Artificial Intelligence to Solve Pervasive Internet of Things Issues

Edited by
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and Marcus Tanque

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ACADEMIC PRESS

An imprint of Elsevier

Academic Press is an imprint of Elsevier
125 London Wall, London EC2Y 5AS, United Kingdom
525 B Street, Suite 1650, San Diego, CA 92101, United States
50 Hampshire Street, 5th Floor, Cambridge, MA 02139, United States
The Boulevard, Langford Lane, Kidlington, Oxford OX5 1GB, United Kingdom

British Library Cataloguing-in-Publication Data
A catalogue record for this book is available from the British Library

Library of Congress Cataloging-in-Publication Data
A catalog record for this book is available from the Library of Congress

ISBN: 978-0-12-818576-6

For Information on all Academic Press publications
visit our website at https://www.elsevier.com/books-and-journals

Publisher: Mara Conner
Acquisitions Editor: Chris Katsaropoulos
Editorial Project Manager: Amy Moone
Production Project Manager: Swapna Srinivasan
Cover Designer: Christian J. Bilbow

Typeset by MPS Limited, Chennai, India

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Dr. Gurjit Kaur is an Associate Professor in the Department of Electronics and Communication Engineering at the Delhi Technological University (DTU), Delhi, India. She has been a topper throughout her academic education. As a testimonial to the same, she has been awarded by the Chief Minister S. Prakash Singh Badal for being the topper in Punjab. After that, she was awarded a "Gold Medal" by the former President of India Dr. A.P.J. Abdul Kalam for being the overall topper of the Punjab Technical University, Jalandhar in B.Tech program. She also received an honor by Guru Harkrishan Education Society for being a topper among all the colleges and all the disciplines of PTU, Jalandhar. She then proceeded to PEC University of Technology, Chandigarh to complete her M.Tech in 2003 and also earned her PhD degree from Panjab University, Chandigarh in 2010 with distinction.

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In recognition of her outstanding contribution as an active researcher, she received "Research Excellence Award" by Delhi Technological University in March 2020. She also received Bharat Vikas Award by Institute of Self Reliance in National Seminar on Diversity of Cultural and Social Environment at Bhubaneswar, Odisha, India and Prof. Indira Parikh 50 Women in Education Leader Award in World Education Congress, Mumbai, India in 2017. Her career accomplishments over the past 16 years include over 90 peer-reviewed publications, including 60 journal publications, 35 conference publications, and over 10 invited talks/seminars. Due to her pioneer research, her name is also listed in Who's Who in Science and Engineering Directory, United States and her biography was also published by International Biographic Center, Great Britain as 2000 Outstanding Scientists.

She also worked as a convener for two international conferences, that is, International ICIAICT 2012 that was organized by CSI, Noida Chapter and International conference EPPICTM 2012 which was held in collaboration with MTMI, United States, University of Maryland Eastern Shore, United States, and Frostburg State University, United States at School of Information and Communication Technology, Gautam Buddha University, Greater Noida, India. Till date, she has delivered many expert talks on the emerging trends in optical for all domain applications at various universities and has served as a reviewer of multiple journals such as IEEE transactions on communication, etc.

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Dr. Marcus Tanque is a highly regarded principal technology advisor, senior cyber strategist, and an independent author. Marcus' expertise blends interdisciplinary areas—advanced, traditional, and emerging technologies. He is also a published technologist, researcher, and scholar with commended skills in various domains—IT governance, security analytics, policy, and strategic business practices. His professional skills encompass multidisciplinary research and development areas spanning digital technology, such as augmented analytics, machine learning, deep learning, quantum computing, and biometrics. His research interest involves policy management, blockchain, identity and access management, and decentralized Internet of Things devices and systems. He has consulted to many government, public, and private customers. His consultative and technical contributions bridge, multifaceted traditional, mission-centric programs, and emerging technologies. Such technological solutions involve artificial intelligence, robotics, advanced analytics, cybersecurity, and the Internet of Things.

Dr. Tanque has supported complex enterprise projects amid science and technology management. His experience in business and scientific domains encompass IT engineering, program and project management, information security and assurance, and natural language processing. He has conducted several studies in machine-to-machine and advanced database systems, computing, information systems, and cognitive science/informatics. His research work merges cyber resilience, business intelligence, cybersecurity operations, risk management, cryptographic solutions, information management, and security policy. He is a recipient of several academic awards, credentials, and professional letters of commendation.

Dr. Tanque is an active member of the Institute for Defense and Government Advancement, the Association for Computing Machinery, the Collegiate National Center for Academic Education, Committee on National Security Systems-Practice & Research, and the Institute of Electrical and Electronics Engineers. He has authored and edited scientific/technical books as well as articles on AI, ML, DL, data science, cloud, data analytics, full-spectrum cyber operations, Telecom, and related interdisciplinary areas. He received a PhD in Information Technology with a dual specialization in Information Assurance & Security, and a Master of Science in Information Systems Engineering. In his spare time, he serves as an independent researcher/author, editorial review board member, and referee for several books, journal articles, and published chapters. He enjoys coaching and mentoring others. He is an enthusiastic reader and researcher who inspires many in academic, professional, and social communities.

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Preface

Dr. Gurjit Kaur, Dr. Pradeep Tomar and Dr. Marcus Tanque

Artificial intelligence (AI) leverages computer systems designed to support tasks that call for human interaction, intelligent design, and computational agents. AI and Internet of Things (IoT) attract the interest of researchers and practitioners. These professionals have worked on machine learning (ML), knowledge representation and reasoning (KRR), and deep learning (DL). Such solutions aim to solve issues affecting IoT devices and systems. AI involves the integration of data from IoT to the ability for devices and systems to perform automated tasks beyond human intelligence. The method integrates AI's deep insights into data provisioning, managing, security, visualization, and monitoring through augmented analytics processes. These AI capabilities support the interaction of IoT devices and systems.

This book applies AI, ML, KRR, DL, and IoT technologies. It focuses on each of these technologies' benefits, challenges, drawbacks, and trends. The book covers other emerging technologies needed for integrating AI-based solutions to solve pervasive IoT issues. It points toward the adoption and integration processes needed for sustaining AI and IoT infrastructure operations and management functions. The content comprises innovative AI and IoT concepts, theories, procedures, and methods. AI and IoT solutions have contributed to the acquisition, planning, execution, implementation, deployment, operation, and monitoring of enterprise technology assets or technological resources. The target audience of this book involves professionals, such as researchers and practitioners working in the fields of AI, ML, and IoT. These experts focus on building knowledge-based agnostic solutions for applications, devices, and systems.

This book contains 20 contributed chapters authored by experts in the field of AI, IoT, ML, DL, and KRR. The book introduces basic AI and IoT components and applications, that is, standards, legal issues, privacy, security, and ethical considerations. Detailed use cases are described, covering a variety of technological advancements, implementations, and challenges. The authors explore other technical domains, which have contributed to AI, ML, and IoT technologies. These domains have emerged over time due to disruptive technical and scientific innovations in the industry.

The book is organized as follows:

Chapter 1: Impact of Artificial Intelligence on Future Green Communication

The chapter explores AI impact on future green communication. It discusses the increase in mobile subscriptions for base stations. Base stations involve systems that require more power to operate. Minimizing the number of base stations while enhancing their energy efficiency poses significant opportunities for green energy. AI plays a crucial role in green areas, which is energy forecasting, energy-efficient, and energy accessibility. This chapter provides a brief foundation and history of AI technology and green communication roadmap. It highlights critical AI-based applications, practices, and future research directions.

Chapter 2: Knowledge Representation and Reasoning in AI-Based Solutions and IoT Applications

The chapter focuses on KRR in AI-based and IoT applications—it explains AI, KRR, and IoT disruptive evolution. Researchers and practitioners develop and integrate analytical solutions to solve pervasive issues affecting computational applications. These technological developments comprise relevant computational areas: devices, sensors, autonomous vehicles, robotics, virtual reality, and augmented intelligence. The author discusses similar technical solutions that researchers need to solve issues affecting AI, KRR, and IoT applications.

Chapter 3: Artificial Intelligence, Internet of Things, and Communication Networks

The chapter examines AI, IoT, and communication networks. AI handles connectivity, self-optimization, and self-configuration. The method assesses and predicts the current state as well as historical data needed to automate the network. Communication networks are becoming more complex to manage, due to the disruption of data, which affects device and systems connectivity. This process comprises low cost, power-efficiency, and high-performance network technologies. Incorporating AI into these networks requires automated solutions to introduce smart and intelligent decision-making processes needed for managing networked control systems.

Chapter 4: AI and IoT Capabilities: Standards, Procedures, Applications, and Protocols

The chapter analyzes AI and IoT capabilities—standards, procedures, applications, and protocols. The authors present AI-based applications, methods, standards, and protocols for interacting with IoT-based objects. Advanced AI technologies interact with IoT devices and systems—technical crossing point, mimics human intelligence interaction, collects, and processes data in real-time.

Chapter 5: Internet of Intelligent Things: Injection of Intelligence into IoT Devices

The chapter discusses the IoT seven-layer model—physical or sensor, processing and control action, hardware interface, radio frequency, section/message, user experience, application. This protocol stack discussion, hence, illustrates each layer's function and overarching operations posture. Similarly, the authors underscore the relationship between AI and IoT and other automated AI/IoT solutions.

Chapter 6: Artificial Intelligence and Machine Learning Applications in Cloud Computing and Internet of Things

The chapter examines AI, ML, IoT, and cloud computing solutions that dominate the global business and technology landscape. These technical innovations contribute to the decentralization of IoT devices and systems. The authors illustrate a detailed AI analytical review and challenges and ML solutions applied to IoT devices and systems. These solutions are essential to the technical and scientific advancement of IoT devices and systems and AI/ML solutions.

Chapter 7: Knowledge Representation for Causal Calculi on Internet of Things

The chapter introduces Pearl's model, Shafer's model, and the Halpern–Pearl's model. This chapter introduces knowledge representation for causal calculus in IoT. IoT devices and systems harness causal inference. Causal calculi are the mathematical foundations for expressing and computing causation. In contrast, causation illustrates how one event may cause another—causal systems founded in logic and probability theories. Pearl's method uses Bayesian networks on acyclic directed graphs. Shafer's method works on the dynamics of probability trees. The Halpern–Pearl model builds on Pearl's model producing two causal views. One of these views attributes causes from past events. The other ones focus on causal reasoning giving predictions.

Chapter 8: Examining the Internet of Things–Based Elegant Cultivation Technique in Digital Bharat

The chapter discusses IoT, elegant cultivation techniques in digital Bharat. These innovative technologies do farm development and management. These technological farming solutions focus on enhancing effectiveness, competence, and leverages international markets—for instance, solutions have diminished human intercession. The authors' research approach focuses on the device, system function, and applications.

Chapter 9: Machine Learning and Internet of Things for Smart Processing

The chapter discusses the relationship between ML and IoT. It defines processes and impacts these technologies present to academic, business, technical, and scientific communities. ML and IoT solutions comprise three distinct areas. These are recurrence groups, spatial channels, classifiers arrangement, and execution required to determine the best settings.

Chapter 10: Intelligent Smart Home Energy Efficiency Model Using Artificial Intelligence and Internet of Things

The chapter analyzes the design and implementation of a smart home system model to safeguard all the electrical equipment and monitoring the performance of each system installed in smart homes. These systems use AI and IoT solutions that optimize energy usage for an intelligent smart home energy efficiency model applying AI and IoT.

Chapter 11: Adaptive Complex Systems: Digital Twins

The chapter reviews the features of complex systems. It proposes solutions to support digital twins and adaptable systems needed for interacting with ML solutions. This method is presented in the chapter through simple tutorial agents' examples using ML technology. The process focuses on authors who use technology to build digital twins for supply chain networks.

Chapter 12: Artificial Intelligence Powered Healthcare Internet of Things Devices and Their Role

The chapter examines AI-based technologies, for instance, the vulnerability, threats, risks, and challenges on the Internet of Medical of Things (IoMT) devices and systems. IoMT is a healthcare domain that complements AI-solutions, IoT devices, and systems.

Chapter 13: IoIT: Integrating Artificial Intelligence With IoT to Solve Pervasive IoT Issues

The chapter examines the Internet of Intelligence of Things, AI-based solutions' integration, IoT devices, and systems. It discusses the ML-Random Forest Regression model that evaluates applicability and preventability with variance score. This process focuses on AI and IoT areas.

Chapter 14: Intelligent Energy-Oriented Home

The chapter discusses two areas—intelligent energy systems and smart homes. The foundations of these fields are presented concisely. This process entails projects on intelligent energy systems for homes, buildings, and associated business ventures.

Chapter 15: Corporate Cybersecurity Strategy to Enable Artificial Intelligence and Internet of Things

The chapter addresses cyber-adversarial system, internal and external threats, the anatomy of a cyber-attack, and financially motivated cyber-attackers. It further analyzes ideologically and politically motivated cyber-attackers. It covers many aspects of cybersecurity, that is, cyber-related laws, cybersecurity Inertia, cybersecurity IT portfolio management, and smarter cybersecurity leveraging artificial intelligence.

Chapter 16: Role of Artificial Intelligence and the Internet of Things in Agriculture

The chapter discusses how AI and IoT solutions help the software and systems engineers develop innovative capabilities for the agriculture industry. These technologies may be built with low cost and few resources.

Chapter 17: Integrating Artificial Intelligence/Internet of Things Technologies To Support Medical Devices and Systems

The chapter argues IoT/AI integration, concepts, procedures, and requirements relating to medical devices and systems. It underlines various security characteristics amid the AI/IoT integration. This process includes several changes in the ecosystem and analyses on the next generation of medical devices and systems.

Chapter 18: Machine Learning for Optical Communication to Solve Pervasive Issues of Internet of Things

The chapter analyzes ML-based solutions for optical communication and technical issues affecting physical and network layers. This process involves selected ML applications along with optical communication systems associated with physical and network layers.

Chapter 19: Impact of Artificial Intelligence to Solve Pervasive issues of Sensor Networks of Internet of Things

The chapter examines AI's impact on solving pervasive IoT-based intelligent sensors and systems issues. It presents a brief introduction of IoT devices and systems, history, characteristics, and network formation topologies. IoT sensor networks and AI-based solutions and features are further discussed in the chapter.

Chapter 20: Principles and Foundations of Artificial Intelligence and the Internet of Things Technology

The chapter explores AI and IoT technological foundations and principles. It illuminates how AI helps computers to learn from various experiences by adapting to new environments. This method includes devices and systems that perform tasks beyond human capacity. Comparably, the chapter analyzes how IoT-based technologies help objects observe, identify, simulate, and understand a situation and/or environment with limited human assistance.

The collected authors in this book explore the concepts, techniques, procedures, and implementations of these combined and/or integrated technologies.

CHAPTER

IMPACT OF ARTIFICIAL INTELLIGENCE ON FUTURE GREEN COMMUNICATION

1

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1.1 INTRODUCTION

Future wireless communication networks (5G) will be highly complex and composite networks due to the integration of the different wireless and wired networks. This integration is known as heterogeneous networks (HetNets) where each network is having its different protocols and properties [1]. This combined HetNet is having various critical challenges for network scheduling, operation, troubleshooting, and managing. In the ongoing scenario the technology paradigm shifts from user-centric to device-oriented communication, which is responsible for converting the simple wireless networks into a complex form. Nowadays to justify and resolve the operational complexity of future wireless communication networks, several novel approaches like cognitive radio, fog computing, Internet of Things (IoT), and so on have become very important. The artificial intelligence (AI) is one of the most promising approaches to make the adoption of the new principles, which include learning, cognitive, and decision-making processes, for designing a strongly integrated network. Integration of AI with data analytics, machine learning, and natural language processing approach is used to improve the efficiency of the future wireless network generations. There are remarkable growth and progress in AI technology, which facilitates to overcome the problem of human resource deficiencies in many fields. Among the countries, the competition of becoming a global leader in the field of AI has officially started. Most of the countries like India France, China, Japan, Denmark, Canada, Finland, Italy, Mexico, the United Kingdom, Singapore, South Korea, North Korea, Taiwan, and the UAE, have already represented their strategies to endorse the development and usage of AI policies [2]. These countries are promoting the various tactics of the AI techniques like technical research, AI-based products, talent, and skills development, adoption of AI in private and public sector, standards and regulations, and digital infrastructure. Table 1.1 is representing the top 10 countries rankings in AI index in the year of 2018−19.

1.2 THE HISTORY OF ARTIFICIAL INTELLIGENCE

AI is one of the latest topics for research in advance wireless communication system. A very interesting fact related to this technology is that this is much older technology than you would imagine.

Artificial Intelligence to Solve Pervasive Internet of Things Issues. DOI: https://doi.org/10.1016/B978-0-12-818576-6.00001-0

Table 1.1 Top 10 Countries Rankings in Artificial Intelligence Index With score in the Year of 2018–19 [3].

Country	Ranking	Score
Singapore	1	9.186
United Kingdom	2	9.069
Germany	3	8.810
United States of America	4	8.804
Finland	5	8.772
Sweden	6	8.674
Canada	6	8.674
France	8	8.608
Denmark	9	8.601
Japan	10	8.582

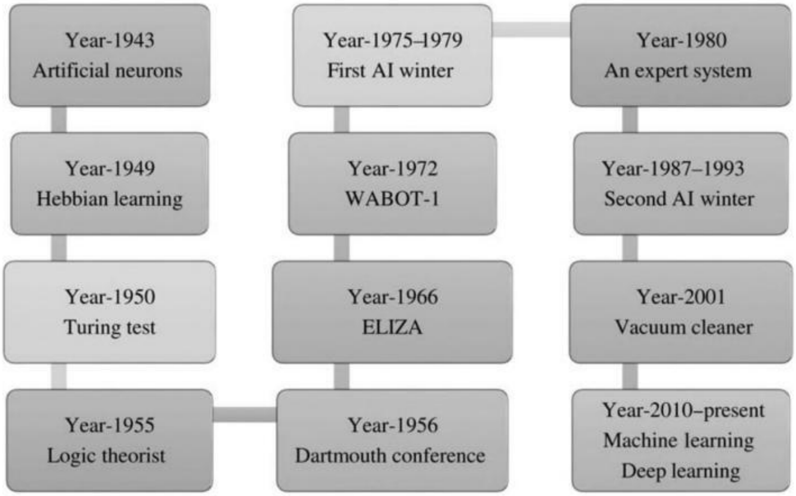

FIGURE 1.1

History of AI. *AI*, Artificial intelligence.

The concept of intelligent robots was presented by Greek myths of Hephaestus "mechanical men" and Talos "bronze man" [4]. Some important milestones of the journey of AI from an initial state to till date are represented pictorially as in Fig. 1.1.

1.2.1 THE FOUNDATION OF ARTIFICIAL INTELLIGENCE

- Artificial neurons: The artificial neurons were the first model of AI, which was proposed by Walter pits and Warren McCulloch in 1943.

- Hebbian learning: A modified rule of construction of neurons is presented by Donald Hebb in 1949. This rule is known as Hebbian learning.
- Turing test: This test can evaluate the intelligent behavior of a machine and also compare it with human intelligence. An English mathematician Alan Turing author of "Computing Machinery and Intelligence" has proposed this test in 1950.
- Logic theorist: "The first AI-based program" that was organizes by the Herbert A. Simon and Allen Newell in 1955.
- Dartmouth conference: The AI technology was the first time adopted by the American scientist John McCarthy in the academic field at this Conference in 1956.

1.2.2 PROGRESSION OF ARTIFICIAL INTELLIGENCE

After the year 1956, the researchers have invented high-level computer languages like COBOL, PASCAL, LISP, and FORTRAN. These language inventions increased the scope of AI in society [5].

- ELIZA: The first AI-based algorithm developed by Joseph Weizenbaum is known as ELIZA in 1966. This algorithm is used to solve the problems of mathematics.
- WABOT-1: Japan has constructed the first humanoid intelligent robot known as WABOT-1 in 1972.
- First AI Winter: This is the time duration (from 1975 to 1979) when the interest of AI was reduced due to the scarcity of funding, for the research of AI.

