

# A Smart System for Future Generation based on the Internet of Things Employing Machine Learning, Deep Learning, and Artificial Intelligence : Comprehensive Survey

C. Ramakrishna<sup>1</sup>, Dr. N. Venkatesh<sup>2</sup>, K.Haripal Reddy<sup>3</sup>, Karanam Uma Rani<sup>4</sup>, B.Ravikumar<sup>5</sup>,  
Karthik Kumar Vaigandla<sup>6</sup>, Radha Krishna Karne<sup>7</sup>

<sup>1</sup>Asst Professor , Dept. of CSE(DS), Vignana Bharati Institute of Technology, Hyderabad, Telangana, India

<sup>2</sup>Assistant Professor, Dept. of CSE, School of CS&AI, SR University, Warangal, Telangana, India

<sup>3</sup>Assistant Professor, Dept. of ECE, CMR Institute of Technology, Hyderabad, Telangana, India

<sup>4</sup>Assistant Professor, Dept. of ECE, Malla Reddy Engineering College (Autonomous), Hyderabad, Telangana, India

<sup>5</sup>Assistant Professor, Dept. of ECE, CMR Institute of Technology, Hyderabad, Telangana, India

<sup>6</sup>Assistant Professor, Department of ECE, Balaji Institute of Technology and Science, Warangal, Telangana, India

<sup>7</sup>Assistant Professor, Department of ECE, CMR Institute of Technology, Hyderabad, Telangana, India

<sup>1</sup>cramakrishna537@gmail.com, <sup>2</sup>naramulavenkatesh@gmail.com, <sup>3</sup>haripalreddy@gmail.com, <sup>4</sup>karanamumarani@gmail.com,

<sup>5</sup>brk5599@gmail.com, <sup>6</sup>vkvaigandla@gmail.com, <sup>7</sup>krk.wgl@gmail.com

**Abstract**— The Internet of Things (IoT) is a networked system including interconnected things, devices, and networks that utilize the internet for communication and data exchange. The entity engages in interactions with both its internal and external surroundings. The IoT is capable of seeing the surrounding environment and responding in a way that is appropriate and adaptive. The utilization of advanced technology in this context enhances the environment and thus enhances the overall well-being of humanity. The IoT facilitates inter-device communication, whether through physical or virtual means. The IoT facilitates the enhancement of environmental intelligence, enabling seamless connectivity across many devices at any given moment. The concepts centred on the IoT, such as augmented reality, high-resolution video streaming, autonomous vehicles, intelligent environments, and electronic healthcare, have become pervasive in contemporary society. These applications have requirements for faster data rates, larger bandwidths, enhanced capacities, decreased latencies, and increased throughputs. IoT and Machine learning (ML) are among the fields of research that have shown significant potential for advancement. ML and IoT are used to build intelligent systems. Those networks will modify the ways in which worldwide entities exchange information. This article gives a comprehensive survey of the upcoming 5G-IoT situation, as well as a study of IoT smart system applications and usages. In addition to covering the latest developments in ML and deep learning (DL) and their impact on 5G-IoT, this article describes a comprehensive study of these important enabling technologies and the developing use cases of 5G-IoT.

**Keywords**-5G, Artificial Intelligence, CoMP, CRAN, CR, Deep Learning, HetNets, IoT, Intelligence, Machine Learning, MIMO, Neural Network , Smart System, Wireless Communication.

