern households has resulted in increased electricity demand, contributing to higher energy consumption and greenhouse gas emissions. Hence to address the above problem, the combination of AI and ML can transform smart home technology by increasing its efficiency, and convenience, and enabling the delivery of personalised experiences to the users to enable data collection and autonomous switching on and off home appliances whenever needed only to save electricity [30]. These improvements in smart security systems and thermostats automate houses, increase safety, and optimise energy usage [31], resulting in a connected and intelligent home environment. The foundation for home automation often focuses on the usage of a local area network to manage temperature, humidity, and critical life components mostly utilising long-range wireless technology LoRa [32-34]. LoRa is a patented LP-WAN technology that often is used in smart home applications to enable data communication with servers for AI and ML decision-making. It uses chirp spread spectrum technology at the medium access control layer to provide cheap bidirectional communication in the sub-GHz ISM frequency spectrum [35]. LoRa technology, which has a battery life of more than 10 years, has flexible bandwidth demands ranging from 7.8 to 500 kHz and can cover up to 15 kilometres in suburban and 5 km in urban regions [36]. Implementing AI and ML in a smart home facility with LoRa application involves integrating various sensors, actuators, and devices to enable intelligent automation and decision-making. Firstly, sensors such as motion detectors, temperature sensors, light sensors, and door/window sensors are deployed throughout the home to gather real-time data on environmental conditions and occupancy. This data is transmitted wirelessly using LoRa technology to a central hub or gateway.

AI and ML algorithms are then employed to analyse the collected data and make informed decisions. For instance, ML models can learn patterns of occupancy and activity within the home, allowing the system to predict and adjust heating, cooling, and lighting settings accordingly to optimize energy efficiency and comfort. Additionally, AI algorithms can detect anomalies or unusual behaviour patterns, such as unauthorized entry or abnormal energy consumption, triggering appropriate alerts or actions. Moreover, AI-powered voice assistants like Amazon Alexa or Google Assistant can be integrated into the smart home ecosystem, enabling voice commands for controlling devices, setting schedules, or requesting information. Furthermore, AI-driven security systems can leverage ML algorithms to recognize and differentiate between familiar and unfamiliar faces, enhancing home security. LoRa's long-range and low-power capabilities ensure reliable communication between devices and the central hub/gateway, even in large homes or environments with limited connectivity.

However, several challenges must be addressed to fully realize the potential of AI and ML in smart home applications. One significant challenge is interoperability and compatibility issues between different devices and platforms. With the proliferation of smart home devices from various manufacturers, ensuring seamless integration and communication between devices can be complex and challenging. Additionally, privacy and security concerns are paramount, as smart home devices collect and process sensitive personal data. Ensuring robust encryption, authentication mechanisms, and data protection measures are essential to safeguarding user privacy and preventing unauthorized access to smart home systems. Moreover, user acceptance and adoption are critical challenges, as many consumers may be hesitant to adopt smart home technologies due to concerns about reliability, usability, and cost. Addressing these concerns requires educating consumers about the benefits of smart home technologies, providing user-friendly interfaces, and offering affordable solutions that deliver tangible value. Furthermore, ensuring the reliability and accuracy of AI and ML algorithms in smart home applications is essential. ML models must be trained on diverse and representative datasets to ensure robust performance across different environments and user scenarios [37-40]. Additionally, addressing algorithmic bias and ensuring fairness and transparency in decision-making processes are critical considerations.

Even with these challenges, the prospects of AI and ML in smart home applications are promising. With continued advancements in technology, increased interoperability between devices, enhanced privacy and security measures, and improved user education and acceptance, smart homes have the potential to transform the way we live, making our homes more comfortable, convenient, and energy efficient.

7. CONCLUSION

The combination of AI and ML has transformed the landscape of IR4.0 in various industries. In the field of medical diagnostics, AI and ML accelerate treatment and boost diagnostic accuracy as these technologies have improved patient treatment and health. Their ability to analyse large amounts of medical data allows medical workers to gain faster and more precise insights. Through quality control, predictive maintenance, and process optimisation, AI and ML are increasing productivity and efficiency in smart manufacturing, lowering operating costs, and promoting resource and sustainability-conscious approaches. Besides that, AI and ML algorithms are reshaping the automobile industry by enhancing smart car safety, efficiency, and environmental friendliness, resulting in lower emissions, fewer accidents, and improved traffic flow. In addition, smart homes powered by AI and ML improve quality of life by providing personalised, intuitive experiences that improve comfort, convenience, and security, with technologies that adapt to changing conditions and learn human preferences. Moreover, AI and ML are changing urban planning and management in smart cities, streamlining processes like trash management, energy utilisation, traffic flow, and public services. Thus, AI and ML are reshaping numerous businesses and society by increasing production, innovation, and living standards. However, challenges faced by the implementation of AI and ML in various fields to enhance IR4.0 development need to be further researched to find solutions that are critical for their proper usage and align with society's benefit.

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