1.2.3 EXPANSION OF ARTIFICIAL INTELLIGENCE

- An expert system: After the first AI winter period, AI came back again into the light as an "expert system" in 1980. This system has ability to take decision like human expert. In this year the first national conference on AI was organized at Stanford University.
- Second AI winter: The time duration from year 1987 to 1993 was the time duration of second AI winter.
- AI in home and business: At the year 2001 first time, AI-based application, a vacuum cleaner used in the home. After that AI entered into business world companies such as Gmail, Facebook, Instagram, Twitter, and so on.

1.2.4 MODERN ARTIFICIAL INTELLIGENCE

Now AI is the most significant technology, which is used in almost all areas. The concept of machine learning, deep learning, cloud computing, and big data are just like a boom for the present scenario. Many well-known leader corporate companies like IBM, Google, Flipkart, and Amazon are focusing on AI for making their remarkable devices to provide their users with a better quality of experience (QoE). The future AI technology will be based on a high level of intelligence and amazing capacity and speed [6].

- Machine learning: Machine learning concept is one of the types of data mining techniques. Machine learning is an approach of analyzing data, absorb from that data, and then make a decision. Now, most of the big companies use machine learning for their working operations like YouTube uses machine learning to offer better suggestions to their subscribers of the movie, shows, and videos that they would like to watch.
- Deep learning: Deep learning is a subclass of machine learning. It is functioning like machine learning but it has some distinct capabilities. The key difference between machine learning and deep learning is, machine learning model requires some guidance to take accurate decision while the deep learning model does it by itself. The good example of deep learning is automatic car driving system.

1.3 A ROAD MAP OF USING ARTIFICIAL INTELLIGENCE FOR GREEN COMMUNICATION

This will be a great step to introduce AI technologies in the field of wireless communication systems. Incorporation of AI technologies in the field of signal processing and pattern recognitions has represented the amazing results [7]. Presently, the key concern of the AI technologies in wireless communication systems is to find out the accurate wireless node position, proper resources allocation and optimization, and secure data transmission without delay. However, new research is to think about how to incorporate AI schemes into wireless communication. Compared to the conventional wireless communication systems, the new AI-based wireless communication systems should have four eminent aptitudes. These aptitudes are analyzing aptitude, thinking aptitude, learning aptitude, and proactive aptitude. The new framework of AI wireless communication systems with these aptitudes is illustrated in Fig. 1.2.

1.3.1 ARCHITECTURE OF ARTIFICIAL INTELLIGENCE-BASED GREEN COMMUNICATION

The future wireless communication networks should have inherent capabilities like low-latency, ultrareliable communication and intelligently manage the resources, energy efficient, and combination of IoT devices in a real-time dynamic environment [8]. Such communication necessities and core mobile edge requirements can only be accomplished by integrating the fundamentals and principles of AI and machine across the wireless infrastructure. Fig. 1.3 represents the wireless network architecture with AI principles for a different environment. The diagram shows the integration of various latest communication technologies used for greening communication in different scenarios (urban, suburban, and rural areas).

1.3.2 OPTIMIZATION OF NETWORK USING ARTIFICIAL INTELLIGENCE

Effective data gathering and information acquisition are the most essential requirements for optimizing the future wireless communication system. To extract the relevant information from the collected data in an effective manner is under the processing of data. In the third step, researches

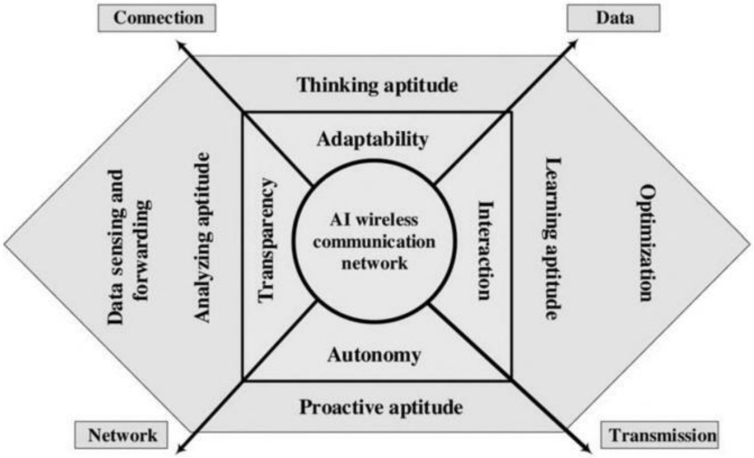

FIGURE 1.2

Framework of AI wireless communication systems with aptitudes. *AI*, Artificial intelligence.

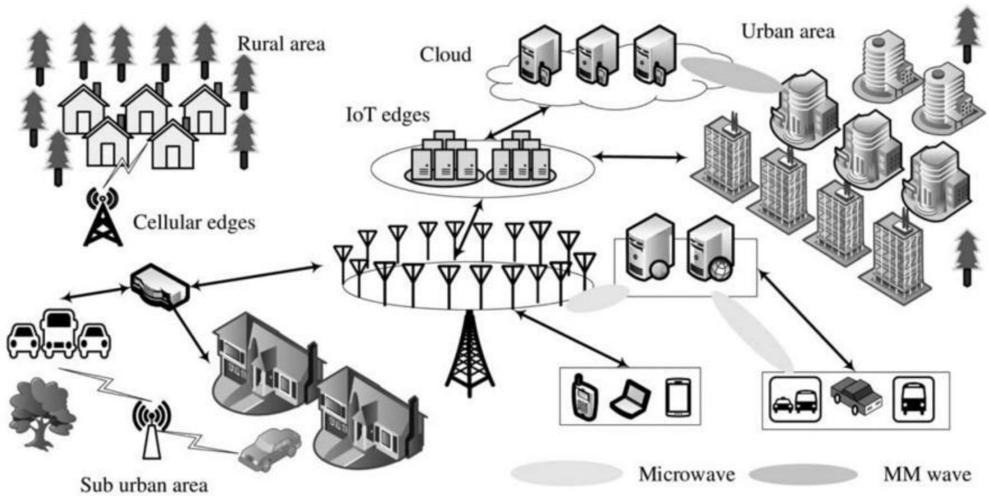

FIGURE 1.3

Energy-efficient wireless network with AI principles analyzing, cognitive, and decision making. *AI*, Artificial intelligence; *mm*, millimeter.

analyze this received information and apply various aptitudes on it. Finally, at the last step, an optimized decision is presented which converts the wireless network into an optimized network. Fig. 1.4 represents the networks optimization process to identify best network for better QoE.

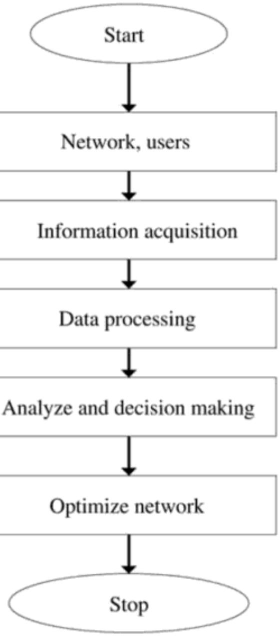

FIGURE 1.4

Network optimization by artificial intelligence technique.

1.4 KEY TECHNOLOGIES TO MAKE 5G IN REALITY USING ARTIFICIAL INTELLIGENCE

The necessity to deal with this rapid progression of wireless services has required a large research activity that explores what are the optimal options for designing of user-oriented context-aware next-generation (5G) wireless communication network. The key components for 5G are multiple input multiple output (MIMO), massive MIMO, ultradense deployment of small cells, millimeter (mm) wave communications, and device-to-device (D2D) communications have been recognized. The integration of these technologies in the wireless system with the cooperation of AI principles in the most effective manner is a challenging task for operators and researchers.

1.4.1 MULTIPLE INPUT MULTIPLE OUTPUT

This is the most promising approach to consider the development of the next-generation wireless network system. In this technique, multiple antennas are situated at both the end transmitter (source) and receiver (destination) [9]. For enhancing efficiency and reducing the errors of the network, these antennas are associated effectively [10]. This technique facilitates to multiply the capacity of the antenna more than 10 times, without increasing the power and bandwidth of the system [11]. This QoE focused approach is made it an essential element of the wireless communication network [12]. The comparison of MIMO with single input single output, multiple input single output, and single input multiple output is given in Table 1.2.

1.4.2 MASSIVE MIMO

This technique is not only energy efficient but also spectrum efficient. Massive MIMO (M-MIMO) is one of the advanced versions of technologies of MIMO having several antennas at the base station of the communication system. This technique requires shorter wavelengths (higher frequencies) because the system needs to physically pack more antennas into a small area than the other mobile networks [13,14]. The main advantage is that a base station can serve multiple subscribers simultaneously within the same spectrum. Fig. 1.5 represents the architecture of the Massive MIMO technique where ten to hundreds of antennas are serving for the communication process simultaneously.

1.4.3 ULTRADENSE NETWORK

In the new age, ultradense network (UDN) has emerged as a prominent solution to fulfilling the requirement of enormously high capacity and data rate of the 5G wireless network. Qualitatively, this network has a much higher density of radio resources than that of other existing networks in the telecommunication market [15,16]. In literature, there are various definitions of UDN suggested by various authors. In Ref. [17], the author has defined the UDN as a network where the access point and base station density exceeds the user density in a particular area. In Refs. [18,19], a UDN is considered as a network where the distance between the access points and base stations is only a few meters. The architecture of a UDN is showing in Fig. 1.6. A UDN plays a vital role in converting the communication into green communication. In this technique, the access points and base stations are presented very close distance to the mobile subscribers. The relation between the power and distance shows that the distance is directly proportional to the power. So, if the distance

Table 1.2 Comparison of Multiple Input Multiple Output (MIMO) With Single Input Single Output (SISO), Multiple Input Single Output (MISO), and Single Input Multiple Output (SIMO).

S. No.	SISO	SIMO	MISO	MIMO
1.	Simple circuitry	Known as receive diversity	Known as transmitter diversity	Improve channel capacity
2.	Diversity not required	Easy to implement	Reduce the problem of interference	Improve channel throughput
3.	Low throughput	High cost than SISO	High cost than SISO	Highest cost
4.	Channel bandwidth is limited	Problem of battery drain	Channel capacity is not improved	Complex circuitry

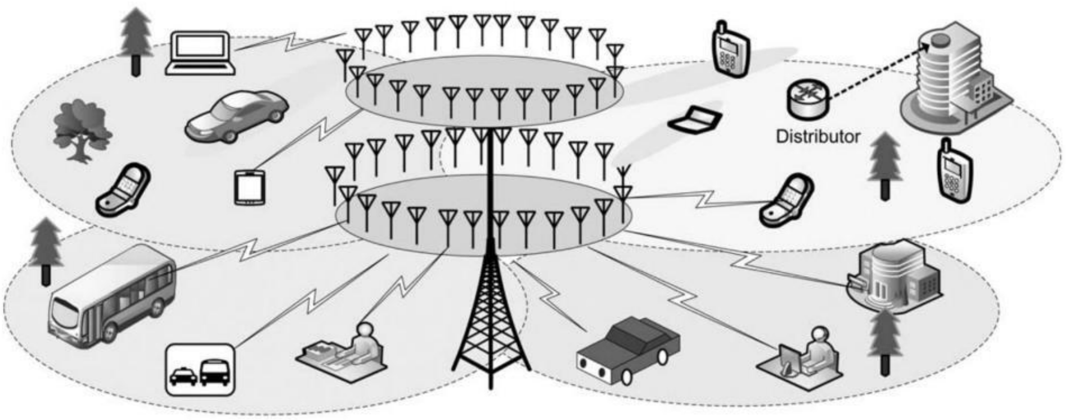

FIGURE 1.5

Massive multiple input multiple output technique in 5G network.

between the mobile subscriber and access point will reduce the power of the communication system will automatically reduce. In this way, by minimizing the power consumption a UDN promotes energy-efficient communication.

1.4.4 MILLIMETER WAVE

The mm waves are one of the most important approaches for the next generation of wireless networks. For delivering fast multimedia services, high-quality audio, video, and real-time services, a large amount of bandwidth is required. To solve this problem of spectrum scarcity, mm wavelength will be used in 5G network communication system. The signals are operating between the range of 30 and 300 GHz and being shifted to a higher spectrum. A large amount of bandwidth is offered at mm-wave frequencies as compared to the bandwidth used by 4G and earlier wireless generation networks.

1.4.5 DEVICE-TO-DEVICE COMMUNICATION

D2D communication is one of the effective technical approaches to reduce the consumption of power and improve the data transmission rate [20]. In this technique, two physically separated nearby located cellular nodes can directly communicate with each other with low transmit power and high spectrum utilization efficiency without considering the base station in the communication process showing in Fig. 1.7. The D2D communication approach is recognized as a public safety network for future wireless communication by Federal Communications Commission because of the low cost and high data rates offered by this technique.

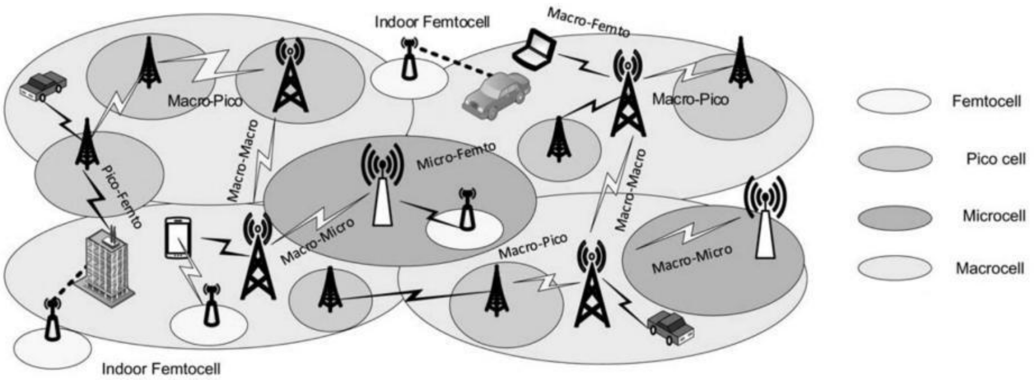

FIGURE 1.6

Architecture of ultradense network.

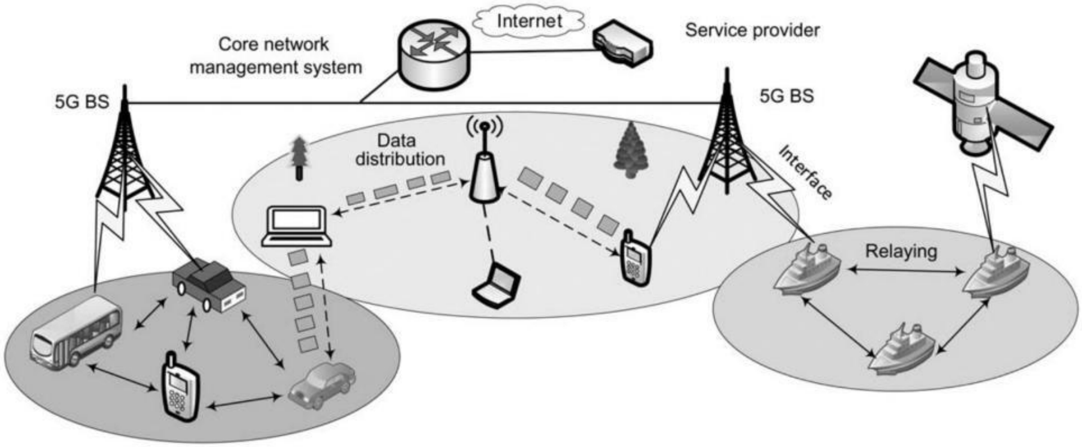

FIGURE 1.7

Architecture of device-to-device communication.

1.5 FEATURES OF ARTIFICIAL INTELLIGENCE-BASED GREEN COMMUNICATION

The present era is based on perceptional, cognitive, and computational intelligence. So, telecom researchers and operators are on the path of creation of AI-based green communication system. For the adoption of AI technology, government and other agencies are encouraging the development of AI algorithms and investing funds and resources for AI-based research activities. By these full supports, the operators have achieved success in the sequence of effective practices in several fields and accomplished productive results.

1.5.1 APPLICATION AND PRACTICES OF ARTIFICIAL INTELLIGENCE-BASED GREEN COMMUNICATION

Nowadays there are various applications of AI from collecting data to give an optimized output. The aim is to apply AI in the mobile industry is to gain a seamless network operation to improve the energy efficiency of the wireless network.

- Appling AI in the planning process: In the planning process AI is used to predict the traffic demand. In AI-driven traffic prediction there are two types of traffic tendencies short-term traffic tendency and long-term traffic tendency.
- Appling AI in network monitoring: Network monitoring and maintenance is the most complicated process. It is very difficult to analyze the requirement of customers because it dynamically changed so maintain the network according to their request is a tough process.
- Appling AI in service monitoring: To monitor the quality of service and QoE for any network is the most important task. Using AI for this purpose will give an accurate result.

1.5.2 FUTURE RESEARCH DIRECTIONS

The major research challenges are outlined in this chapter. A widespread effort is required from academia and industry in this area listed to contribute to green communication.

- Energy saving in telecommunication equipment using AI: Telecommunication systems and operators are having a large number of equipment and data centers. These data centers are made by many hardware like processing unit, input output devices that consume a large amount of power for operation. Therefore, the communication system is facing a shortage of power and energy. Various power-saving techniques based on AI like deep learning and machine learning is using to fight with this serious situation.
- Ability to improve data interaction: An AI-based system organizes the available data in a very effective manner and converts this data into relevant information.
- More effective and efficient collaboration: The benefits of AI in a collaborative manner comprise sending information more effectively at a global level. For example, real-time language translation, fast feedback, and accurate scheduling.
- Secure and seamless services: AI-based applications motivate the intelligent security management system. Based on AI services such as big data, cloud computing, and IoTs are the technologies that provide secure data transmission.

1.6 CONCLUSION

For the Information and communication technology (ICT) industry, the next-generation AI-based 5G communication network is considered as the key enabler and offers a diversity of features and services with various requirements. This chapter represents the mutual concern of the AI and next-generation wireless communication systems and technologies. The AI-based 5G wireless communication network will adopt a greater number of candidate recent technologies in the future. Therefore to manage and monitor the next-generation wireless communication, inclusion of AI with communication is very important. In this chapter, advanced wireless networks like MIMO, M-MIMO, UDN, mm wave, and D2D communication for 5G network designing and the relationship between AI and green communication are discussed. Applications and future research directions of AI-based wireless communication are also highlighted in this work. The prediction is that AI-empowered 5G communication networks will make the acclaimed ICT enabler a reality.

ACKNOWLEDGMENT

The authors would like to thank the Women Scientists Scheme-A under the Department of Science and Technology Government of India for its financial support of this work under File No: SR/WOS-A/ET-154/2017.

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CHAPTER

KNOWLEDGE REPRESENTATION AND REASONING IN AI-BASED SOLUTIONS AND IoT APPLICATIONS

2

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2.1 INTRODUCTION

The chapter explores and addresses the intersection between knowledge representation and reasoning (KRR) applications, artificial intelligence (AI) solutions, and the Internet of Things (IoT) objects, notably intelligent devices and sensors. This chapter focuses on smart homes and cities. It discusses the fundamental transformations that researchers have made in the fields of KRR, AI, machine learning (ML), deep learning (DL), and IoT [1,2]. Hybrid AI-KRR capabilities interact with human-to-machine and device-to-system [3]. AI is an integrated, technology-based capability, which incorporates human intelligence (HI) and smart objects, such as devices and sensors [1]. The triad forms a single or multiple computer systems capable of performing massive workload computer processing [1]. AI-based solutions are developed to support and solve various events [3]. The studied process involves human insights, ability to ensure the performance of smart objects, and determine when these sound devices and sensors can interact. AI has reshaped the global technology landscape through its incorporated analytical capabilities [1].