## I. INTRODUCTION

The Internet of Things (IoT) possesses the capacity and versatility to readily adjust to its surroundings. According to [1], the use of apps on intelligent environments enhances their overall intelligence. The IoT exhibits superiority over many communication technologies such as M2M communications, GSM, GPS, microcontrollers, microprocessors, GPRS, and 2G/3G/4G networks. The IoT is a convergence of hardware and software components, as noted by [2]. The primary objective of the IoT is to facilitate continuous connectivity and network access for devices across many locations [3]. The IoT has emerged as a result of the evolution of M2M. In the realm of M2M communication, devices establish a connection with

the cloud infrastructure to oversee the management of gathered data. Conversely, in the context of the IoT, an extensive array of intelligent devices, sensor nodes, and applications together create and promptly exchange data to facilitate timely decision-making. Thus, M2M technology facilitates the establishment of connectivity within the IoT [4]. The architecture of the IoT comprises the things layer, the gateway layer, and the cloud layer. These layers encompass a wide range of components, including sensors, devices, and objects. The architecture of the IoT is depicted in figure 1 and figure 2. The gateway encompasses IoT protocols, including Bluetooth and ZigBee. The cloud plays a vital role in facilitating wireless communication technologies, including cellular networks and Wi-Fi connectivity. Edge computing is a

fundamental component of both gateway and cloud systems [5].

The IoT facilitates the interconnection of devices and things using wireless technologies over the internet. The IoT facilitates the seamless transfer, communication, and sharing of data across various locations and at any given moment through the utilization of internet connectivity [6]. The technology establishes a decentralized infrastructure for data retrieval and has found extensive use in many real-time domains, including but not limited to the concept of smart cities, smart industries, smart homes, smart agriculture, smart energy systems and smart living environments has gained significant attention in academic discourse. These interconnected systems use sophisticated technologies and data-driven approaches to enhance efficiency, sustainability, and quality of life in urban and rural settings. The integration of intelligent infrastructure, such as sensors, automation, and AI, enables the optimization of resource utilization, improved decision-making processes, and the offering of innovative services. This holistic approach to urban and rural development fosters a more intelligent and interconnected society, addressing many societal and environmental challenges. The IoT demonstrates several characteristics, including interconnectivity, safety measures, heterogeneity, extensive scale, dynamic fluctuations, and connectedness. Figure 3 provides a visual representation of the IoT ecosystem. Classification of IoT is based on their respective functions. The system has three distinct features, namely Things-oriented, Semantic-oriented, and Internet-oriented. The primary objective of the IoT is to facilitate operational efficiency, offer remote access control, support configuration capabilities, and enhance the overall user experience. The IoT facilitates uninterrupted communication in addition to supporting diverse networks [8]. Significant advancements in WSN, telecommunications, and informatics have facilitated the achievement of ubiquitous intelligence [9-10], which encompasses the concept of the future IoT. The inception of the IoT may be attributed to the 1980s, a period during which the notion of ubiquitous computing began to take development. The primary aim of ubiquitous computing was to integrate technology into various aspects of daily life [11].