2.2 BACKGROUND

In the last two decades, KRR, IoT, and AI-based capabilities have been used to support other technology domains. This technology evolution involves HI, smart devices/sensors, and reasoning systems that interact when deployed in a decentralized IoT networks [2,4]. This advance is due to continuous technological innovations involving AI, KRR, ML, DL, artificial neural networks (ANNs), IoT devices and sensors. KRR is a subclass of AI that focuses on data displaying and processing [1]. The research discusses other interdisciplinary areas, such as psychology and mathematics [1,2].

In 1955 John McCarthy coined the term AI, as a "science and engineering of making intelligent machines" [5]. In the summer of 1956 McCarthy organized a technology workshop at Dartmouth College. At that conference, other AI research leaders, namely, Allen Newell, Arthur

Artificial Intelligence to Solve Pervasive Internet of Things Issues. DOI: https://doi.org/10.1016/B978-0-12-818576-6.00002-2

Samuel, Herbert Simon, and Marvin Minsky, joined McCarthy [6]. As part of the conference proceedings, these experts presented a research project on AI topics. The researchers also received positive feedback from those in attendance. Those who attended the workshop at Dartmouth in 1956 were deemed to be one of the AI research leaders [7,8]. These researchers along with a group of students developed a computer program called "astonishing." In 1954 AI researchers conducted an array of tasks to satisfy past research work. Those projects led to successful technology breakthroughs, some of which today are called AI, KR, ANN, HI, ML, and DL [5].

In 1959 computers were able to play the "checkers strategy game" at a much-accelerated pace than an average human. Checkers' strategies consisted of information processing system-based games that researchers designed to solve issues involving the algebraic "proving logical theorems" [5].

2.3 KNOWLEDGE REPRESENTATION AND REASONING

Knowledge representation (KR) is a method that involves formalism [4]. KR is a subclass of integrated AI functions [4]. It lies in the accepted concept and design theories for information visualization, logical thinking, and processing [3]. This concept includes "semantic networks (SNNs), systems architecture, frames, rulers, and ontologies." Automated reasoning differs from "inference engines, theorem provers, and classifiers" [4].

AI is a domain that integrates technological areas namely HI, computers, and intelligent machines [3,9]. These domains range from AI intelligent systems to fused KRR capabilities required to process tasks through perceptive methods [2,4]. AI dates to the era of the Greek philosopher, Aristotle's earliest events.

Aristotle's findings examine the relationship between philosophy and logic concepts and theories [3]. Aristotle describes "reasoning" a *syllogism* [3,9]. He defines syllogism, a speculation that involves objects, ideas, factors, events, phenomena, or entities. A syllogism describes initial results in Aristotle's investigative methods [3]. Whereas the term "reasoning" has originated from the disciplines of computer science, sociology, and psychology. In contrast, logic is a process for gathering and blending methods, it operates at the heart of an assumption that man makes to ensure collaboration of two or more concepts and thoughts [9]. This concept illustrates different forms, such as providing or displaying data through analytical conclusions [9–11], as summarized by McCarthy [10]:

"A program delivers a common sense if it automatically deduces for itself a sufficiently wide class of immediate effects of anything, it is ordered and what it already knows... For a program to be capable of taking something, it must first be capable of being stated it." "Programs with Common Sense" [10].

2.3.1 KNOWLEDGE ENGINEERING

Knowledge engineering (KE) plays an essential role in applied AI research sphere. Researchers argue that an idealistic way to address, KRR, AI, KE, ML, and DL issues is by collecting and parsing data. This method ensures that researchers have the capacity they need to examine machine reasoning and how each of these systems can do specialized jobs. Thus KE is a cognitive operation that represents scientific and societal features. Such method plays a critical role in designing and supporting knowledge-based systems.

2.3.2 EXPERT SYSTEM

Expert system (ES) is an application that clinicians use to carry on medical diagnoses [12]. Edward Feigenbaum is one of the first scientists who coined the term "expert system" [12]. The first ES did not embrace a standardized functional process. Hence, the system lacked the capability researchers needed to extend their investigative scope, which subsequently contributed to the development of inference engines and software applications [12]. The original ES consisted of the following software processes: conventional and development methods, and the need for designing unique programs for tuning or streamlining the requirements for building ES. Whereas knowledge acquisition (KA) gives companies such as Andersen Consulting, the ability to secure research opportunities. KA ensures that the redesigning processes use different versions of prototypes [12].

2.4 KNOWLEDGE INFERENCE, FORWARD AND BACKWARD CHAINING, AND KL-ONE LANGUAGES

Knowledge inference, forward chaining (FC) and backward chaining (BC) or backward reasoning (BR), and KL-One languages are applications or engines that are being employed today. These applications/processes are deployed along with ES prototypes [12]. ES is a hardware that stores large volumes of datasets. The stored data contain large volumes of data or datasets about the world. On the contrary focuses on dual methods of reasoning prototypes [12]. Researchers argue that this process occurs when there is a logical description of the interface engine. The ES implementation process is extremely complicated. The logical process moves the commercial enterprise and production-based rule system prototypes [12]. BC/BR is a process that relies on artificial intelligence applications (AIAs), automated theorem evidence ES, and proof assistants. BC and FC are concepts integrated in AI, game theories, and other ES prototypes [12]. In KE, domain ontology (DO) and domain-specific ontology (DSO) describe many things, such as objects that exist around the world. Humans view ontology as a process, which involves poker domain prototypes [12]. This concept describes a method for modeling, computer hardware, notably "punched and video cards" imports, and others. In the DO, ontology meanings are interpreted through domain perceptions prototypes [12].

In 1977 Ronald J. Brachman discussed the term "KL-One" in his doctoral research—KL-One is an integrated NR system [13]. Preceding Brachman's research work, other scholars conducted more studies focusing on "representation." The research was independent of other studies that incorporated similar domains. KL-One permeates the representation of the indistinctness in SNNs. Its process describes technical data, logically, called a structured inheritance network [14,15]. This method aims to new technologies, namely epistemological level (EL). EL focuses on dealing with complex concepts, such as attributes, instantiations, descriptions, uses, and inheritances [14–16].

Brachman [17] states that, in early investigative studies, each of these concepts was illustrated as "representation systems" [18]. These systems range from traditional and technological SNNs and form networks (FNNs). The progress and fine-tuning methods have improved over the years. These schemes are used in scientific research areas, to implement new knowledge-based concepts and basic research methods for the AI society [15].

KL-One kernel points out that AI researchers rely on to formulate structured complex descriptions [15]. This knowledge-based method is applied to identify and defines the relationship between network theories [13]. SNNs or FNNs are networks that describe systems, which can be deployed to a KR environment. These systems focus on direct and undirected graphs equipped by the vertices [13]. In this context, vertices symbolize "concepts and edges." Vertices describe relationships between concepts [13]. SNNs are identified as semantic triples. The networks are used to support an array of applications, such as NLP [13].

2.4.1 TECHNOLOGICAL SINGULARITY AND RECURSIVE SELF-IMPROVEMENT

In 1959 Allen Newell and Herbert A. Simon developed KR. KR is designed to resolve complex issues affecting technology singularity and recursive self-improvement [4]. Newell and Simon developed a method to integrate plan and analyze data structures [3]. These strategies stem from outlining conceptual plans to supporting predicted outcomes. AI solutions are deployed to support general search algorithms [19]. These procedures include ($\boldsymbol{A}^*$) frequently known as (A star). The "A star" computer algorithm was produced to support AI solutions and issues involving GPS systems. The failure of these scientific research efforts resulted in a cognitive change [3,19]. Fig. 2.1 explains an adapted-logical relationship between the triangle of cognitive science fields [3,19]. The picture in Fig. 2.1 depicts a theoretical explanation for cognitive skill fields and variables.

2.5 ARTIFICIAL INTELLIGENCE

AI provides intelligent machines with the ability to translate external data [6]. AI collects and examines datasets, to help identify, predict, and probe the origins, applicability, or qualities of data needed for processing. In AI, the process to visualize data gives analysts and scientists the ability to discover and display dataset patterns [1,6].

Decision makers rely on the collected, analyzed, and processed data to draw informed decisions about specific goals and tasks [6]. The complexity and lack of scalability affecting neural networks are different from that of the traditional systems [1,3]. In AI, regression reasoning can be insignificant, irrespective of the relationship that these variables display in a limited heuristic reason [3,10,11].

Kaplan and Haenlein [6] cite AI researchers argue that traditional computer systems are not immune to comparable functional behavior. Despite these integrated intelligent functions, AI shows pseudointelligent reasoning. It incorporates "strong and weak" behaviors within the environment—these computers often display a substantial degree of parallelism [3]. Weak AI

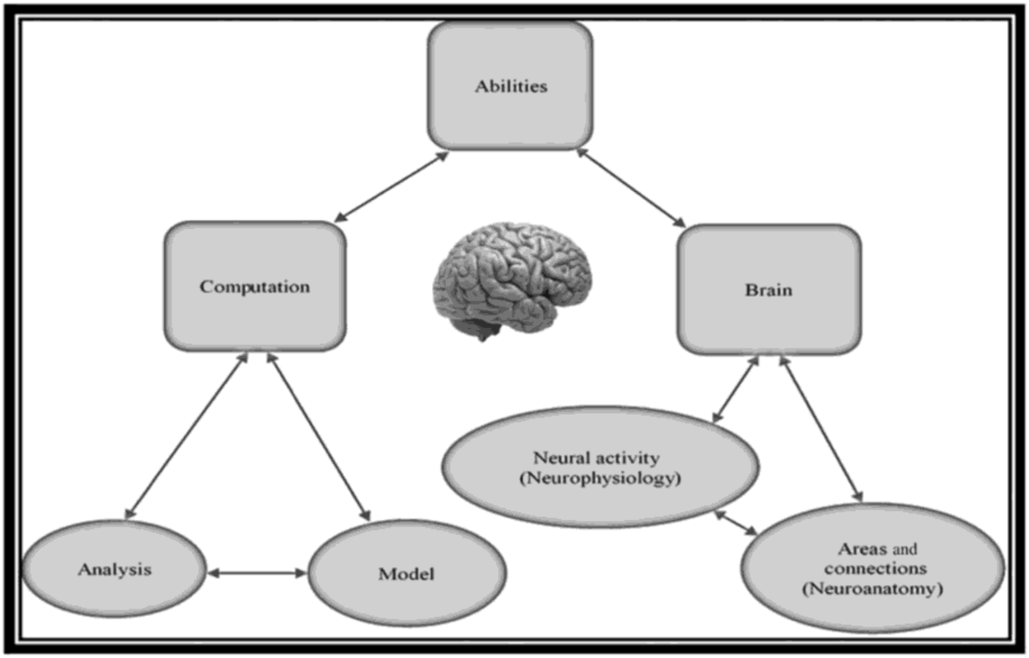

FIGURE 2.1

Cognitive science studies.

consists of information processing system-based applications that have limited interaction with other intelligent objects [5,6]. This method stems from applied knowledge and exceptional characteristics, that is, autonomous systems and heuristic ability search algorithms [10,11]. Despite the progress that scientists and researchers made, AI-based organizations view performance limitations as a challenge to AI technology. These technical constraints include "strong and weak" AI capabilities. Such restrictions are attributable to systems with autonomous interaction [3].

2.6 ARTIFICIAL INTELLIGENCE FOR INFORMATION TECHNOLOGY OPERATIONS

Artificial intelligence for IT operations (AIOPS/AIOps) was previously known as "algorithmic IT operations analytics." AIOps is a solution that provides agile and cost reduction for public and private sector. AIOps is an "umbrella term" that was coined for advanced technological domains: ML, big data analytics, and AI. Researchers developed AIOps to provide technical support for the identification, automation, and resolution of various issues affecting the IT field. In the recent decade, business, scientific, and research communities have used AIOps to monitor IT solutions while acquiring clear visibility into dependencies beyond IT systems.

Despite this adaptive terminology, researchers define AIOps a platform, which syndicates big data and AI functionalities. AIOps focuses on IT operational structure—for example, AIOps processes tasks, executes, deploys and provides continuous backup to functional areas in the enterprise. Commercial enterprise and technological functions can be deployed as a toolkit. AIOps capabilities support performance monitoring, event requirements, and business/data analytics solutions. IT service management and automation offer customers hybrid technical solutions to ensure that middle management and senior executives have the capability they need to make informed decisions. AIOps capabilities are vital to an organization's mission success and agile IT resource distribution. AIOps delivers integrated technical functions, such as propelling an organization's business capability, while providing infrastructure, continuous monitoring to support end-to-end IT solutions. Engineering science measures, automates, and monitors business practices to boost productivity and increase efficiency or streamline operational delivery timeframe. AIOps platforms are deployed as technical solutions to support enterprise integration of IT solutions. Such solutions involve monitoring, automating, and providing maintainable business/functional posture needed to sustain the holistic enterprise functioning. Managers and executives rely on these cognitive operations to make informed decisions. Organizations should invest in AIOps capabilities. These IT solutions are vital to organizations' digital business transformation and sustainability. The integration of AI into IT operations ensures that businesses have the seamless capability needed to perform at a faster rate and supply that the layer of productivity.

2.7 AI, KRR AND IoT FUNCTIONS

In 1956 John McCarthy coined the term "AI" at a conference organized by Dartmouth as part of his scientific exhibition. CS involves the following technical areas [19]: psychology, linguistics, anthropology, AI, neuroscience, and philosophy. In the same year, McCarthy devoted more time to research on parallel topics—NLP, image identification, sorting, and ML. McCarthy's research yielded significant AI results from, most of which many industries have used for many years [3,19]. Today, research and development and academic institutions are taking advantage of these AI-based results to grow operations management functions [3]: technology assets and technological resources [10]. Implementing AI and KRR capabilities gives clients the tools they need to operate effectively and efficiently in the digital era [2,4]. Despite this progress, other industries have employed similar AI/KRR processes to support their daily operations—these industries describe AI and KRR as different things [3]. Many researchers state that AI and KRR can be embedded with ML and DL to provide a hybrid functionality [3].

AI is a subclass of computer science that focuses on the study of human behavior. Researchers argue that AI does not focus on human behavior only; instead, it encompasses the interaction between humans and computer systems. The process includes complex activities that comprise awareness, perceptual experience, reasoning, mimicking, and the environment [10]. These computer systems consist of swarm intelligence (SI) networks, standard algorithms, intelligent robotic systems, and neural systems [1,2]. There is a sheer functional characteristic between traditional computer systems and AIAs. The variances between the core and established systems or the AI-based applications include, but are not limited to [2–4]:

- Sophisticated and functional features involving AI-based applications;
- A complicated step-by-step algorithmic procedure that computer systems should play along to execute/perform functions effectively; and
- The time AI computer systems need to model and process data in nontypical functional behavior.

In the 1950s “cognitive revolution” was an experimental intellectual term. This term was named as cognitive science (CS). CS involves transdisciplinary or systematic areas that emphasize the underlying research on HI and operations. These methods include the functions executed in the CS and cognitive functions of human awareness.

In the last decade, cognitive scientists developed the use of logical thinking to analyze the behavior and intelligence of the human mind [19]. Reasoning defines the computer logic needed for automating and sorting distorted scientific issues. It further describes how humans utilize the “application of instructions” amid a group of objects and subclasses of relationships [1,3]. Researchers are studying neural systems, theatrical performance, and how these operations can be enhanced to process information in real-time. This process includes language, belief, attention, abstract thought, memory, and emotion.

2.8 ARTIFICIAL INTELLIGENCE APPLICATIONS AND TOOLS

AIAs solutions are designed to solve complex problems. These products provide the capacity required to hold up the decision-making process within an organization [3]. AIAs relies on integrated applications, that is, chatters and others. The results are projected to mimic HI by providing seamless, timelessness, consistency, and cost-effectiveness unified technical and business approach [3]. AIAs are deployed to solve complex issues that may affect an organization’s daily operation. Some of these problems range from system agility and holistic IT solutions that decision makers need to make informed decisions [3]. These processes are provide decision makers with the tools they need to make an informed decision, using “qualitative and quantitative” data processing methods.

Many researchers indicate that AI is a technology that its analytical methods have not fully matured [3]. AIAs continue to support different businesses while collecting, assessing, processing, monitoring, and furnishing decision makers with automated toolkit needed to solve complex issues [3]. AI analytical processes consists of algorithms, mathematical optimization, and advanced computational reasoning. These presented solutions are developed to solve AI complex issues, such as broad-based scientific solutions integration.

The following processes are built in to the artificial intelligence tool (AIT) operationalization [2,4]:

- Logical thinking
- Premises to conclusions
- Inference rule
- Planning

- Means-ends analysis
- Robotics
- Local searches in configuration space
- Learning and optimization

AITs include various research and development areas. AIT was developed to solve complex issues involving AI [2,4]. In AI, "logic" is a cognitive operation that supports KRR and problem-solving processes [3]. The advocated methods can be used interactively to support IT operations, some of which involves algorithms, planning, and logic programming. Each of these results are provided as integrated capabilities to sustain the scholarship process [3].

2.9 MACHINE LEARNING AND DEEP LEARNING

ML is part of the AI; there is a symbiotic relationship between AI, ML, and DL [20]. AI provides learning process categories, for instance, unsupervised, supervised, and reinforcement [21]. Unsupervised and supervised learning processes focus on the classification and mathematical regression theories. ML is implemented when machine classifications of things are allocated into various groupings to achieve a unique business objective.

This process applies to regression, which is a practical solution, a single machine can generate as a function. This solution produces inputs and outputs ([21,22]). How these inputs and outputs generate roles is key to delivering ML operational functions. In this context, the agent is rewarded for giving first-rate answers. The process runs agents analyzed for incorrect responses [22,23]. In the ML, agents depend on rewards and punishments to find practical strategies. Some of these concepts are designed to ensure that intelligent machines perform within assigned AI boundaries or settings [23]. For that reason, unsupervised, supervised, and reinforcement learning strategies that can be broken down within the decision theory and through the operation of judicial decisions, that is, utility and others.

2.10 ROBOTIC PROCESS AUTOMATION

Robotic process automation (RPA) is software that involves AI and ML solutions. RPA processes volumes of metadata and datasets. The term "robotic process automation" dates back to the early or mid-2000s despite its existence that goes as far as many years ago. The term spans a trio of technologies, notably screen scraping, workflow, the automated arrangement, as well as AI-based solutions [23]. Screen scraping involves machine processing and data display screen collection. Its capabilities range from traditional applications needed for data displaying through the user interface methods. The automated workflow software streamlines the process that takes for data to be sent to multiple system interfaces manually. This progress gives mechanical systems a continuous capability needed to increase the production timeframe, like efficacy, and accurateness. In IoT, this process is agile and interactive, allowing for computer systems to deliver requested or assigned services without experiencing any single point of failure [22]. The concept involves tasks that, in the past, humans used to achieve them.

In the database, AI and ML projects involve queries, computer or computerized processing, electronic recordkeeping, and other types of business transactions [23]. RPA is not an enterprise IT infrastructure enablement application. RPA can be offered as a Software as a Service (SaaS) enterprise solution to facilitate smooth deployment of technical capabilities. The technology cycle will take place without impacting IT infrastructure downtime [22].

In ML, the mathematical analysis is a branch of theoretical computer science [22,23]. The field is a computational learning theory, offering robots the capabilities they need to acquire new skills and to adapt to other environments. This unified capability supports autonomous self-exploration and social interaction involving human educationalists. Steering mechanisms, like active learning, development, and other synergic aspects can be arbitrary and repeated throughout the general learning process ([24–26]).

DL is a computer science discipline that includes other technology areas, such as deep network learning, ANNs, and cognitive computing. These three key areas are built upon computer science concepts. Vendors and researchers have used the term "cognitive computing" to exemplify a significant association between these technological areas: DL, deep network learning, and ANNs [3]. This term is generally applied and converged to support the enterprise—in part, researchers examined DL and related technologies as rapidly involving phenomena. AI objects can process data with limited human involvement ([22,23]).

2.10.1 PLANNING, SCHEDULING, AND LEARNING

Planning, programming, and learning are processes that provide intelligent agents (IAs) with the capability to determine and achieve realistic objectives.

In classical planning problems—the agents can accede that within an AI only one organization should be deployed and running at the time; such concept, yet, allows brokers to be precise about the consequences surrounding similar activities [23].

The below list explains an existing relationship between the hierarchical AI-controlled organization. Such an association includes the relationship between actuators/sensors, controlled systems, operations, and environs.

- Top level node
  - Specific goals and projects
  - Sense data and results
  - ***Node (1)***
    - Actuators—actions can be embedded into the controlled system, process, or surroundings
    - Sensors—sensations from the controlled system, method, or environment into sensors
  - Node (2)
    - Actuators/sensors
      - Actions from sensors/actuators into the controlled system, method, or surroundings
      - Sensations from the controlled system, method, or environment into sensors/actuators

If a single agent or multiple brokers are not acting alone within AI, the desired process assumes that the assigned agent can reason through a layer of ambiguity. This process ensures for agents that are incapable of inept or understanding environments, to make proper estimations, or become accustomed to a specific or assigned/designated environment [23].

2.11 INTERNET OF THINGS

In 1999 Kevin Ashton coined the term "Internet of Things" after conducting several types of research at the Massachusetts Institute of Technology (MIT) Auto-ID Center. Ashton preferred to address it, "Internet for Things" [27,28]. Ashton embarked on a new research project involving the radiofrequency identification (RFID). Through such complementary research findings, Ashton was able to incorporate RFID technology into IoT-based applications. This advance allowed objects to interact and manage data or other things through a distributed or an interconnected physical network [27,29].

IoT is a dynamic network of distributed and decentralized or distributed physical objects. IoT consists of smart devices and intelligent systems [30]. These smart objects can be embedded as sensory systems—RFIDs, actuators, driverless vehicles, smart buildings, and closed-circuit television [27]. The objects range from smartphones, tablets, smartwatches, home appliances, and consumer applications, explicitly creative industries, home automation, and wearable devices [31,32]. These technological solutions can be equipped with network connectivity beyond standards. This method allows devices and organizations to collect, examine, exchange, and store data in real-time [31]. More consumers have smart devices connected to interconnected/distributed networks [32]. These objects can be interlinked via the Internet with the ability to send or receive data. These objects' embedded functions are designed for remote monitoring and supervisory [27]. According to Wigmore [32], the number of IoT objects in late years has developed significantly. This disruptive technology surge is due to a rapid increase in AI, ML, DL, commodity sensors, and others [32]. The demand for innovative methods to power the IoT devices and organizations is paramount [33]. In 1982 a group of researchers discussed IoT technology at Carnegie Mellon University. The discussion was about a technology concept on a "coke vending machine." It involved proof of concept entitled "Internet-connected appliance."

In the same year, McCarthy dedicated time to research on parallel topics, notably NLP, image identification, categorization, and ML. His research yielded significant AI results, which comprised AI analytical processes, that is, search algorithms, mathematical optimization, and advanced computational reasoning. These domains are deployed to solve AI complex issues through a wide-ranging scientific solutions integration. The proposed methods can interactively be applied to support processes, for example, algorithms, planning, and inductive logic programming. These methods allow for a unified and principal learning process among smart objects [3].

AI objects can process data in real time and interact with limited human involvement [22,26]. If a single agent is, or multiple agents are, not acting alone within an AI the desired process assumes that the assigned agent can reason through a degree of ambiguity. According to Wigmore [32], IoT objects in late years have developed significantly. In essence, such disruptive technology scale is due to a rapid increase in AI, ML, DL, commodity sensors, and others [32]. The demand for innovative design methods to power the IoT devices and organizations is paramount [33].

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2.11.1 INTERNET OF HEALTHCARE THINGS

The emerging of mobile technologies in the digital era has increased considerably. This rise is due to the constant demand for patient care, data provisioning, and the modernization of the electronic health record (EHR) system. Tech companies and governments are on the verge of modernizing and deploying their capabilities to meet patient's needs better. Most of these revolutionary transformations in public, private, and government sectors are due to the increase of patient data, for example, private EHRs [34].

The Internet of healthcare things (IoHT) is a concept that involves mobile technologies, ranging from intelligent systems, sensors and wearable devices. This method includes smartwatches that can be deployed in the distributed or decentralized IoT networks in support of the patient's EHR system. As a result of the disruptive and ubiquitous challenges that the governments and industry have dealt with in the past decade, data provisioning, visualization, parsing, and allocation, and the need to modernize legacy healthcare infrastructure are paramount [34].

IoHT involves intelligent devices: mobile technologies and smart machines. Vendors are still grappling with developing a new analytic baseline that supports the EHR modernization and data provisioning via integrated cloud solutions. In the IoHT environment, intelligent devices and sensors are deployed to collect and process data with less time than the traditional healthcare systems. The need for a flexible and integrated healthcare system will ensure that providers and patients have a continuous interaction and the ability to share information in real time. This interactive capability can only be possible if a robust healthcare infrastructure is built to support such a patient's need. Through biometric technology, patients and providers would be able to share private data and ensure for its protection [34].

2.11.2 REAL-TIME HEALTH SYSTEMS

Real-time health systems (RTHS) are convergence and integration, data collection, and intelligent sensor-based systems that can be deployed to collect patient information via IoT platforms. These devices comprise mobile technologies such as RTHS. Mobile devices collect, analyze, and process data between RHTS and IoHT devices. Data sharing is processed via the RTHS-integrated portal. In the clinical data ecosystem, EHR does not only address patient-based situational awareness [34]. It collects a patient's health information besides the care that each patient can receive at any medical facility, like hospitals or clinics. This application, captures patient's critical data. RTHS is responsible for gathering, analyzing, and processing the patient information and make it available to the assigned clinicians, who are accountable for the patient's continued care [34].

RHTS collects IoHT patient information, parses and provides actionable clinically based results. The data offer relevant indicators and trends concerning the current patient's health status as well as continuing treatment [34]. Within an integrated EHR/RTHS environment, patients and providers can exchange data securely and in real time. Researchers note that this revolutionized the healthcare capability industry predicting for many years [34]. Vendors argue that more work needs to be done to ensure that the EHR system continues to meet patients and health providers' needs. With the support of RTHS, health providers are now able to collect, process, and analyze patients' confidential data faster. This process encompasses identifying clinically relevant datasets, indicators, and forecast that provider use to predict future illnesses. Establishing an integrated and friendly solution that providers need to monitor data and alert the patient of potential or catastrophic diseases, some of which might lead to death. These health IT solutions include mobile devices that are paramount capabilities of a patient's continued healthcare [34]. With the new and integrated health, IT solutions will be able to provide the patient with real-time notifications of probable illnesses and ensure that such diseases are treated immediately before reaching an irretrievable stage [34].

2.12 NATURAL-LANGUAGE UNDERSTANDING AND INTERPRETATION

Natural-language understanding (NLU), is a subclass of NLP. In AI, NLU/NLI is a technology area that focuses on the study of machine reading comprehension [35]. It addresses AI-complex issues [36].

In 1964 Daniel Bobrow from Massachusetts Institute of Technology made the first computer, try to address NLU [36]. Aside from Bobrow's ambitious attempt presented in the dissertation entitled "natural language input focused on the computer problem-solving system," nearly 8 years later, a proven AI researcher, John McCarthy invented the term AI. NLU focuses on global marketable relevance, straddling AIAs, to systematized analysis and reasoning [36].

The NLI method involves the following AI areas [36]:

- Machine translation
- Question answering
- Newsgathering
- Text categorization
- Voice activation function
- Archiving
- Large-scale content analysis

These significant areas incorporate text postprocessing, which is central to NLP algorithms stage-processing along with some parts of speech identification using context from other recognizable devices such as automatic speech recognition and sight recognition [36]. NLU is a term that can broadly be working in AI, robotics, and other complex software engineering fields. Researchers suggest that this applied method can be used in computational applications involving small, medium, to large-scale tasks that are assigned to robotic systems [36]. It can support diverse computer applications, for instance, text classification needed for email automatic analysis, and others. NLU focuses on promoting and sharing pieces of standard algorithms elements, explicitly language lexicon, parser, and grammatical rules, needed to divide or to structure sentences as well as core illustration. Semantic theories must complement AIAs. These theories are developed as interpretative capabilities to translate applications in the language-understanding system.

In contrast, semantic methods consist of [36]: naive semantics, stochastic semantic analysis, pragmatics, and semantic parsers. This concept spans technologically advanced applications aimed at integrating logical inferences into the framework. In NLU, there are two types of logic, that is, "predicate logic and logical deduction." These logics, when simulated or applied to NLU, aid in reaching logical conclusions [36].

2.12.1 CLASSIC ARTIFICIAL INTELLIGENCE METHOD

Many researchers describe the classic artificial intelligence method (CAIM) as an early version of AI. Researchers invented CAIM to process and support extensive computer programs and network applications. It focuses on translation of complex mathematics, algorithms, and computer problems, preventing human brains from performing any activities. The need for user-friendly computer applications to interpret text messages and related software features is paramount to CAIM's functions. These applications traverse the human's ability to recognize AI objects in an image. Researchers argue that more research findings will improve AI solutions.

At present, there are millions to billions of IoT objects on the planet earth. These intelligent devices and systems are generally deployed to several areas to perform a straightforward or complex activity or mission. IoT devices are ubiquitous objects that can be found almost everywhere around the world. Researchers predict that in the coming years, there will be trillions of IoT objects around the world. These objects will be deployed to support various activities and missions [3,19]. The need for user-friendly computer applications to interpret text messages and related software features is paramount to CAIM's functions. These applications intersect the human's ability to recognize AI objects in an image. Researchers argue that more investigative findings will improve AI solutions [3,19].

As many researchers would antedate, natural intelligence (NI) is not a subset of AI; instead, it incorporates systems of control, which are not artifacts. NI involves the functioning of animals and human brains [37]. AI objects comprise neuroscience, researchers believe that NI continues to play an integral role in the medical field [37]. With the advent of AI, KRR, and OCR, many researchers suggest that "physicalism and functionalism," can be the two breakthrough assumption that often gives an insight into how the human's mind functionalities.

Identicality in human reasoning is documented as a reductive method that associates one's intellectual faculties with other human phenomena, like neuronal activities. The mind can trigger responsiveness and intentionality toward an environment. Such action leads to a perceived, responsiveness, and actable stimuli within the brain. This involuntary activity in the human's mind, prompt the human brain to begin thinking, while generating perceptive feelings toward others or an environment [38].

2.13 LEARNING USING PRIVILEGED INFORMATION

Learning using privileged information (LUPI) has been used in academia, industry, and other business sectors. LUPI is a process that transfers knowledge such as privileged information. In the new learning developmental paradigm, LUPI constitutes a part of the training phase that includes multidimensional methods needed for delivering tangible results. Vapnik and Vashist adopted and popularized LUPI as a transformational concept. In academia and industry, LUPI is used to compare data, provide a consistent level of reasoning. This approach involves logic, emotion, or metaphorical reasoning. LUPI privileged information may involve confidential communication, nondisclosure agreement, and need to know.

Privileged data is a process that handles confidential data, such as patient records. How data are handled, processed, and shared is essential to the provider and the patient. In ML, LUPI denotes a new paradigm that balances the digital era of information, technology, innovation, and processing digitized resources over the enterprise. Such concepts may be conditions for consistency and how machines may learn from their environments. LUPI focuses on practical algorithms, for example, support vector machines. In each environment, machines are programmed to execute diverse functions. These roles include processing or ruling potential algorithmic outliers. LUPI is embedded in technology and science. This method focuses on “human and classical ML” systems.

2.14 PICTURE ARCHIVING AND COMMUNICATION SYSTEM

Picture archiving and communication systems (PACS) are used in the healthcare industry. PACS is a medical imaging solution that ensures clinicians, have the permission to store the patient’s confidential and nonconfidential information. The solution gives healthcare providers access to cost-effective storage capabilities. This repository retrieves patient’s data, such as archived dental and medical records.

Using the AI and ML technological capabilities, medical providers are now able to view images that are daily received and processed from multiple sources of intelligent devices and sensors. In the PACS’ healthcare ecosystem, electronic images and other data can be uploaded, processed, and parsed digitally. This healthcare e-capability focuses on streamlining the processing time that providers often take to send and share a patient’s information to selected entities within the medical community. This technology has given medical practitioners and providers the capability they need to conveniently access, retrieve, parse view, and processing patient’s data in real time or with a limited human error. Due to this critical process, today, practitioners can conduct computed tomography, magnetic resonance imaging via a dedicated, distributed, or secure network system. The process ensures that a patient’s data can be transmitted and viewed through a secure portal. This capability protects and secures patient’s confidential medical records. The technology streamlines and minimizes physical and time-barrier-based accessibility to confidential patient data, which unauthorized users may obtain. The data are stored on the provider’s medical database systems. With the disruptive and ubiquitous IoT intelligent devices and sensors, providers can process patient’s images or other confidential data with minimum/without disruption to the provisioning system. The PACS consists of four distinctive domains. Each of these domains can provide remote access, electronic image integration platform, and radiology workflow management. PACS has a robust capability to process data between local and wide area network distributed nodes. These capabilities can be deployed via a virtual private network and a secure socket layer. It supports interactive applications, like ActiveX, Javascript, and Java Applet.

2.15 INFRASTRUCTURE-BASED MOBILE NETWORKS

The industry continues to research and develop proven infrastructure-based mobile capabilities, like ad hoc networks, to fulfill customer’s urgent and long-term needs. These decentralized capabilities come in many flavors, such as those equipped with intelligent sensors and devices that can provide quick and responsive results. The network infrastructure consists of a hardware and software solution that is implemented to support an IT environment [39]. These IT resources are used to provide seamless connectivity, communication, operations, and management solutions for small and large networks. Through these capabilities, users can share services and data through decentralized/distributed, unified, and interactive IT networks. Wireless and mobile ad hoc networks are vital to day-to-day customer's IT requirements. In the IoT, ad hoc systems are deployed to support other hardware and software solutions [39].

2.15.1 IoT CONSUMER APPLICATIONS

IoT consumer applications continue to play a crucial role in the integration of smart objects needed to support/interact with MI, ML, DL, and KRR applications [27]. IoT spans a total of six consumer applications. These applications comprise the following IoT consumer applications [27,39].

- ***Home security and smart domestic***: This type of IoT consumer application includes domestic safety (DS). DS is a critical area that has promoted the IoT services. Despite this progress, researchers concluded that in IoT, most devices and systems continue to experience network and security vulnerabilities. Such breaches are due to a series of weaknesses and threats affecting IT assets. Vendors have been working tirelessly to develop new software applications to avert or minimize some of the weaknesses and threats against the IoT devices and systems. Home security often ranges from a method that is designed to provide home appliances the level of protection needed to protect them from unauthorized users, for example, hackers and intruders. These devices are acquired and deployed in homes, business offices, and related facilities. Most of these objects can be attained in the market at an equitable economical price.
- ***Private healthcare***, ***healthcare carriers***, ***and healthcare players***: In healthcare, IoT devices and systems have been deployed to provide governments and enterprises with proven capabilities needed to support mission-critical solutions. These solutions can be deployed in smart homes and smart cities. These capabilities are designed to provide the ecosystem with a blend of continuous monitoring capabilities needed to protect data and patient records. Similar IoT devices are deployed or used as a wearable device that clinicians can use to diagnose patients. These wearable devices are ubiquitous in the sports industry. Athletes use these types of tools to monitor activities on the field, for instance, following heart rates, steps, and among other things. Such devices have the capabilities of monitoring, collecting, uploading, and storing data to a remote repository for future processing.
- ***Wearable technology***: In this context, are used in either individual or multiple persons' activities. These devices have been used in sports or in healthcare, but also for one's daily use. Some people use wearable devices instead of watches or other types of tools designed to serve a particular individual's purpose. In heavy industries, these smart objects are used as smartwatches and health monitoring devices. Vendors continue to develop new methods that can better meet the consumer's day-to-day requirements.
- ***Asset tracking or tracking valuable assets***: Wearable devices that can be employed as technology assets, which serve the consumer's needs. The global positioning system is a perfect example of intelligent machines that monitor or track an individual's requirements. IoT consumer applications have evolved over the years. This rapid evolution in IoT is due to the advent of advanced applications that vendors have built in recent years.
- ***Workplace***: Having IoT devices and objects deployed in the workplace can improve the level of work while providing the level of security that decision makers and employees might need.

Today, most of these devices and objects can track, store, collect, and disseminate actionable data to relevant sources within the workplace, by providing continuous monitoring within a physical security perimeter for the ability to function as sensors. Most sensors are designed to adjust the room temperature in residential and commercial buildings.
- ***Play***: IoT devices play an essential role in everyone's individual life and in the workplace. These devices and objects can perform activities beyond the human imagination. Some of the devices and objects can be found in luxurious resorts where people often plan annual vacations.

There are millions to billions of IoT objects on the planet earth. These devices and objects are generally deployed to several areas to perform complex activity or mission. IoT devices are identified as ubiquitous objects and can be deployed almost anywhere around the world. Researchers predict that in the coming years, there will be trillions of interconnected IoT objects in the world. These objects are deployed to serve activities and missions [27].

2.16 DYNAMICALLY CREATED MOBILE AD HOC NETWORKS

Dynamically created mobile ad hoc networks (DCMANs) consist of autonomous and dynamic network systems. In a distributed network, DCMANs are connected by nodes that can be deployed or redeployed to the decentralized networks. Despite this progress, DCMANs lack the infrastructure complexities and setup. Dynamic wireless networks are administered via the process of enabling smart objects [37]. These devices can be configured and deployed in assigned networks at any given time.

2.17 INTELLIGENT AGENTS, CONVERSATIONAL AND NATURAL INTELLIGENCE

IAs are AI-independent objects or software applications designed to analyze, retrieved, or display information collated from the Internet. IAs extract data from the Internet for immediate or future use [37]. These intelligent objects consist of computational activities ranging from macros in the Excel spreadsheet and Word pages [40]. Such objects process or monitor data flow through sensory devices and act within the environment as believed necessary. In an IA, sensing devices can interact with actuators known as agents [37]. This process allows actuators to autonomously send data to intended nodes or systems to meet a business goal.

In various business sectors, decision makers often rely on IAs to study or gather data needed to be used toward a business goal [40]. IA includes devices and objects, for instance, a thermostat, complex systems, and other reflex machines [37]. In AI, human's traditional perception of conversational intelligence (CI) means different things. Researchers define CI as a method that describes a human's most authoritative and hardwired ability to be able to engage with other humans through conversation mechanisms [37]. When decision makers talk to each other, whether by using verbal or gestural language and being able to translate whatever message they have into real action that can be called a part of conversational intelligence known as CI process [37]. The following are three dimensions humans rely on to communicate in an office setting or the public domain [37]:

- ***Biochemical***: Gives decision makers the ability to gain control of independent methods of thinking or cognition. If a manager in the workplace is either unfulfilled or exhausted, this type of dimensional way can display such reaction. Decision makers must be cognizant of their surroundings, when a similar response occurs in the presence of others, for example, employees, peers, and others [37].
- ***Relational***: Every human has ambitions and needs in life. When interacting with others, we tend to develop a last-long affinity and bond, which helps shape our relationships [37]. The relational dimension is a critical factor in the workplace. Managers should be aware of these steps when interacting with employees, whether on a project or other forms of engagements [37].
- ***Cocreational***: How to cocreate conversations among humans in the workplace? This type of discussion ensures people have the ability to interact and be able to show or create new conversational forums, which often lead to positive results. Concreating conversations is a concept that allows people to forgive, learn from past mistakes, and be able to refocus attention on more positive future interactions. The ability to help or work with others to achieve a common goal part of the cocreative conversation. For example, being humble, respect others, and is also listen to others' views among other things is key to proactive and/or healthy dialogues [37].

CI performs as a platform to connect these three-dimensional processes in the workplace and in our livelihoods [37]. Three-dimensional conversations focus on developing creativity among cultures and people while giving them the opportunity they need to thrive in society [37]. In the context of NI, organizations and decision makers should be more aware of how this process is accepted in the workplace. As many researchers would antedate, NI is not a subset of AI. Instead, it includes systems of control, which are not objects. NI involves the functioning of animals and human brains [37]. AI objects span neuroscience, researchers suggest that NI continues to play an integral role in the medical field [37].