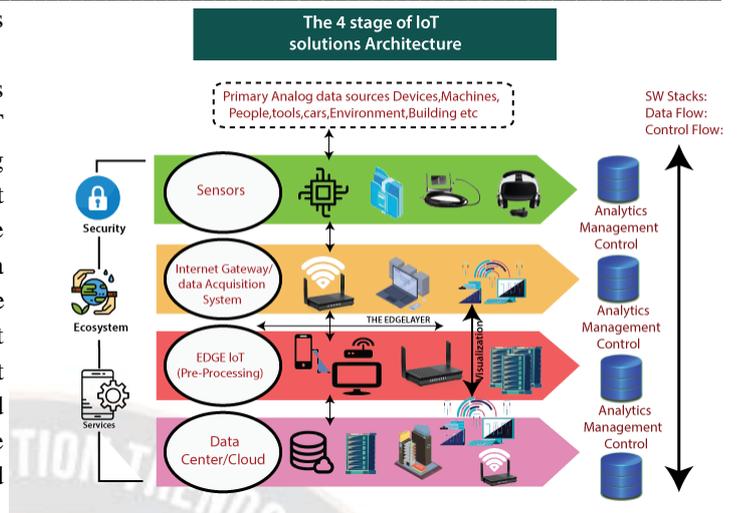


Figure 1. IoT Architecture

The IoT is now being conceptualized and implemented at both the individual and professional levels. The IoT significantly assists to enhance the quality of life for individuals through various applications such as smart health, smart home systems, and smart learning platforms. The IoT is utilized by professionals in several industries, including automation, smart supply chain and transportation, remote monitoring, and logistics. The proposed concept envisions a global communication network characterized by a significant growth in per area data volume, with a target of 1000-fold amplification. Additionally, the number of linked devices is expected to rise, and the user data-rate is projected to see a boost ranging from 10 to 100 times its current capacity. In addition, the battery life of enormous machine communication devices may be prolonged by up to tenfold, as stated in [12]. Moreover, there is a potential reduction of end-to-end latency by a factor of five. Therefore, there has been a notable increase in the attention of academics towards the convergence of different technologies, including the integration of sensors and embedded systems (ESs) with cyber-physical systems (CPS), D2D, and the incorporation of 5G systems with the IoT as the main focus. Presently, effective implementation of IoT necessitates the adoption of new business models that priorities extensive connection, stringent privacy and security measures, comprehensive coverage, exceptional dependability, and minimal latency. The current popularization of 5G-enabled IoT technology involves enhancements in data transfer speeds, improved network coverage, and higher data throughput. These advancements offer potential solutions for various business models and enable the integration of IoT with robotics, actuators, and drones [13].

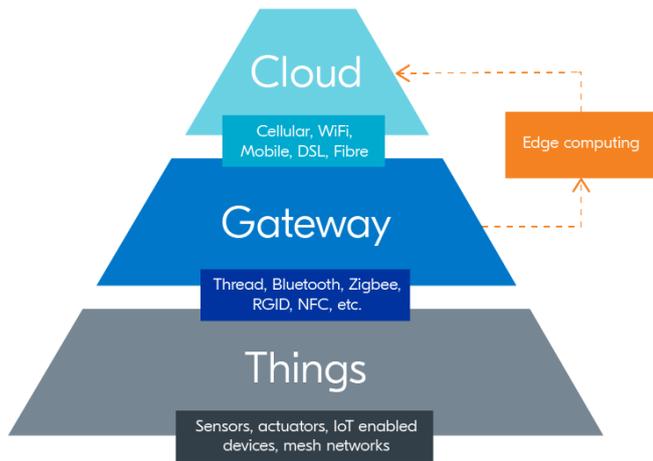


Figure 2. Wireless IoT Architecture

In order to evaluate and safeguard IoT smart systems (SS), many research endeavours have employed algorithms based on machine learning (ML) [14]. Several individuals developed ML architectures that used the connection between signals obtained from several sensor nodes across both temporal and spatial dimensions. Furthermore, further data processing techniques were employed, including the utilization of time-series analysis. In [15], the development of a robust IoT-based security system would be facilitated by employing models that use temporal and geographical correlations to enhance the detection of signs associated with infected or corrupted data. It is noteworthy to emphasize that within the realm of IoT-based SS, there has been a recent inclusion of early warning systems (EWS) in addition to traditional technologies. The efforts given in the field of seismology, such as risk reduction, and site specification parameter evaluation, would be beneficial in addressing this matter [16-19]. Hence, the imperative to establish a sophisticated integration between traditional and contemporary technologies has become unavoidable in order to address the vulnerabilities inherent in these systems.

In recent years, there has been a significant improvement of ML and deep learning (DL) algorithms aimed at tackling a wide range of research concerns. The utilization of DL techniques [20-22] has significantly enhanced the effectiveness of this approach. The use of various ML approaches to address a wide range of complex research difficulties has garnered significant attention. ML technologies can be employed to construct highly intricate relational models due to the constraints of conventional methodologies. ML techniques have shown effective in resolving several challenging research problems, including as recommendation systems and autonomous driving vehicles [23-25]. The achievement may be attributed to the flexibility of ML in comprehending intricate systems, as well as the requirement of a suitable ML model and appropriate datasets for executing the ML algorithm. This reduces the requirements imposed on

conventional models, which are predominantly based on complex, restricted mathematical models. Furthermore, ML algorithms have the capability to acquire and assimilate crucial elements from the information in order to retrieve them.