2.18 ADVANCED METERING INFRASTRUCTURE

Advanced metering infrastructure (AMI) was coined and popularized to support the infrastructure and smart meter solutions. AMI involves two-way communication networks that businesses use as the metering capability in support of the enterprise utilities and consumers' needs. It provides automatic and embedded functions, in which legacy systems did not have in the past, to sustain the holistic efficiency or customer networks. AMI monitors the consumption of electricity that data centers and the comprehensive infrastructure need to power devices or systems. It is a time-based rate and incentives, which boosts a client's interest when deciding on the best cloud services that fit their immediate and long-term business needs. The solution reduces electricity cost, during a peak time, and manage the foreseeable consumption.

AMI provides global customers and businesses with the ability to monitor operations and maintenance cost savings. This process involves remote billing services designed to provide them with services and reduce the electricity cost. Its intelligent devices and sensors benefit from the adoption of AMI capabilities. The services provide a real-time metering capability that customers need to reduce energy consumption while boosting productivity. The service is designed to monitor, read the meter, remotely diagnose any issues concerning intelligent devices and sensors within the ecosystem. AMI capabilities are deployed in public, private, and government sector datacenter environments. These services provide clients with decentralized regional distribution of services, which includes top energy cost-saving results. The capabilities have a remote service connection and disconnection methods. These methods allow providers to connect or disconnect any customer service that has a past-due billing or payment balance.

2.18.1 CONTENT DELIVERY NETWORKS

Content delivery networks (CDNs) are decentralized proxy servers or data centers. In the digital network, CDNs deliver ease of use and "high performance" capabilities [41]. These technological resources provide the end users to distribute IT-server capability needed for businesses and consumers [41]. CDNs deliver large-scale Internet content services to many consumers around the world. CDNs' capabilities range from web objects, like text messaging, visuals, and scripts. These types of enterprise networks have empowered the end users with supreme capabilities needed to download small, medium, and large-scale files, applications, and documents [42].

Over the years, end users have taken advantage of these enterprise Internet services to video/live substantial streaming content of data, media materials, like on-demand streaming of substantial content of the information [41]. In IoT devices and machines are deployed to supply a range of content delivery services. These decentralized capabilities include [41,42]:

- Video streaming
- Software downloads
- Web/mobile content acceleration
- Licensed and managed CDN
- Transparent caching
- Internet services

These objects are capable to power devices and systems across multiple domains. Such interoperability ensures that there is a redundancy between objects, to reducing the cost of bandwidth, speed up the uploading and downloading time. In CDN, end users can access data in real time without experiencing a single point of failure. Devices and sensors benefit from continuous data synchronization, which can be surviving through a multitude of nodes [42]. With the rapid increase or the omnipresence of AI web analytics, nodes can provision data in real-time, augmenting for performance, and delegation of routes that these systems believe that is more convenient for transmitting data between nodes. Edge servers are the most excellent example of the CDN architectural environment. Edge servers can be deployed between the upper layer of the cloud infrastructure and the end-user environment.

These classes of servers give businesses and end users the advantage needed to readily access or provisioning data without having to access the upper cloud layer [42]. Edge servers have a unique advantage of performing within a point of presence. The nodes provide the end user with the capability needed to access data within reach, without having to deploy more solutions. Within CDNs, there is large-scale end-to-end leverage provided by the transport layer of the Open Systems

Interconnection (OSI) model. It allows for data distribution and provisioning and use of smart objects and applications deployed on the Internet. Several types of CDNs include but are not limited to peer-to-peer, provide CDNs and others [42].

2.19 DISTRIBUTED AUTOMATION NETWORKS

Distributed automation networks (DANs) are innovative technology-based end-to-end solutions. The DANs deliver intelligent automation cloud capabilities to a multitude of users worldwide. Today, the industry continues to reinvent its technology capabilities to serve its consumer's cloud requirements best. The DANs are designed to boost system dependability, for example, reliable or solid-state transformers. Researchers argue that in the future, DANs capabilities may transform into the next generation of advanced distribution automation (ADA). The ADA provides advanced functionality of hybrid cloud solutions within a single or distributed networks.

Future cloud capabilities will be built with embedded solutions. These capabilities will prevent an outage and allow for immediate datacenter self-healing. The reliable state transformer is designed to ensure that when deployed to the cloud environment, they can minimize power losses, also known as power failures. In the IoT ecosystem, the distributed automation network interactive technical approach brings many advantages to intelligent devices and sensors. These systems are deployed to distributed networks providing intelligent devices and sensors with the operational efficiency and minimization of potentially incurred operating costs. In data centers, distributed automation services deliver reliable electric capabilities that help to power machines and applications. The use of arc sense technology gives the detection capability of any faults within the network. In AI, distributed automation systems can be miniaturized into intelligent devices and sensors. These capabilities are deployed to plug-in electric vehicles or autonomous cars. The service ensures that vendors and consumers can save costs and minimize autonomous-vehicle-associated system losses.

2.20 OPTICAL CHARACTER RECOGNITION AND HUMAN MINDS

In the digital information era, many terminologies like optical character recognition (OCR) are often misconstrued. This dilemma is due to many in the technology space, not having a clear grasp or understanding of the term OCR and the context of usability [38]. Similarly, OCR is a term that was devised in concert with the software development landscape [43]. It is the process of scanning documents while trying to understand any designs or patterns that are exhibited on a computer screen. These patterns often are shown in the form of letters, characters, or even calligraphies. When arranged properly, these items can show results in the method of "pictures of letters" that can then be deciphered into texts [38]. Researchers have studied the difference between letters or texts displayed in word or picture format for many decades [43]. OCR technology still is a complex and dubious science. Infinite variations and screen displays have contributed to the continuing improvements of OCR software and underlying technology specifications [44]. This technological progress, in AI, KRR, and the genealogical fields, OCR are still an essential software that allows for various analytical studies. It involves the reviews on the descent of persons and family trees, and others [43]. The OCR's evolution has been useful, whether in reading human handwriting, letter varies, and the complexity of word text and word picture design/patterns [38]. The digitalization of calligraphies and document scripts has given a new view of the OCR evolution [43]. The birth of AI, KRR, ML, and DL has streamlined the time that professionals or consumers need to work on word text or word pictures [44]. OCR technology still uses today—OCR has taken on a pivotal part in criminal investigation and court proceedings [38].

In social science, perception of a collection of reasoning abilities includes, but is not restricted to [38,44]:

- Awareness
- Sensing
- Reckoning
- Mind
- Speech
- Storage

They may be labeled as a reasoning function that includes a human's brainwave and feelings. The mind can process, imagine, make out, and appreciate any human activities [43]. In scientific terms, the mind deals and processes a person who is an emotional state of being, reactions, opinions, and related activities [38]. In the ancient era, the phrenological mapping of the brain was among the prime efforts to associate cerebral functions with specific fields of HI [38]. The research involved other intelligence analogous methods, such as "dualism and idealism." Researchers continue to contend with the underlying nature of the cognizance [43]. With the advent of AI, KRR, and OCR "physicalism and functionalism" might be the two breakthrough assumptions that would yield some insights into how the human brain uses. Identicality in human reasoning is a reductive method that associates one's intellectual faculties with other human phenomena, like neuronal activities. The mind may trigger a reaction and intentionality toward an environment. Such activity leads to a perceived, responsiveness, and actable stimuli within the psyche. This involuntary activity in the human's mind, prompt the human psyche to begin thinking, while generating perceptive feelings toward others or an environment [38].

2.21 SIMPLE NEURAL AND BIOLOGICAL NEURAL NETWORKS

Many bay windows around the globe, such as research centers namely the International Business Machines or IBM Corporation at Thomas J. Watson Research Center is one of the global AI leading research and development institutions [45,46].

In recent decades, IBM researchers refocused their attention on parallel technological areas, for example, the simple neural and biological networks, and "biological neural networks," commonly known as BNNs. Such an advance is attributed to researchers, who devoted countless analytical and exploratory hours on critical technological domains—classic AI, simple neural networks, and biological neural nets. At the starting time, IBM did not have unique technological capabilities to solve AI problems with its early research inventions. In late years, IBM has had a competitive advantage over other significant players worldwide [45,46].

2.21.1 ARTIFICIAL GENERAL INTELLIGENCE

Artificial general intelligence (AGI) is an intelligent process that includes smart systems that may successfully execute intellectual activities, for example, tasks than a human [47]. The AGI supports complex tasks that do not humans' involvement [47]. AI has played indispensable parts in several technical areas: research & development, robotics, defense, healthcare, aeronautics, entertainment, social media, marketing, maritime, climatology/meteorology, and others [48]. Many industries define AI as "hard AI" or "full AI" [48]. These terms show that a machine could execute a general intelligent action [47]. AI is a technology that includes "strong and full" functions [48].

In AI, the terms "strong AI and full AI" give machines the capability required to do chores, like the general intelligence action [47]. In a hypothesis, "strong AI" gives machines the ability to officiate or perform the desired task [47,48]. This concept is reliably functional to complicated and specific research, problem-solving, and cognitive outcomes. There is a difference between "weak and strong AI solutions," like variances. Any inconsistencies may be well defined by random patterns that machines run through in the ecosystem. These results do not include human reasoning, though there might be a parallel between these capabilities [47,48].

2.22 MACHINE INTELLIGENCE LEARNING AND DEEP LEARNING

In machine intelligence learning (MIL), smart objects mimic activities that human intelligent performs [49,50]. Deep or hierarchical learning covers great ML methods. The world of advanced AI-based solutions and IoT systems/applications aims to give technological resources or technology assets the desired communication leverage. This stage of computing autonomy ensures that devices or objects can interact when connected to a physical or virtual network. The ability of these generation of tools and computers will ensure these solutions provide the services that consumers need to execute tasks. These devices/objects can be embedded in capabilities such as intelligent automation.

ML and DL capabilities continue to supply an acceptable level of computing automation that is required to scale the operation and optimization of IoT devices/objects [4,49]. These processes are developed to extract datasets and process data representations, aside from task-specific algorithms. In contrast, MIL is a supervised or an unsupervised method that involves subclass of AI and ML solutions [20,49,50]. In this setting, smart objects mimic activities that are done by HI [49,50].

Deep and hierarchical learning covers extensive ML processes and mining. ML and DL capabilities are the principal ingredients in processing data images as an alternative to task-specific algorithms. MLI functions involves supervised and unsupervised intelligent systems [20,50]. In the recent decade, technology companies developed DL and deep network learning solutions to solve AI problems. AI issues stem from language translation, email spam identification, the ability to arrange images, and others. SNNs are sophisticated mathematical methods developed to identify large volume patterns, notably a static set of data. Researchers predict that in the future, CAIM and SNN will be fitted with embedded with innovative software solutions capable of processing complex tasks analogous to machine intelligence systems. CAIM and SNNs continue to affect AI, especially the machine intelligence system performance. Despite these challenges, researchers have produced a new genesis of intelligent machine systems known as systems of intelligence [49].

2.23 UPPER ONTOLOGY AND MACHINE TRANSLATION

In 1993 ontologies were built to defend the "PANGLOSS," the accretion of facts or information for the machine translation system [51]. Ontology is a formal KR concept that spans theories or perceptions, that is, devices, processes, and objectives. These concepts stems from various fields and relations. In information science, ontology spans upper, top level, or foundation ontology. The terms range from objects, attributes, and relations [51]. These three elected attributes involve domain system structure. Upper ontology focuses on comprehensive semantic interoperability, notably domain-specific ontologies.

In a "natural philosophy computational implementation" method, these concepts continue to play a substantial part, whereas in "physicalism," physical ontology is a metaphysical thesis. This hypothesis means that everything under the sun is physical. It involves monism, substance, dualism, materialism, and others [51]. Large-scale ontologies have been produced to sustain the machine translation system [15,51]. The WordNet hierarchies, LDOCE aim to complement the ontology's upper region. The PANGLOSS MT system constitutes a pragmatic model of engineering innovations, like ontology concepts. These methods supplement knowledge base functions, that is, the generation element(s).

In PANGLOSS, there are active 50,000 nodes—these computer-based solutions are merged into manually built and smaller upper ontologies. Corresponding elements include definition match and hierarchy match algorithms [15,51]. A large-scale ontology is required for analyzing activities that would happen within the machine translation system's active modules. In PANGLOSS, each client can perform autonomous self-conception. PANGLOSS merges with LDOCE online and WORDNET applications. The objective is to syndicate definitions of Longman and semantic relations—this attack calls for an ontology semiautomatic taxonomization concept using a WordNet [15,51].

2.24 FRAME PROBLEM AND CYCL PROJECTS AND SEMANTIC WEB OF THINGS

Build or frame problem (FP) and CycL projects have been about since the advent of AI capabilities. FP is a process that defines a problem [52]. It functions using first-order logic (FOL). FOL determines how robots may interact with each other when deployed to the AI ecosystem [52]. In AI, the robotic state is represented by traditional FOL settings—the approach comprises several computational requirements.

In AI, the use of axioms ensures that there is no single change among objects—whereas, in centralistic terms, the FOL system grants more axioms. This concept also gives axioms the ability to make inferences about AI to which are deployed [53]. FP is a method that concentrates on identifying desired assemblages of axioms that may be applied to support any descriptive method that requires a robotic network. Despite any complexity involved in the research, some of the AI researchers at Stanford University suggest that setting up a problem or frame problem often involves an in-depth analytical investigation [52]. Further, they concluded that framing a problem would be a drawn-out process. It might include multiple or challenging methods, most of which might wander from the influence of action. If large numbers cannot be presented, there will be no effect of activity. Some researchers believed that framing a problem might be a suggestive procedure, which takes a broader epistemological series of issues [52,53].

Semantic web of things (SWoT) comprises technological semantic web processes and interfaces that can be utilized to support IoT solutions [54]. SWoT consist of architectural and programming design patterns [54]. These unified architectural-software capabilities are planned to interact with IoT and Swat intelligent devices and sensors [54].

In the next 4−5 years, Microsoft corporation plans on investing ***$5B*** in IoT [54]. This effort, will assure that customers have the first-hand capabilities they need to connect applications, devices, and systems to the digital environment [54,55]. It focuses on ensuring that billions of its intelligent devices, sensors, and other objects can interconnect around the universe; this includes interacting and provisioning data in real time [54]. Such a conversion ensures that many customers worldwide stay interconnected and can interact in real time [54]. Given this technological revolution, customers shall be able to reduce costs and bolster productivity [54]. The web of things consists of five interdependent unified pillars, notably social network, semantic network, programmable web, physical web, and real-time web [54,55]. Microsoft predicts that in the future, the interoperability between its and the semantic web/network of things (SWoT) will be defined by how these applications exhibit continuous interaction once deployed in the IoT environment [54,55]. Some researchers believe that more studies will be warranted for these unified domains [55]. Integrating legacy applications: JSON-LD, HTTP, JSON, REST, and Microdata interfaces are key examples of revolutionized technology trends. As these objects replicate by day, researchers predict that in the future, marketers will develop enhanced applications to confirm the workload delivering to support the daily operationalization of interconnected intelligent devices and sensors [54,55]. If properly integrated into KRR and AI, SWoT will support the infrastructure data provisioning. In some way, this process aids the collection and data processing through linked open data application [55]. It ensures that a unified capability will offer asynchronous device-to-device data processing. The approach spans continuous abstraction of intelligence devices, detectors, and other services [55]. For example, distributing generic nodes and ensuring that its applications may balance and processing power or communicate with objects deployed to a decentralized digital environment without a single spot of failure [54,55].

2.25 PRESENTING, REASONING, AND PROBLEM SOLVING

Early studies in AI and KRR focused on developing algorithms to mimic a consistent human performance and reasoning [2,4]. This theory involves techniques that people use to unravel puzzles and draw reasonable inferences. In the 1980s and 1990s, AI was described as an advanced scientific method that gathered, analyzed, and processed data. As a domain, AI involves mathematical probabilities and cost-effective results [56]. Its concept includes applying combinatorial analysis to process memory and computer activities. In a joint AI/KRR setting, humans might generate intuitive decisions—despite the systematic presumptions that early AI research relied on events.

Similarly, these systems are designed to perform tasks to support humans or animals' necessities—like problem solving, which is an area that has played a critical role for many years [56]. The use of conventional, ad hoc, and transformative analytical or mathematical methods has resulted in the unearthing of complex AI/KRR issues [56]. For example, problem-solving methods might be given to routine personal and job activities. These methods are not limited to interdisciplinary areas— AI, computer science, systems technology, math, medicine, project, and program management. As a result, these technologies might spin fields of exploratory or empirical scientific research [56]. The global research community defines reasoning as a procedure by which researchers, applied scientists, practitioners, and sellers may use or be able to measure, identify and find resolutions to issues are affecting enterprise business and professional settings [56,57]. This process stems from logical facts to adapting and defending sound practices. These methods describe institutional and moral principles. In general, reasoning applies to rational, perception, and intellectual capacity [56,57].

2.26 SIMPLE NEURAL NETWORKS, ARTIFICIAL NEURAL NETWORKS, AND NATURAL LANGUAGE PROCESSING

In the 1960s researchers developed ANNs to aid in solving global issues affecting science and technology sectors. On that occasion, researchers did not know much about ANN capabilities. ANNs changed how researchers view ANN technology capabilities—for example, the adoption of biological realism has substituted for early editions of similar technology solutions proven to be performing at a special rate. It changed the way ML and other smart objects performed mathematical calculations and statistical processes—ML supports large data workloads. It concentrates on extracting statistical information that researchers require to work out tasks, like turnouts. Researchers rely on AI solutions to support ML capabilities. These solutions include DL and deep network learning. ANNs are central systems that promote DL and deep network learning methods [22,23]. Such processes involve DL and related network learning solutions: ML algorithms intended for processing datasets, to selected multitier environments—have built in graphics processing units (GPUs). GPUs are embedded systems built for managing thousands of core processes. These operations can share large data workload transactions without interruption [19,22,23].

2.26.1 NATURAL LANGUAGE PROCESSING

NLP is a subcategory of computer science, AI, and computational linguistics. NLP centers on the interaction of information processing systems and natural human languages when deployed in the IoT environment [58]. Computer programming returns massive quantities of natural language data process [58]. This concept includes "machine-readable, logical forms, connecting words, machine perception, dialog systems, speech understanding, and natural language generation" [58,59].

In 1950 Alan Turing first coined the term "NLP." In the same year, Turing published a journal article entitled "Computing Machinery and Intelligence." Today, Alan's research body of work is known as the Turing test. Turing's research describes the criterion of intelligence, which remains relevant in today's scientific research community [58,59].

In 1954 the Georgetown scientific community held an experiment. The research includes a programmed conversion of sentences from Russian to English language [58,59]. Many scientists predicted that in the future, machine translation would solve AI, IoT, ML, and DL issues [58,59]. Fig. 2.2 illustrates a unified neural network structure and its relevant procedures.

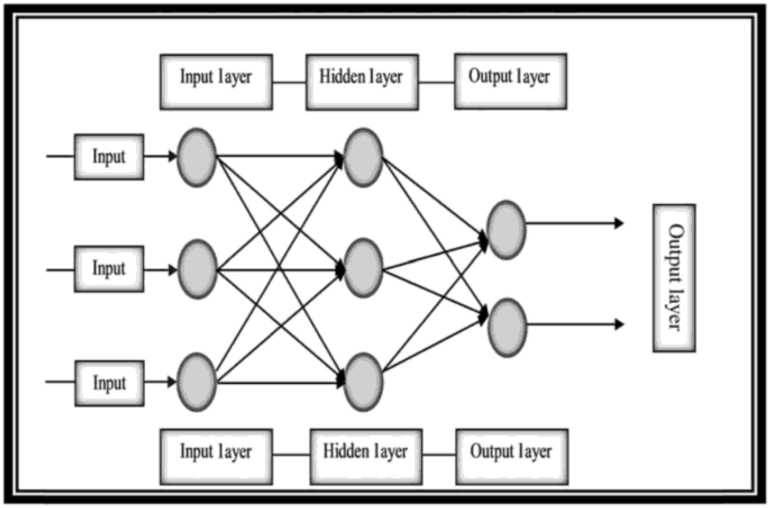

FIGURE 2.2

Unified neural network infrastructure.