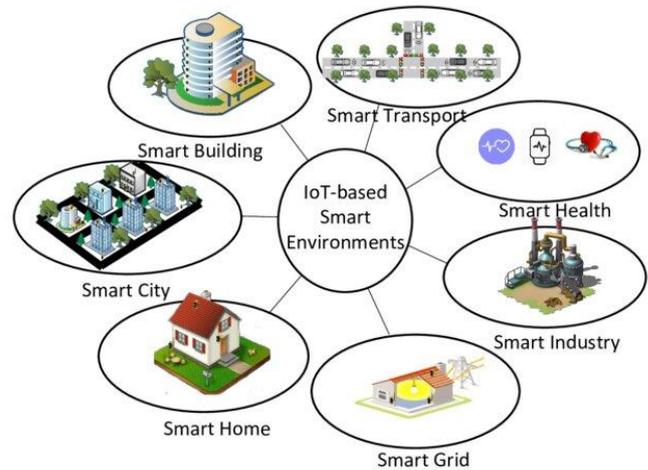


Figure 3. IoT smart Environment

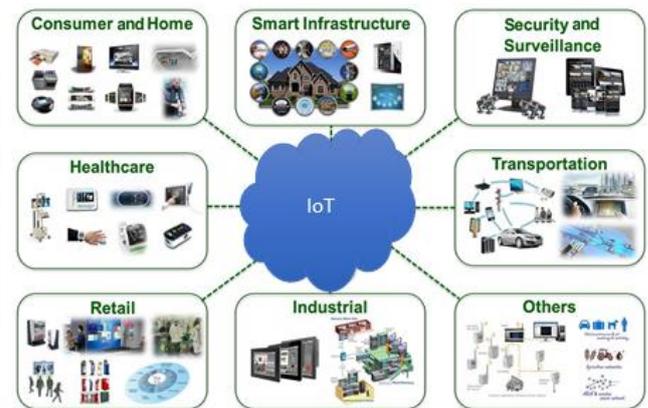


Figure 4. IoT Applications

## II. BACKGROUND AND RELATED WORK

According to estimates, by the year 2025, it is projected that the internet nodes might be present in every individual item, this has led to a substantial rise in the quantity of internet-enabled devices [26]. According to Cisco, it is projected that the number of internet-connected devices will reach 500 billion by the year 2030. In 2013, Telefonica made a prediction that by the year 2020, around 90% of automobiles would be equipped with internet connectivity [27]. Nevertheless, according to a survey conducted in 2015, it is projected that the global number of connected vehicles would exceed 250 million by the year 2020, representing a substantial growth of 67% [28]. The IoT is a prominent growing concept within the present decade. According to Gartner's IT Hype cycle [29], it was projected in 2011 that the IoT would require a period of 5-10 years for widespread

acceptance in the market. According to the International Data Corporation (IDC), it is projected that the United States would spend around \$1.7 trillion on the IoT by the year 2020 [27]. Managing a substantial volume of large-scale IoT data originating from all network nodes can be a laborious undertaking. Additionally, considering the energy effectiveness of data centres holds significant importance. Therefore, in order to address these concerns, it is imperative to utilize artificial intelligence (AI) techniques, innovative fusion algorithms, cutting-edge temporal ML methods, and neural networks for the purpose of automated decision making and enhancing energy efficiency [30]. The preservation of security and privacy is a significant unresolved matter within the realm of IoT architecture. It is imperative to safeguard end-user data from the potential risks of eavesdropping and interference. It is imperative to ensure the authentication of data and retain its integrity at the user's end. Several cryptographic techniques have been suggested for data authentication; nevertheless, they present significant concerns about energy and bandwidth use. Therefore, many cryptographic techniques have been devised and introduced in previous studies [31-32]. The integrity and confidentiality of an IoT network are also affected, when a new node is introduced or when apps running on nodes require installation or updates. In this particular case, a technique for remote wireless reprogramming is suggested in [11]. The aforementioned protocol facilitates the detection of any harmful attacks during the installation process and ensures the verification of each code. The majority of these are mostly derived from a widely used technique known as Deluge [33]. Several IoT designs have been developed in academic literature to solve a range of concerns. In [34] propose a hierarchical architecture consisting of the Sensing and Control Layer (SCL), the Information Processing Layer (IPL), and the Application Layer (AL). This architecture is designed to handle the energy restriction problem. The sensor nodes (SNs) operate in two distinct modes: periodic mode, which is excellent for regular occurrences, and trigger mode, which is appropriate for both periodic and critical events.