2.26.2 UNIFIED NEURAL NETWORK INFRASTRUCTURE

Neural nets are a nonlearning examination of ANNs—Walter Pitts and Warren McCulloch developed ANNs to solve analytical and computational problems [45].

Frank Rosenblatt defines "perceptron," an algorithm-based method for supervising the learning of binary classifiers [45,46]. However, perceptron processes date back to the era of such algorithm-based research projects, which took place in the late 1950s [45]. These algorithms were shown to support the functioning of ANN custom hardware. These functions ensure that a statistical vector gives details on each input, output, and hidden entries [45]. The unified neural network infrastructure process consists of data, protected, and output layers. There is a synergistic interaction between information, protected, and output layers [23,60].

2.27 CONTEXTUAL ARTIFICIAL INTELLIGENCE PERSPECTIVES

In 1956 AI founders/researchers, like Newell et al. developed another computer application that was called "logic theorist." This application was built to solve issues associated with the English language [5,6]. Later, these successful inventions, Simon predicted that "machines will be capable, within twenty years, of doing any work a man may serve" [7,8]. While Minsky had a different prediction that summarizes "within a generation, the problem of creating 'artificial intelligence' is considerably solved" [11,61]. Despite little progress that was made in AI research tasks, some of the researchers who came before us failed to complete other inventions, due to the lack of research funding [5]. Counting how many times AI was redefined, in the 1959s, Samuel describes the term "machine learning" as a logical concept to support human interaction with smart objects [62]. Samuel invented another application called computer checkers [3,62]. During his research findings, Samuel made some corrections to his previous research theories, some of which are discussed in this chapter [3]. Preceding this scientific research, Samuel failed with some of his first innovations. A few months after, Samuel decided to pursue other inventions in data mining solutions, which were brought out in the 1990s. In the same year, Samuel documented his designs in data mining as a proven technology solution that focused on the role of algorithmic theories [4,62]. At the starting time, Samuel tried to assess dataset patterns, even with other researchers continued investigative efforts, which were more centered on data mining and ML solutions. These advances served as a benchmark for the future development of AI solutions and KRR applications [3,62].

In 1974 the US Congress insisted that Sir James Lighthill identified other feasible research projects. Hence, the United States and the British governments decided to stop funding future "exploratory AI research projects" [5]. Several years later, the project was called "AI winter." The AI winter was the name that was passed on to the AI project, which would not qualify for extra funding [5].

In the early 1980s commercial research experts launched another project known as "expert systems." This project was analogous to the one that the United States and the British governments decided not to carry on funding. This commercially funded program "expert systems" was later named the "AI program." Therefore the intent was to simulate human-machine cognitive and analytical sciences. This task was established to carry on scientific studies on simulated human experts [5].

In 1985 the AI market and research projects increased over a billion US dollars [5]. This progress allowed scientists to go on more innovative AI-based analytics solutions [6,62]. Researchers predict that in the future, AI and KRR capabilities will be more technologically advanced [1,5]. This prophecy is accredited to the presentation of advanced technologies, that is, AI, ML, DL, and IoT [1,2]. Many researchers predicted that the disruption of AI would put in new technological areas of meaning. Humans, thinking systems, and smart objects will rely on more or less of these emerging technologies, namely ML, DL, and IoT, focused on processing small- and large-scale datasets [3]. Whereas, technical and nontechnical users will equally rely on these innovative AI/KRR solutions to simplify the time asked to execute, implement, check, and deliver projects within schedule and under budget [1,3,62].

In 1959 Arthur Samuel coined the term "machine learning" or "machine intelligence concept" [6,62]. These similar nomenclatures date back to the 20th century when many scientists were focusing the efforts on parallel scientific research projects. In the same decade, Samuel's late and successful innovations set a new era of computer systems [3,5] Therefore Smith describes KR:

"Any mechanically embodied intelligent process will be made up of structural ingredients that a) we as external observers naturally take to represent a propositional account of the knowledge that the overall process exhibits, and b) independent of such external semantic attribution, play a formal but causal and essential role in generating the behavior that manifests that knowledge..." (as cited in ref. [63]).

2.27.1 USE CASE

Strong AI focuses on an intelligent machine's ability to undertake tasks and being aware of the respective environs [64,65]. In AI, "belief" may be described as nature and quality of perception. It illustrates humans' ability to pay attention to external objects within environs [64,65]. Strong AI was first cited in Latin and English literature interpretations, for example, sentience, qualia, awareness, subjectivity, feel, wakefulness, selfhood, and soul [64,65].

2.28 COMPLEX ARTIFICIAL INTELLIGENCE SYSTEMS AND SWARM INTELLIGENCE

Many researchers suggest that there is a parallel between AI and sophisticated AI systems. However, these domains might differ in how solutions may be exhibited to the IoT environment. In the last decade, vendors developed CS to complement AI's research activities (at the outset, 2006). The relationship between objects and attributes may further note the distinction between AI and complex artificial intelligence systems (CAISs). For instance, most attributes in AI and CAISs may be separated by nonlinear behavior. Having a better understanding of CS and how these attributes may be tested and associated with each is vital to the overall relationship [66]. In AI, the integration of these systems/objects determines how CAISs can be deployed with AI/MI, KRR, DL, and ML to solve pervasive issues affecting the IoT environment. Researchers suggest that there is a parallel or shared value between complex biological networks and AI. For example, the human's immune system, social insects, cellular metabolism, and SI may be a perfect case scenario of such a relationship [66]. SI is an interdisciplinary area that involves both artificial and natural systems. It consists of smart objects, human artifacts, or animals, notably ants, termites, fish, and groups of birds with similar collective behavior [67]. These colonies of ants and termites, as well as herds of land animals, communicated in a decentralized control environment [67]. SI research makes up four distinctive domains, markedly artificial, natural, scientific, and engineering.

Natural swarm intelligence (NSI) research concentrate on the study of biological systems. However, artificial swarm intelligence (ASI) addresses the study of human artifacts, particularly individual characteristics classify ASI and NSI. Such characteristics include the study of the nature of which dictates the objects being examined.

In scientific and engineering environments, SI may be categorized into alternative areas, which is defined through the informative arrangement to the specification of the nature of the system or object that is being evaluated [66,67]. Researchers conducted many experiments using a swarm of robots in recent years [66]. These studies span the regular stream of the SI domain. In the 1990s, however, Deneubourg et al. proposed a distributed probabilistic model. This model focused on clustering behavior—as part of lab experimentation, these researchers developed a model that allowed ants to pick up and drop items. Probabilities were the underlying factors of such a study. It relied on corpse density that they made it available for the ants [68].

In an ideal world, SI systems focus on scientific variables, whether those involving a little understanding of each object's natural behavior or the specific mechanism. This method, however, aims to ensure that systems may interact among themselves, or with the environment to which they are deployed [66]. Engineering stream is a field of science that focuses on exploiting the understanding of how scientific stream concepts and techniques may be shown. It allows for the designing of systems capable of solving problems of a practical significance. There are two contrasts in natural versus artificial and engineering versus science methods. Researchers suggest that regardless of any existing dichotomies between these scientific domains, SI has been used in the robotic scientific research sphere [66,68].

2.29 THE IMPACT OF SMART DUST ON IoT TECHNOLOGY

Many researchers have suggested wide-scale concerns that smartdust or smart dust (SD) poses to global consumers. These issues involve the adoption of technology, regulatory compliance for data protection, security, and privacy. Given the miniaturization of these devices, many consumers are worried about how the safety of data, considering that these sensors may be embedded in other units [69]. These devices have the ability to record data in real-time. The cost of intelligent sensors can be inflated, given that sensors are connected via satellite technology [69]. SD is an evolving wireless technology that consists of small devices that the world has ever experienced. It is also a newly unveiled technology that involves microelectromechanical devices [70]. SD is built on a sensory model concept to be embedded into miniaturized devices with sensors [69]. This advanced technology is found on CCTV cameras and similar devices that are built with an ability to send the data. They are useful technology assets that may be used in data collection, parsing, and storing [69].

Global tech and production companies namely General Electric, IBM, Cisco Systems, Cargill, and many others have led the charge in the development of SD devices. These technologically advanced companies continue to invest millions of United States dollars toward research and development of these miniaturized SD devices. Researchers predict that SD devices will disrupt the global economies in the upcoming years or so [70]. Such disruption will continue due to new applications that are being developed to support the adoption, deployment, and functioning of these devices [69]. In real-time brain function monitoring, SD has contributed immensely to the constructs of leaps or bounds. This technology may be used on humans to monitor and measure behaviors. Such activities involving single or multiple neurons, that is, uses magnetic resonance imaging. This technology may is used in interdisciplinary areas, like those involving the brain-machine interfaces, where humans could control machines by thoughts [70]. Aside from these technological advances, which might have led to more meaningful results, researchers suggest that the limited spatial resolution of these devices may yield a lack of movability and risky invasiveness [69]. These intelligent devices and sensors may generate ideas that may be used to sprinkle miniaturized electronic sensors.

Neural dust (ND) has been around for many years. Unlike SD, ND is equipped with embedded sensors that may generate ultrasound that may power ND sensors. These intelligent systems, when deployed into the environment, may listen to potential messages or responses and may have a similar effect in terms of capability as that of the RFID system. Partly, the system is tetherless, which means the data may be collected, parsed, and stored on the cloud for immediate or future use [70]. These types of systems often run in lower power capacity, despite the special high resolution, and the ability to be transported easily. Brain-machine interfaces, also known as BMIs, do not have an embedded implantable neural interface system. It makes it difficult for them to remain operational or functional for a long-time [69]. Now, a technology, such as microelectromechanical devices known as MEMS or motes may be rated by its hi-tech and agile platforms that are designed to interact with the SD operations.

In AI analytics capabilities, MEMS/Motes capabilities may be embedded into smart objects, to support the decentralized interoperability of SD decides and systems deployed to the IoT environment [70]. These devices are proven to be equipped with sensors, computing, and wireless capabilities that enable them to communicate seamlessly. Researchers suggest that the devices may collect data involving acceleration, stress, pressure, humidity, sound, and other relevant items within the environment [69]. Once the data are stowed into the sensors, these devices could process the information through an onboard computer system. Each sensor can store the data in internal memories for immediate or future accessibility [70]. Through embedded wireless capabilities, miniaturized devices may remotely upload data onto the cloud or even share with other MEMS/Motos within the IoT environment [69].

With the disruptive gain of AI, KRR, and IoT, SD technology has played an instrumental role in the aid of data collection, physical security, infrastructure monitoring, and more. In recent years, however, millions to billions of IoT intelligent systems have gained a footprint in the SD technology landscape. Most of these devices were used in various industries, like in the agricultural fields, to monitor crops on an unparalleled scale. The technology is deployed to determine sprinkling, fertilization, and pest-control requirements. This technology is implemented with monitoring capabilities to facilitate proper maintenance and harvest forecasts [69].

2.29.1 INTELLIGENT DEVICE MANAGEMENT

Intelligent device management (IDM) is a term that has been used in software engineering for many decades. IDM is a field of engineering science or scientific engineering software that involves products and services [3,19]. These areas of engineering science aim to support industry leaders, that is, managers, during the software development lifecycle management. This process focuses on hardware and software areas that every engineering company in the industry would need to monitor services and product manufacturing in an advanced engineering environment. IDM is built-in software that is deployed to ensure that managers have the capability necessary to get the job done [3,19]. This method stems from involving technical teams while ensuring they have the tools needed to effortlessly coordinate or monitor different layers of internal communication channels among various production teams. This process may take place within the same geographical area or deal with multifaceted approaches. The process spans the virtual networks or through production settings.

In a traditional engineering network, IDM spans a multitude of service management, to managing on-site technological resources. It supports day-to-day production or standard service processes [3,19]. This approach includes the following industrial production areas: incident, change, configuration management, and problem solving. In the IoT environment, IDM delivers a rapid solution deployment amid decentralized objects, mostly intelligent devices and sensors. It guarantees that if these objects are connected to AI, they interconnect with other peer smart objects without any downtime. IDM continues to play a vital role in the industrial production sector, the deployment of IoT applications, and the object [3,19].

2.29.2 COGNITIVE SIMULATION AND ANTILOGIC OR NEAT AND SCRUFFY

Several decades ago, Herbert Simon and Allen Newell conducted scientific research on social problem-solving skills. These researchers' scientific investigative efforts aimed to confirm the research hypothesis. These researchers' investigative findings led to the practicalities of what is now known as AI or CS. The research led to the fundamentals of other interdisciplinary areas, like operations research and management science [3,19]. The scientific investigation was founded on psychological experiments that they needed to develop simulated programs. The simulation of such programs further involves simulated techniques that are used on humans to solve complex issues. Most of this critical research work was conducted at Carnegie Mellon University in the 1980s. Thus CS applies to cross-vertical and horizontal scientific research areas. CS is functional in the medical, engineering, and stimulating fields. For instance, in the medical field, it is applied to therapeutic programs, such as rehabilitation techniques. When applied to therapeutic programs, CS solutions focus on cognitive reserve and neuroplasticity. In this context, the program intends to improve a patient's mobility and performance [3,19]. CS is used in medical or scientific laboratories, where experts are heavily engaged in complex brain simulation research and findings.

CS programs are designed to humans from existing lives, like adults, children, elderly/seniors, infants, teens, and others. In the clinical network environment, CS may be used to performs, implanted tasks associated with the human brain. It includes the repetitive projection of myelinated neural circuits into the mind, to restore its cognitive activities or functions [3,19]. This method essentials to restore human brain functions if concoction, nerve disorders, or even brain damage, which may eventually affect cognitive functions. However, antilogic is a branch of science that tends to lean toward the central difference involving humans, for example, men and women. This variance might range from how men and women interact with one another to identify at birth. According to researchers, these variances are unassailable and unchangeable among humans of different gender identity.

Despite these differences, researchers suggest that the existence of antilogic may develop personal tendency among men and women [71]. Researchers believe that in AI, there is a distinct difference between neat and scruffy. Neats are labels that determine elegance, clearness, and correctness. While scruffies view intelligence as much of a complex concept or computational obturation, such apparent differences can be determined for a similar system. Newell defines neat and scruffy, as new logical approaches that could lead to successful scientific breakthroughs [71]. In cognitive models, such as personal psychological data "neat and scruffy" may have a single system execution and representation. However, the rules are introduced to each ad hoc system. Neat solutions focus on logic or formal methods [71]. These concepts consist of pure and applied statistics. Thus scruffy are methods that hackers use to attack or break into AI systems. Scruffy hackers can assemble a team that focuses on conducting malicious attacks on AI systems, like ML [71].

Researchers argue that the difference between these two methods, for instance, neat and scruffy, is that the latter can perform diverse and successful activities based on randomized results [71]. If providential, the directed AI system produces intelligence insights that hackers often need to break into the ML system. Neat is a method that is founded on formalism. Despite its functions, it can appear to be sluggish, breakable, and boring, mainly when deployed to real systems. Researchers are still investigating whether "neat and scruffy" methods could mimic HI [71].

2.29.3 COGNITIVE INFORMATICS AND COGNITIVE COMPUTING

Cognitive informatics (CI) is a maturing scientific field that focuses on NI and core data processing methods. It involves computational-reasoning subcategories, such as brain, processes, sense, and cognition [72,73]. As an interdisciplinary area, CI provides researchers with proven capabilities needed for conducting scientific studies. Applying a sequence of mathematical functions helps advance analytical research [72,73]. These results range from research and engineering areas, primarily CS, cybernetics, systems science, software engineering, neuropsychology, KRR, and software engineering concepts [72,73].

CI comprise two distinct critical areas [73]: information technology and human information interaction (HII). HII is a process, which involves the advance of computational methods, to increased human activity, or performance of human-machine systems [72,73]. Learning and skill development are areas that focus on developing modernized system applications needed to interact with parallel technology solutions. These technological features have embedded functions built to support learning and skill development practices [72,73]. Cognitive systems include analytical processes—adaptive, interactive, iterative/frequentative, state of interaction/stateful, and contextual methods [4].

Researchers have argued that both "CI and cloud computing (CC)" are modern scientific disciplines consist of human reasoning, computational intelligence practices, and procedures, or the denotational of large-scale mathematical concepts [72,73]. The advance of innovative engineering program applications needs deep thinking and learning or reasoning [72,73].

2.30 THE NEXT GENERATION OF COMPUTERS AND FUNCTIONAL TRENDS

For many years, humans have performed some of the computational and functional mathematical tasks. Such responsibilities incorporate but are not limited to new standards, functions, procedures, management/security policies, regulations, and protocols. As these objects continue to acquire more intelligence, there will be an even-steven/shared level of collaboration between public and private sector organizations and the research community. The author predicts the next generation of computers will consist of highly developed smart devices and intelligent systems. The integration of these super objects with cognitive sensors will continue to mimic human perception, cognitive functions, and environmental awareness. It will help hyperscale sophisticated IoT devices and objects with processing data faster than today's machines. The author envisages that the next generation of computers will be smaller and equipped with powerful processors and sensors. The devices and objects will be embedded with hyperperformance computerized functions.

From an ecosystem perspective, the next-gen's intelligent devices and smart objects will be able to adapt, interact, process, and share data. The data will be provisioned through a decentralized physical or virtual computing environment. These faster AI chatbot functions are integrated with super objects, like central processing units or GPUs capabilities. The goal is to process a large amount of data faster than humans. This convergence ensures smart devices and intelligent machines have a unified autonomous-robotic capability to interact effortlessly by analyzing, exchanging, monitoring, managing, supervising, and predicting daily events with limited human's participation. The integration of these smart objects into the next generation of super machines will ensure that such purposes have the independent ability and influence to perform a collection of tasks with accuracy and faster than humans. The author predicts that future AI and IoT capabilities will be deployed through a decentralized node environment. The process of delivering tasks to each device or machine will be faster with a shorter timeframe for executing each instruction. These objects, analyze, predict task/project implementation and execution, receive/provision data, process/monitor, or interact with each other independently or without human participation. In the future, machines and systems will be performing various tasks within an unlimited boundary and unified ecosystem, commonly known as the artificial intelligence of things (AIoT). The author predicts that

AIoT will be an integrated technology with unified capabilities to support the next generation of computers. As these intelligent devices and systems continue to mature, they will be capable of performing other complex tasks.

2.31 CONCLUSION AND FUTURE READING

The author emphasizes how researchers and practitioners can solve issues affecting AI-based solutions, KRR, and the IoT applications. The researched process stems from human perceptions and the ability to warrant the functioning of smart objects and determine faculty to interact. AI has reshaped the global technology landscape through incorporated analytical capabilities.

AI-based solutions have been used to solve KRR and IoT complex problems around the world [1]. Checkers' strategies were a computer-based game that these researchers designed to address many issues involving the algebraic "proving logical theorems" [5]. The term "reasoning" derives from the fields of computer science, sociology, and psychology. Both BC and FC are concepts that can be implemented in AI, game theories, and other ES environmental prototypes [12]. DO and DSO are methods that describe things that can be observed throughout the world. There are performance limitations between AI-based system functions. Such technical constraints include "strong and weak" AI capabilities. These limitations are due to the ability these systems have for autonomous interaction [3].

In the beginning, IBM did not have unique technical capabilities to solve AI problems through its new research inventions. In recent years, IBM had a competitive advantage over other significant players worldwide [45,46]. While supporting AIAs, limited capability, like CAIM and SNNs, have proven can be the main factor affecting machine intelligence system performance. PANGLOSS was designed to help merge LDOCE online and WordNet applications. The intent was too concise syndicate definitions of Longman and semantic relations. The goal, however, was to give a semiautomatic taxonomization for other ontologies using WordNet [15]. There is a difference between "weak and strong AI solutions," for example, variances. Any inconsistencies can be defined by random patterns that machines go through in the ecosystem. These solutions do not include human reasoning, though there might be a parallel between these capabilities [47,48].

Humans, intelligent systems, and smart objects will rely on some of these emerging technologies, that is, ML, DL, and IoT focused on processing small- and large-scale datasets [74]. Technical and nontechnical users will equally rely on these innovative AI/KRR solutions to simplify the time needed to execute, implement, check, and deliver projects/tasks within schedule and under budget [1,3,62]. In the future, the advance of innovative engineering program applications will require in-depth thinking/analysis as well as learning or reasoning [72,73]. The author prophesies that AIoT is an integrated technology that will be the next generation of computers. These devices and sensors have become more intelligent to be able to execute similar tasks that are being performed by humans. For many years, humans have implemented some of these tasks—the robotic systems are beginning to take over. Some new standards, functions, procedures, management/security policies, regulations, and protocols are discussed in this chapter. As smart devices, sensors, or objects continue to acquire more intelligence, there will be an even-steven/shared level of collaboration between public and private sector as well as the research community.

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CHAPTER

ARTIFICIAL INTELLIGENCE, INTERNET OF THINGS, AND COMMUNICATION NETWORKS

3

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3.1 INTRODUCTION

Artificial intelligence (AI) and machine learning (ML) are coming up as the two most diverse technologies creeping into every industry and influencing the business world with their features. The data shows that 81% of industries were affected positively by AI in 2017 and that has jumped to 54% this year [1−3].

To reveal the hidden potential of consumer data businesses are progressively are using AI and ML.

With the help of AI and ML in networks, one can think of a world having a universal network, which will have minimum issues on connectivity and data availability with no lags for surely. One can think of it as all the connections are pooled by a single dynamic automated network that is capable of analyzing the user behavior and capable enough to continuously switch the low-speed connection with a fast one to ensure uninterrupted services. This will leave individuals free from switching the network from mobile data to WiFi for a better connection.

The merger of AI and ML seems like IoT in nature because as the Internet of Things (IoT) means all things connected through the Internet the same is in AI. AI and ML are capable enough to automatically connect, switch with the better network providing uninterrupted services that result in increased workload over the network. AI is the best solution to deal with the exponential increase of data as AI can analyze and computes at a much faster rate than humans. Additionally, there are other ways also in which AI and ML affect the network.

3.1.1 TECHNOLOGY COMBINED HUMAN GENIUS

Human inventiveness and brightness joined with the gigantic learning approach of AI and ML will help networks to handle the burden of countless management techniques and new designs. None of this would be conceivable without each other, that is, AI depends on humans and humans on AI would change the systems drastically. In any case, there is a requirement of human insight in building the actual network infrastructure.

Artificial Intelligence to Solve Pervasive Internet of Things Issues. DOI: https://doi.org/10.1016/B978-0-12-818576-6.00003-4

3.1.2 USING METRICS TO FIX NETWORK ISSUES

Traditional networks have a dependency on deep-packet inspection (DPI) techniques to creep into one's networks to gather the information required to trace and fix the network problem. While this method is much time consuming and due to an authentication problem, these technologies have limited access to one's data and will be unable to trace and fix the network problem. This problem will be removed by incorporating AI and ML. AI with ML competencies can be skilled to diagnose the network problems by using the data gathered from various channels. By using the existing metrics, AI can diagnose the problems and gives 80% accurate practical solutions.

The use of AI and ML in networking implies that some fields like analysis and detection can be automated to find a solution automatically. This enables IT, professionals, to shift their attention to other issues that cannot be resolved without human intervention. In the coming future, AI and ML will become that much smart, that they will not require the metrics and DPI also.

3.2 MACHINE LEARNING/ARTIFICIAL INTELLIGENCE-ASSISTED NETWORKING

The volume of data crossing over the networks is so astronomical that it has become unmanageable for humans to analyze, act, and process. By exploiting the benefits of ML and AI in harnessing for this data and process in an efficient, faster, and smarter way. As the generation is moving toward autonomous era, ML and AI-based solutions can automate the operations, improve the security, and enhance the user experience as mentioned in the following text.

3.2.1 PROACTIVE OPERATIONS

Through automation, proactive actions, and self-healing capabilities the IT operations have been revolutionized by extreme networks. The engine based on ML provides predictive analytical technology that is capable enough to automatically understand the nature of wireless networks and heals it. It offers proactive resolutions to IT despite traditional reactive mode, making IT free for other business-related activities.

To improve the security of network ML and AI are used. Unsupervised form of ML is used in the networks to study the estimated behavior of IoT network endpoints. If IoT endpoint behaves unusually then an alert will be raised automatically. Therefore with the help of AI, threats for IoT devices can be detected and mitigated without any human intervention.

3.2.2 ENHANCES USER EXPERIENCE

AI-based systems can detect and correct the problem before they appear to the end user. This will reduce the maintenance burden on IT and will enrich the end-user experience.

3.3 ARTITICIAL INTELLIGENCE IN COMMUNICATION NETWORKS

AI can be used to enhance the operation and configuration of devices used in the network, optical performance monitoring devices, fiber nonlinearities mitigation, modulation format recognition, and estimation of the quality of transmission (QoT) that upgrades the overall performance of the network. The use of AI in optical networks will make it *cognitive* [4] and cognitive optical networks are those who are supported by an intelligent "brain" or an intelligent control functions implemented in software defined networking framework. This cognitive controller uses the data gathered from the network monitors and additional data sources also and will use the AI techniques to enhance the performance of the network.

All together with benefits, AI possesses challenges along with opportunities in decision making and automating operations because of the huge amount of data collected through heterogeneous sensors and network devices, and time-varying parameters. AI is particularly valuable for performance prediction and optimization of complex optical networks. In this viewpoint, traditional algorithms used for signal processing are not as productive as AI techniques. Nowadays ML, a subpart of AI, is getting popularly used in the optics field, covering all its areas like optical networks and communication along with Nanophotonics and quantum mechanics.

A couple of simple ML algorithms have been used in the optical area by delivering favorable outcomes. For example, upgradation in the limit of transmission was seen without adjusting the infrastructure of the network. This is considered that ML devices will gain much more usage beyond usual systems like for diversity of fiber plant, applications in a meshed network, and adaptable network. Since it has been observed that ML can recuperate random noise from noisy signals, this will be conceivably advantageous for different applications, for example, networks for 5G, visible-light-based communication, satellite-based communication, and even for optical sensing also. AI can be yoked to catch laser dynamics and parameters that are hard to model by standard approaches.

3.3.1 THE MOTIVATION FOR USING MACHINE LEARNING IN COMMUNICATION NETWORKS

From the last few years, researchers have tried to practice mathematical approaches in optical communications and networks and ML is one of the examples of that effort. The overall motivations for the use of ML in optical networks can be identified as follows:

1. **Increased system complexity:** The implementation of innovative coherent technology-enabled transmission practices [5], along with exceptionally flexible networking principles, for example, the elastic optical networks technique. These new technological advancements require a high number of tunable parameters like symbol rates, adaptive coding rates, modulation formats, adaptive channel bandwidth, and so on for their implantation that has ended up with an extremely complex design and operation of optical networks. Modeling of such systems with the help of closed-form formulas is next to impossible and in fact "margins" are normally assumed in the analytical models, resulting in the underutilization of resources that lands up with increased system cost. To resolve these issues ML methods are gaining attention as they can handle these complex and nonlinear systems with comparatively simple training of supervised and/or unsupervised algorithms. These algorithms are capable of solving typical cross-layer problems of optical network fields through exploiting the historical network data information [6].
2. **Increased data availability:** Current optical networks have several monitors that are used to give different forms of information about the whole system like monitoring of traffic, indicators

of signal quality bit error rate (BER), system failure notifications, and so on. The development brought by ML comprises simultaneously leveraging the plethora of gathered information and discover hidden relations among numerous information types.

3.3.2 MACHINE LEARNING IN OPTICAL NETWORKS

Nowadays optical networks are getting themselves ready for future applications through making their availability at edge level networks. Which requires smart and intelligent working to handle high-speed data with minimum latency, for example, 5G. The greatest obstruction in using software controls in optical networks is its analog nature of optical transmission, which increases the operational and managerial complexity of the networks. Moreover, there is a threat to traditional capacity-based applications because of spectral density limits on optical systems. There is a need for new efficient scaling methods to further enhance the cost/bit/s despite depending on capacity improvements alone.

AI with ML algorithms provides a novel approach having the potential to for wider use of software controls in optical systems and also optimizes their efficiency across all dimensions. Reference data sets for ML would advance the operability and functionality across the industry, which further enables scaling and efficiency. For the enhancement of scalability and performance, software-driven networking is required in optical systems. For optical communication systems, there is a need for reference training data sets of ML including needs for new or different methodologies to be analyzed to make optimum use of ML in optical networks. There is a need to understand the basic models of ML to utilize it fully, that is, neural network and genetic algorithm.

Neural networks are motivated by the conduct of biological neurons leads to the development of artificial neurons. This is a software-based module that is connected in layer format. Each neuron can transmit signals to the neuron of the next layer along with connections that have weights according to input importance from a previous layer. After receiving the desired strength signals a neuron will send its signals. The sent signal is further tuned by ML algorithm and connection weights are decided with the help of proper training process.

Genetic algorithms are also a nature-inspired technique. Multiple methods of detecting the right output based on input have been developed by the developers. Then ML is used to mimic the behavior of nature, by them. Weed out the least fit options, mix and mutate the survivors, and repeat the cycle to improve results over time. This is all done in a genetic algorithm to solve the network issues [7].

3.4 TRANSFORMING OPTICAL INDUSTRIES BY ARTIFICIAL INTELLIGENCE

The introduction of AI in networking gives an abundance of opportunities for connectivity to the most emerging systems like IoT-enabled autonomous vehicles and always-connected smart-city systems. AI has revolutionized the present business model by combining the advancements of ML and data mining making it feasible to analyze a huge amount of data gathered from numerous sources, to recognize the patterns, give interactive understanding and to make intelligent predictions.

One of the most emerging technologies of AI is software-defined networking that can dynamically schedule the traffic between the internet and private network. This helps in ensuring the seamless, secure, and super-fast access of the network for all applications and data, wherever in the world they are. Through this technological advancement, networks have gone through more profound evolutions across all industries.

If we talk about the retail sector, AI has vast applications as it can provide accurate and faster detection products for the customer that increases the order value with the conversion rate for their company's shopping portals. Similarly in the healthcare industry, it is very easy to analyze thousands of documents in a minute through a network built on AI that helps doctors to make well-informed decisions about patient care. For the moment, AI is also a big support for call center business because AI-supported network can quickly and accurately route and service customer inquiries.

The aforementioned are very few industrial examples where AI has gained popularity and served their requirements. All the available expertise along with data and research are combined into an AI algorithm. Moreover, this algorithm can be further developed and augmented, so that people can use it except restricted to few. Undeniably, this alteration will need a lot of work from the human's side first. This will require a summary of all the continued research and data form all networks at a global level to make a reliable AI-based system to meet the growing digital demand for businesses.

After understanding the use of AI in networking for business purposes, now it is a turn of data that how it is acquitted. The desired raw data is gathered by using axial motion sensors like gyroscopes and accelerometers installed in wearable devices and portable devices like smartphones. This motion data is obtained along the three axes (x, y, z) in an entirely unobtrusive way, that is, movements are continuously tracked and evaluated in a very user-friendly manner and then processed through supervised learning approaches to AI. For better and accurate results it is advisable to gather several sets of samples from limited users than smaller sets of the sample from a large number of users. Only getting raw sensor data is not sufficient enough. There is a need for a highly precise organization of that data to carefully define certain features because AI is an iterative process. Thus there will be some guesstimates also based on domain knowledge.

3.5 ARTIFICIAL INTELLIGENCE IN OPTICAL TRANSMISSION

The table shows the use of AI techniques in the field of optical transmission that has been used until now and is available in the literature [8].

Application in Optical Transmission	AI Technique Used
Transmitters	1. Bayesian filtering and expectation-maximization [9] 2. Simulated annealing [10] 3. Machine learning and genetic algorithms [11]
Optical amplification control	1. Kernelized linear regression [12] 2. Linear/logistic regression [13] 3. Multilayer perception neural network [14]
Linear impairment identification	1. Kalman filter [15] 2. Neural networks [16] 3. Principal component analysis [17]

OSNR monitoring	1. Deep neural network [18] 2. Neural networks [19]
Modulation format recognition	1. Principal component analysis [17] 2. Support vector machines (SVM) [19] 3. Clustering k-means [20]
Receiver nonlinearity mitigation	1. Maximum a posteriori [21] 2. Maximum-likelihood [22,23] 3. Maximum-likelihood and maximum a posteriori [24] 4. Bayesian filtering and expectation-maximization [25] 5. Nonlinear support vector machines [26] 6. K-nearest neighbors [27] 7. Clustering k-means [28] 8. Nonlinear support vector machines and newton method [29]
QoT estimation	1. Case-based reasoning (CBR) [30] 2. CBR with learning/forgetting [30−31] 3. Random forests classifier [33] 4. Linear regression [34] 5. Support vector machines [35]

3.6 ARTIFICIAL INTELLIGENCE IN OPTICAL NETWORKING

Below given table gives the use of AI in optical networking that has been used till now and is available in the literature.

Optical Networking Application	AI Technique Used
Survivable optical networks	1. Genetic algorithms [36] 2. Ant colony optimization [37]
Regenerator placement	3. Genetic algorithms [38,39] 4. Ant colony optimization [37]
Resource allocation	5. Genetic algorithms [38,39] 6. Particle swarm optimization [40] 7. Ant colony optimization [41] 8. K-means clustering [42] 9. Markov decision processes [43]
Connection establishment	10. Swarm intelligence [44] 11. Genetic algorithms [38,45−49] 12. Ant colony optimization [50−51] 13. Case-based reasoning [52] 14. Simulated annealing [53,54] 15. Tabu search [55,56] 16. Backpropagation neural network [57] 17. Q-learning [58] 18. Game theory [59] 19. Neural networks and principal component analysis [60] 20. Kalman filters [61] 21. Markov decision processes [62,63]

Continued

Optical Networking Application	AI Technique Used
Network reconfiguration	1. Genetic algorithms and colony optimization [64] 2. Genetic algorithms [65,66] 3. Genetic algorithms and cognition [67] 4. Neural networks [68]
Failure/fault detection	1. Bayesian networks, clustering [69] 2. Cognition-based methods [70] 3. Bayesian inference networks [71,72]
Software-defined networking	1. Methods based on Cognition [73,74] 2. Neural networks [75]
Reduction/estimation of burst loss	1. Learning automata [76] 2. Q-learning [58,77,78] 3. expectation-maximization and hidden Markov model [79] 4. Bayesian networks [80] 5. Feed-forward neural network and Q-learning [81] 6. Extreme learning machine [82] 7. Ant colony optimization [83]
Statistical solution for prediction	1. Hidden Markov model (HMM) [84] 2. Bayesian methods and game theory [85]
Intelligent ROADM	1. Linear Regression [34]

3.7 ADVANTAGES OF MACHINE LEARNING IN NETWORKING

ML-driven analytics tools are best in the learning process where traditional networks fail. There are three main reasons for which ML is used in networking and that are: managing the performance, managing the health, and security.

3.7.1 MANAGING THE PERFORMANCE

ML tools can handle traffic management moment-by-moment having larger planning for range capacity and management. These ML tools can automate the traffic if it is spiking in some areas to another area. Management tools of ML may move half of the traffic set out toward a back-end framework starting with one server farm then onto the next dependent on traffic conditions. ML tools additionally can extend patterns of traffic for the future decision-making process [86].

3.7.2 MANAGING THE HEALTH

Initial failure stages of the network can be detected through ML-driven analytics and also predict about their appearance as a healthy node for those initial stages. Vendors of network equipment are increasingly using these types of analytics in management tools, particularly for SaaS offerings.

3.7.3 SECURITY

Detecting irregularities in the behavior of the network can support the cybersecurity group in finding all the information whether it is about a hardware node that has been compromised or an employee getting rouge on the company's network. ML-based techniques have immensely enhanced the analytics space for behavioral threat along with distributed denial-of-service detection and remediation.

3.8 OPTICAL TECHNOLOGIES TO SUPPORT INTERNET OF THINGS

Optical technologies, in particular, fiber optic technologies, contribute to a loT of networks and applications in various aspects, ranging from data transportation, networking, and sensing and imaging.

3.8.1 TRANSMISSION AND SWITCHING

loT generates a large amount of data. Even though some of the data are processed locally at the fog layer and do not require further analysis or storage, a large portion of data requires processing in the cloud. Therefore transporting a large amount of data between the devices and local fogs and the cloud is an important part of the loT network. Besides high transmission bandwidth for large data volume, the data transmission in loT has other requirements like low latency, long distance, security, and flexibility. Fiber-optic communication network provides the most suitable platform, due to its stable channel with low attenuation, high transmission speed, and bandwidth along with multidimensional multiplexing capability. Optical circuit switching is by nature bit-date and protocol-independent and can support heterogeneous signal formats simultaneously. Flexibility can be further enhanced through utilizing CDC ROADMs, flexible grid WDM networks, and variable rate transponders, with the intelligent centralized control through transport SON. Optical layer encryption adds physical level security to the existing security measures at the higher layers [87].

For the last segment of the network, that is, between the devices and the rest of the network, wireless technologies are mostly used due to the mobility advantage. However, for devices that generate a large amount of data, especially in industrial loT applications, optical transmission is still a good solution. Fiber-optic communication is also advantageous in locations where the RF interference is an issue or RF channels are unavailable. The current passive optical network and FTTx can be expanded to support more loT of data and applications. Free space optical (FSO) communication provides another alternative to connect an IoT of devices to the network. This includes laser-based high-speed, long-range FSO systems, and LED-based low-data rate, short-distance indoor visible light communication systems.

3.8.2 DATA CENTER NETWORKING

Cloud computing, a major part of IoT, is driving up the traffic volumes in the data center. It is forecasted that 83% of global data center traffic will come from cloud services and applications by 2019, with a total data center traffic volume of 10.4 zettabytes per year [88]. Optical technologies have been used in the data center networks (DCNs) for high-speed point-to-point links. The developments of complementary metal oxide semiconductor (CMOS) technologies, photonic integrated circuit technologies, and digital signal processing (DSP) technologies enable optical transceiver module hardware with a higher data rate, longer transmission reach, and lower cost [89]. Spatial division multiplexing technologies will further increase the bandwidth capacity per fiber without increasing the fiber count [90].

There is also an increasing need to achieve geo-distribution for the cloud service data centers, due to the requirements of low latency, redundancy, computation power, scalability, and location restriction. Inter-DCNs are almost entirely based on fiber optic technology [91,93].

3.8.3 OPTICAL SENSING AND IMAGING

Besides transporting and routing data, optical technologies can be used to generate data in the IoT network, especially in terms of optical sensing and imaging. Optical sensors measure various physical phenomena, like temperature, pressure, displacement, vibration, acceleration, electrical field, chemical, and so on, by observing the optical property change in the light beam caused by the phenomena. The optical properties to be monitored include intensity, phase, wavelength/frequency, polarization, spectral distribution, and so on. Optical sensing offers high sensitivity, low latency, and long sensing distance. It is also immune to electromagnetic interference and can be implemented in a harsh environment.

Based on how the medium that the light travels, optical sensing technologies can be divided into free space optical sensing and fiber optic sensing (including optical waveguide sensing). Fiber optic sensing does not require line-of-sight and can perform distributed or quasi-distributed sensing over a long distance with remote monitoring capability. Distributed fiber optic sensing utilizes the backscatter of light pulses directed down a fiber optic cable. Because the backscatter occurs down the entire length of the cable, every single part of the optical fiber acts as a monitoring device. Common distributed fiber optic sensors include Rayleigh scattering-based vibration and acoustic sensors, Brillouin scattering-based temperature and strain sensors, and Raman scattering-based temperature sensors. There are also single point sensors that use sensing elements like fiber Bragg grating to conduct sensing at a targeted location. Quasi- distributed sensors contain arrays of multiple sensing elements along with the optical fiber. FSO sensing and imaging does not require fiber installation and is thus more flexible and nonintrusive. The sensing and imaging distance can be range from less than a millimeter (like optical coherent tomography) to hundreds of kilometers (like space lidar). The spectrum range in free space optical sensors is also broad. The optical source and receiver can be located at the same end (like in most standoff detection) or different ends of the light path.