In recent years, IoT networks have demonstrated their advantageous nature in many SS designs. The authors in [35] presented a comprehensive analysis of IoT technology, encompassing its data analysis and design developments, challenges, uses, and prospects for upcoming advancements. The authors additionally presented a thorough and extensive evaluation of the emerging 5G-IoT technologies, including SDWSN, CRAN, MIMO [36], massive-MIMO (M-MIMO) [37], CoMP, D2D communications, and CRs. In addition, the article included an extensive examination of the essential technologies that facilitate the functioning of the IoT in the context of the 5G of wireless communication. Furthermore, it delved into the developing use cases of 5G-IoT that have

arisen due to advancements in AI, as well as the continuous efforts in 5G initiatives, QoS standards, and active 5G projects. The research addressed the challenges associated with the deployment of 5G-IoT, specifically focusing on the high data rates. The researchers in [38] conducted an analysis of security solutions for the IoT that utilize ML techniques, including supervised learning (SL), unsupervised learning (USL), and reinforcement learning (RL). Their focus was on examining the attack model specifically designed for IoT systems. The study primarily examined the topics of identification of Viruses, Safe offloading, and ML-based IoT confirmation in order to enhance the protection of data privacy. The authors further discussed the challenges that must be addressed in order to employ these ML-based security solutions in practical IoT devices. The paper conducted a comprehensive examination of the needs for security, points of attack, and current safety measures for IoT networks [39-42]. The weaknesses inherent in these security solutions, which necessitate the use of ML and DL methodologies, were further emphasized. Ultimately, the aforementioned document extensively delved into the ML and DL methodologies that are now being employed to address diverse security concerns inside IoT networks. Additionally, the authors discussed other prospective topics for future study in IoT security that utilize ML and DL techniques. The authors in [40] conducted a thorough examination of the architecture of the IoT based on an extensive assessment of literature on ML. Their analysis focused on the significance of IoT security, specifically in relation to several potential attack vectors. Furthermore, this study highlighted ML-based prospective solutions for enhancing security in the IoT domain. Additionally, the paper examined the future issues that need to be addressed in this area. The primary aim of the authors in [41] was to provide scholars with a comprehensive resource that highlights the prevailing research trends in the field of IoT security, specifically focusing on the utilization of ML techniques. This study developed models that may integrate advanced big data and ML techniques and technologies in response to the rapid growth of extensive IoT security risks. The objective was achieved by the identification of optimal algorithms and models for the real-time or near real-time detection of IoT threats, with a particular emphasis on ensuring accuracy and efficiency. The research conducted in [42] presented an innovative ML-based security architecture that was dynamically adjusted to address the changing security requirements within the IoT field. In order to mitigate a range of vulnerabilities, the framework employed the utilization of SDN and NFV enablers. In order to achieve its goals, the framework utilized SL, neural networks(NNs) and a decentralized data mining system. The paper [43] examines the application of ML in the domains of cybersecurity and CPS / IoT through an analysis of its positive, negative, and