3.9 APPLICATIONS OF INTERNET OF THINGS WITH OPTICAL TECHNOLOGIES

IoT is a ubiquitous network that connects a huge amount of devices, aiming to cover every aspect of daily life and every business sector. Therefore it has a wide range of applications. Here are a few examples where optical technologies play a key role.

3.9.1 UTILITY NETWORK

The fiber optic broadband connections to homes and other buildings are used with wireless networks to connect individual smart meters to the utility company's network, allowing the utility operators to monitor the usage in real-time or near real-time, pinpoint outrages and reduce restoration time, automate billing validation, and better manage and balance energy load during different usage periods. The fiber optic support network also ensures always-on, gigabit per second speed Internet service required for supercomputers that constantly monitor the power grid throughout the city.

3.9.2 DIGITAL OIL FIELD

Digital oil field (DOF) is a direct example of industrial loT. It consists of both the tools and the processes surrounding data and information management across the entire suite of oil/gas exploration and production activities. The combination of advanced fiber optic sensing technologies with integrated networking and big data analytic technologies allows more accurate underground resource exploration and smart good monitoring and management, realizing DOF with improved production and optimize facility performance. For example, distributed fiber sensors provide the operators with high-resolution 3D or 4D vertical seismic profile images for accurate underground reservoir characterization.

3.9.3 AUTOMATIC TOLL BOOTH

All toll booths equipped with emission cameras and optical gas sensors of multiheight multispecies to do the real-time scanning of the vehicles passing through to check the vehicles with failed emission regulations without disturbing the traffic. Aided by automatic plate recognition, the vehicles' information, including manufacturer, model and year can be linked with the emission screening results. Other information, like vehicle occupancy can also be detected. The toll booths can also exchange information with the passing by vehicles, like extracting vehicle running status data and sending test results and repair instructions.

3.10 CONCLUSION

To attain a viable improvement in the network edge, there is a need to improve the services for better customer experience. This requires technologies that are capable of handling such a massive amount of user data daily. These requirements have created pressure on present optical networks for performance, security, and bandwidth availability and to handle this pressure there is a need for implementing AI and ML in available networks.

ML is a part of AI that mainly focusses on using the computer to solve the problems despite human guiding it on how to solve the issue. When it comes to networking part ML can be used to improve management, analytics, and security. However, to fully understand this there is a need for understanding the ML models, for example, neural networks and genetic algorithms.

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CHAPTER

AI AND IOT CAPABILITIES: STANDARDS, PROCEDURES, APPLICATIONS, AND PROTOCOLS

4

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4.1 INTRODUCTION

The wave of development in computing, pulling us outside the realm of the traditional desktop era. Now the computing world is not limited to conventional computers like desktop or laptop, instead it is expanded to many things being used in day-to-day life of human being like air conditioners, refrigerators, washing machines, cars, and many more. Many new entities are participating in the meaningful computation to make human life more organized and comfortable. The inclusion of these new entrants in the world of computing was made possible by a new computing paradigm popular as Internet of Things (IoT) paradigm. In the IoT paradigm, the gadgets and appliances around humans will become part of network and participate as a node. The data collected at different levels, transferred, stored, and processed for making decisions based on data. The devices and type of data ranges from normal CCTV cameras, sensors for different type of data like temperature, distance, elevation, and so on to small pill-shaped cameras in human digestive tract to collect several images for identification of illness. Now the traditional farming is also getting benefitted from IoT and intelligent information system through which farmers can get suggestions regarding farming conditions, irrigation need, and crop selection for particular areas [1]. The IoT technologies and its applications are creating a basic transformation in individual and society views toward collaboration of technology and business. The business models are also getting updated and sometimes dynamic models used like offering different discount to different customers based on buying preferences. The efficiency of these business models can be increased with introduction of various kinds of sensors in controlling different processes like manufacturing. The usage of IoT is widespread and getting support from underlying technologies. The improvement in wireless communication and standardized communication protocols make data collection from IoT nodes/sensors more efficient and fast. Now the collection of data is possible almost anytime, anywhere, and of any size. The support from cloud computing has drastically increased storage and computing power at a reasonable cost. With the excessive creation and flow of information, the world nowadays is becoming an information system itself.

The upcoming developments in IoT infrastructure and related services will interact with technologies responsible for creating autonomous systems in order to deliver more efficient advance

Artificial Intelligence to Solve Pervasive Internet of Things Issues. DOI: https://doi.org/10.1016/B978-0-12-818576-6.00004-6

functionality. This blend on technology will lead to development of new business models and open new funding opportunities for business organizations. The effective use of data analysis enhances decision-making capability. The business processes are governed or modified by actuators on the basis of feedback coming through network. This feedback is generated by the commands created by data analysis of data collected through IoT. In this way the data becomes root for automation and control in business processes. The use of artificial intelligence (AI) to make applications capable of adjusting itself for complex situations with limited or nil human intervention increases productivity. In this way the human reactions to specific situations can be imitated up to a satisfactory performance levels with AI decision-making.

The chapter will address all the procedures involved in IoT, standards for IoT and AI both, various protocols supporting IoT, and application domains where both technologies are being implemented.

4.2 INTERNET OF THINGS

Many appliances (electronic, electrical, and nonelectrical) and gadgets are being embedded with sensors and becoming capable to communicate. The IoT is created by using devices capable to be part of communication-actuating network. Such devices are exploding rapidly around us wherein sensors and actuators composition with the environment around us and the information shared across platforms creates a common operating picture [2]. IEEE described the phrase "Internet of Things" as [3]: *A network of items—each embedded with sensors—which are connected to the Internet*.

Another definition of IoT given by OASIS is [4]: "System where the Internet is connected to the physical world via ubiquitous sensors." The things in IoT refers to computers, sensors, people, actuators, refrigerators, TVs, vehicles, mobile phones, clothes, food, medicines, books, cameras, and so on.

The Internet Society describes the IoT as follows: "Internet of Things generally refers to scenarios where network connectivity and computing capability extends to objects, sensors and everyday items not normally considered computers, allowing these devices to generate, exchange and consume data with minimal human intervention" [5].

So it is easy to understand that the network of anything which is capable of communicating is simply IoT. The things participating in an IoT network have identities, physical attributes, and simulated personalities [6]. As per the report of Economist [7], the proposed smart cities projects will keep IoT at its base. The people and things work together digitally to achieve much greater efficiency.

The radiofrequency identification (RFID) and sensor network technologies made it possible to cater increasing number of things as node of networks. The interaction with physical environment is achieved using sensors and actuators. To get useful inferences form the data collected from sensors, it is important to collect, store, and process data intelligently.

Fig. 4.1 shows the relationship of things with respect to IoT, all the things equipped with compatible sensors to collect data and compatible communication device and medium (mostly wireless) to send and receive data. All of these things are connected to an IoT-enabled server. These IoT-

FIGURE 4.1

Internet of Things (IoT).

enabled things automate certain activities through machine-to-machine (M2M) interaction. The various communication standards suitable for IoT-compatible devices for M2M communication are Bluetooth, ZigBee, IPC Global standards, and low-power wireless fidelity (WiFi) [8].

The IoT has a ubiquitous applicability that makes it more beneficial. Many organizations and individuals find IoT useful as it utilizes different kind of physical objects (things) coordinate to help in decision-making and sharing information. The IoT applicability has three aspects: individual, business, and society. For instance, an individual may employ IoT devices to control household appliances remotely and can get alerts for healthcare based on vital heath monitoring. In business scenario, IoT can help in consignment tracking, inventory monitoring and ordering, automatic security monitoring and alerts, optimization of manufacturing process, and so on. At social front, IoT can be used as part of smart city project, for effective transportation planning, for reducing energy consumption, and so on.

To understand the IoT more closely, IoT architecture, standards, protocols, and application domains are need to be discussed.

4.2.1 ARCHITECTURE OF INTERNET OF THINGS

IoT is a vast concept already being implemented. Many architectures for IoT are proposed but there is no uniformly accepted architecture is available yet. The working of IoT includes a range of sensors, network, communication, and computing technologies. Some of the popular architectures are discussed here.

4.2.1.1 IEEE standard for an architectural framework for Internet of Things (P2413)

IEEE P2413 standard [9] considers IoT as a three layer architecture as depicted in Fig. 4.2. The different layers of this architecture address the similarities, interactions, and relationships among different domains and elements. This architecture considers different IoT domains, abstractions, and

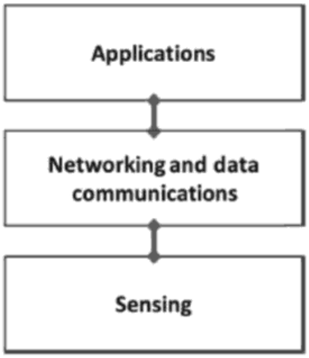

FIGURE 4.2

IEEE P2413 architecture.

commonalities among domains [10]. P2413 follows the architecture defined in ISO/IEC/IEEE 42010 [11]. The IEEE P2413 leverages existing standards for the specified architecture. The abstract "thing" object of this standard may incorporate apps, things, and services. In this standard the information can be shared horizontally or vertically or in both directions. This reference architecture incorporates the essential parts of basic architecture as well as its proficiency to become part of multitiered systems.

4.2.1.2 International Telecommunications Union reference model for Internet of Things

As discussed by Kafle et al. [12], the International Telecommunications Union (ITU) reference model is described as layered architecture. This ITU reference model is based on ITU-T Y.2060 [13]. This architecture includes the common understanding, functionalities, and capabilities of IoT. This architecture has four layers capped with management capabilities and security capabilities:

- Application layer
  - IoT applications
- Service support and application support layer
  - Generic support capabilities
  - Specific support capabilities
- Network layer
  - Networking capabilities
  - Transport capabilities
- Device layer
  - Device capabilities
  - Gateway capabilities

This layered architecture is capped with two capabilities:

- Management capabilities
  - Generic management capabilities
  - Specific management capabilities

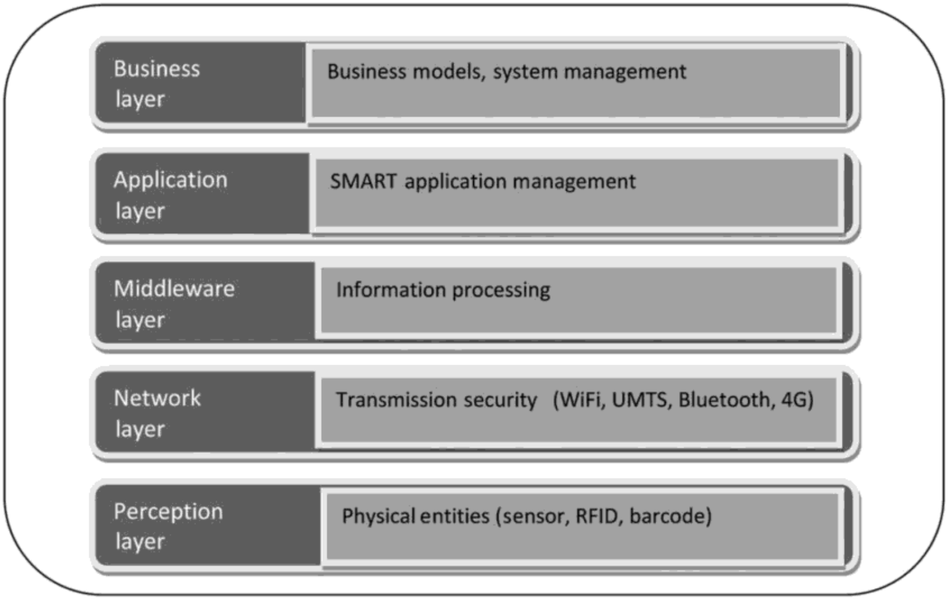

FIGURE 4.4

Five-layer architecture.

The five-layer architecture contains the following layers:

- business layer,
- application layer,
- middleware layer,
- network layer, and
- perception layer.

The business and middleware layers are the additional layers. The business layer is added to manage the IoT system for implementing business and profit model, at the same time user privacy is also handled by this layer. This layer manages the overall applications and services in line with business model. It may build models and graphs as per the data received from application layer. The success of any business depends on its business model and efficient implementation of that model. This layer is responsible for fulfilling the requirements of business model like analysis of information, presentation of important information to determine future actions, and strategies.

The other addition is the middleware layer, which is sometimes treated as processing layer also. The middle layer is responsible for storing and processing a bulk of data received from the transport layer. This layer not only manages a diverse set of services but also made them available to lower layers. These services may include various technologies like cloud services, database services, and big data processing services. This layer has link to database, where it stores the information received from network layer. The automated decisions are made after information processing. The various types of devices deployed in IoT implement compatible services and communicate with devices implementing similar service types.

Who	What	When	Where	Why	How
					
Who would want to attack your organization?	**What** data would an attacker want?	**When** is the attacker likely to strike?	**Where** is the organization vulnerable to attack?	**Why** would an adversary attack your organization?	**How** will the adversary conduct the attack?

FIGURE 15.2

"Who, what, when, where, why, and how" to plan cyber-attack mitigations.

Where is your organization most vulnerable to a cyber-attack? Cyber-attackers exploit the weakest link in your defense and identifying where your organization is most vulnerable will be a good indicator of where the cyber-attacker will initiate the cyber-attack (e.g., people, process, and technology)?

Why would an adversary want to attack your organization? Are they seeking financial gain or executing the cyber-attack for ideological reasons? This will help you identify what data the person may be seeking.

How will the cyber-attacker launch the cyber-attack against your organization? What tactics and techniques will the cyber-attacker use? In addition to technical skill and resources, the cyber-attacker will leverage tactics to exploit the organizations weakest link. Is the organization following secure development practices? Are the organization's IT systems patched, upgraded, and the personnel appropriately trained not to fall for phishing and social engineering?

15.17 US DEPARTMENT OF DEFENSE ARCHITECTURE FRAMEWORK

The US Federal Government has reinforced the need for architectures to support business decisions through federal law. The 1996 Clinger-Cohen Act mandates that US Federal Government agencies select and manage their IT resources by leveraging enterprise architectures [37].

Furthermore, the E-Government Act of 2002 requires the development of an enterprise architecture to promote electronic government services [30]. Architecture-based decision-making provides US Federal Government agencies with a repeatable approach to communicate IT business decisions that is scalable across organizational boundaries.

The US Department of Defense Architecture Framework (DoDAF) is used by US Department of Defense agencies. DoDAF communicates the enterprise architecture through a variety of architectural viewpoints. These viewpoints include All Viewpoint, Capability Viewpoint, Data and Information Viewpoint, Operational Viewpoint, Project Viewpoint, Services Viewpoint, Standards Viewpoint, and Systems Viewpoint [30]. Researchers have demonstrated the value of leveraging

One tool research proposes is a rapidly deployable model that facilitates expression of cyber-attack scenarios via enterprise architecture to develop cybersecurity enterprise architecture attack maps (CEAMs). A CEAM describes cyber-attack scenarios using architectural language, thereby providing a common taxonomy that can be leveraged across the enterprise for swift architecture-based cybersecurity decision making. Using architectural language to express cyber-attack scenarios via a CEAM provided a common taxonomy that can be used to inform IT portfolio management. Mapping the CEAM to the IT portfolio enables decision makers to perform rapid cybersecurity architecture-based decision-making supporting their business goals and mission needs [49].

15.20 SMARTER CYBERSECURITY LEVERAGING ARTIFICIAL INTELLIGENCE

AI can speed response times of underresourced security operations by analyzing massive quantities of risk data. Given the growing number and complexity of cyber-attacks, this helps security operations that are underresourced stay ahead. AI provides instant insights that can help organizations fight through the noise of thousands of daily alerts and drastically reducing response times by leveraging millions of news stories, blogs, and research papers to curate threat intelligence. Leveraging natural language processing and machine learning AI technologies, analyst can act on threats with speed and confidence [50].

AI is trained by consuming billions of data artifacts, leveraging both structured and unstructured data sources like news stories and blogs. AI leverages deep learning and machine learning techniques to improve its understanding cybersecurity threats and risks. AI identifies relationships between threats, like malicious files, suspicious IP addresses, or insiders by gathering insights and using reasoning. Security analyst can respond up to 60 times faster to cybersecurity threats as this analysis only takes a second to a few minutes depending on data set size. AI provides curated risks analysis and eliminates onerous research tasks, resulting in a reduction of time security analysts take to make strategic decisions and launch a choreographed response [50].

For example, IBM's cognitive AI, Watson for Cyber Security, enables organizations to respond to cyber threats greater speed and confidence. It provides actionable insights by learning and connecting the dots between threats with each interaction. IBM cognitive computing is an advanced type of artificial intelligences that leverages various forms of AI, including machine-learning algorithms and deep-learning networks, that get stronger and smarter over time [50].

15.21 IOT AND GROWING CYBERSECURITY RISK

In our current IoT world, daily 2.5 quintillion bytes of data are generated. The IoT will consist of up to 30 billion connected devices by 2020. Cybersecurity risks grow as the scale of IoT grows [51].

IoT is the architecture and suite of technologies needed to create, communicate, aggregate, analyze, and act upon digital information in the physical world [50]. Attackers work to infiltrate IoT deployments by identifying security weaknesses across the enterprise architecture. It is imperative that we secure by design through our cybersecurity systems engineering efforts and architect in cybersecurity mitigations across the layers of the enterprise architect.

Organizations must consider the cybersecurity lifecycle (protect, detect, respond, and recover) and implement both proactive and reactive mitigations. Organizations must build muscle memory around designing for and responding to cyber-attacks. Similar to how first responders develop strategy, train and prepare for a catastrophic event; organizations must develop cybersecurity strategies, train and prepare for the inevitable cyber-attack to help mitigate organizational catastrophe to the infrastructure, business, and brand.

Building security into an organizations IoT platform is essential to minimize risks to private data, business assets, and reputation. Ninety-three percent (93%) of consumers believe manufacturers need to do more to secure their IoT devices and 72% of companies with mature IoT programs have an appointed C-level IoT champion [53].

The Deloitte Information Value Loop is an IoT blueprint for how technologies create value and fit together. The value loop accelerates the relationship between action and data, shifting the focus from what we connect to what we enable. This enables organization to drive value more effectively and efficiently.

When thinking about how to construct the Information Value Loop, organizations should consider five key capabilities to include:

1. Create: Sensors collect data on the physical environment. For example, measuring things like device status, temperature, location, or air.
2. Communicate: Networks facilitate devices sharing data with a centralized platform or other devices.
3. Aggregate: Common standards aid data from various sources to be combined.
4. Analyze: Analysis tools spot patterns that indicate actions needed or anomalies for further investigations.
5. Act: Insights resulting from analysis either frame a choice for the user or initiate action [52].

By getting a better picture of what IoT is, organizations can learn how to best interact with IoT as well as reduce uncertainty and security risk. The value resulting from IoT data can be accelerated by extending the value loop or addressing bottlenecks [52].

In this highly connected complex IoT environment there are numerous cybersecurity threats to be considered across the cybersecurity systems engineering lifecycle from enterprise architecture to requirements, test and implementation of solutions. Four of the biggest cybersecurity threats in an IoT world are: hidden exploitable potential; forgotten and disused devices; understanding IoT attacker goals; and balancing security with user expectations [51].

Many IoT devices are designed for narrow tasks, like sensing temperature or recording movement. However, these devices have hidden exploitable potential. They run on microcontrollers and operating systems capable of doing much more in the background without impeding their primary purpose. This is a rich opportunity for attackers [51].

It is important to have an accurate inventory of devices in an IoT environment to ensure each device is adequately patched, upgraded, and integrated into the cybersecurity architecture. Like a cluttered home, sometimes old devices are simply forgotten about and not used. These devices provide an opportunity for cyber attackers to reintroduce the device to the ecosystem and leverage it as a foothold into the IoT architecture [51].

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Index

Note: Page numbers followed by "*f*" and "*t*" refer to figures and tables, respectively.

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