detrimental aspects. The discussion delved into a comprehensive analysis of the numerous benefits that ML offers in the domains of security, CPS, and the IoT. Specifically, the focus was on the progress made in enhancing intrusion detection systems (IDS) and improving decision accuracy within CPS and IoT contexts. The vulnerabilities of ML systems, when examined from the perspectives of security, CPS, and the IoT, encompass the various methods via which ML systems can be deceived, manipulated, and undermined across all phases of their life cycle. The utilization of ML in the perpetration of cyber-attacks and infiltrations was also taken into account. The study conducted in [44] provided a comprehensive examination of IDS for IoT for the period of 2015-2019. This study has addressed several approaches pertaining to the deployment and analysis of IDS inside the IoT architecture [111]. The study encompassed an analysis of various incursions in the realm of IoT, while also delving into the exploration of ML and DL techniques for the purpose of detecting intrusions within IoT networks. The research also addressed the challenges and issues associated with IoT security. A complete analysis was presented in [45], which provided an overview of the latest advancements in ML techniques for the IoT. Additionally, the analysis included a detailed description of various uses of IoT. The integration of ML in the field of IoT enables users to access comprehensive data and develop highly effective and intelligent applications [46]. The article encompassed several topics such as traffic profiling, identification of IoT devices, security measures, architecture for edge computing, network administration, prevalent uses of IoT, as well as unresolved issues and research obstacles.

### III. 5G-ENABLED IOT FOR WIRELESS COMMUNICATION TECHNOLOGIES

Numerous global efforts are being made to embrace and establish standardized implementation of 5G-enabled IoT, as stated in figure 5.

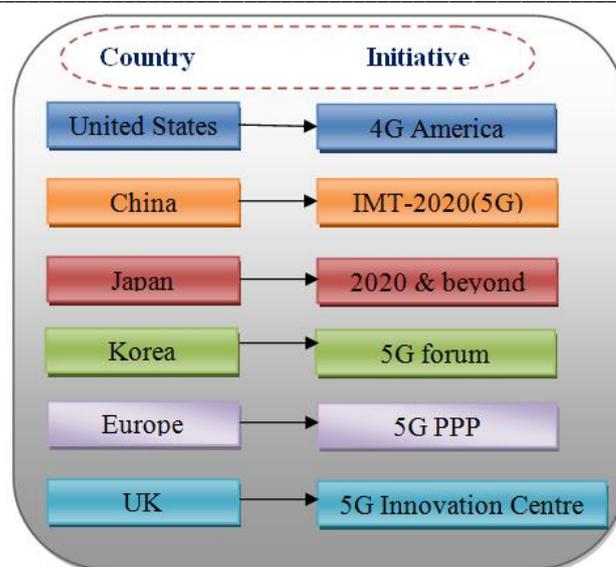


Figure 5. Implementation of 5G efforts in several countries.

Various European initiatives exploring advancements beyond the 4G of telecommunications may be found in [47-48]. In a similar vein, the International Mobile Telecommunications (IMT) consortium started its research and technological endeavours in 2013, followed by the standardization efforts in 2016 [49]. In the year 2015, a decision was made to establish a group inside the 3GPP known as the technical specification group (TSG). This group was assigned the responsibility of developing the 5G RAN [50]. In the same time period, the International Telecommunication Union-Radio Communication (ITU-R) has assumed the task of describing and specifying 5G technology by the year 2020 [51].

The advancement of wireless domains, the emergence of next-generation technologies, and the evolution of 5G networks are crucial for enabling the IoT [52]. These advancements necessitate the provision of state of the art services and solutions, as well as the allocation of broadband spectrum, in order to effectively address the escalating demands of fast increasing data traffic. Hence, it is recommended by 5G Americas [53] that a suitable approach for effectively handling the use cases of 5G-enabled IoT involves the utilization of a spectrum comprising low, mid, and high-band frequencies. The use of various bands in combination is advantageous in effectively addressing specific use cases compared to singular band deployment. In addition to the broad spectrum requirements, the 3GPP has established a new air interface New Radio (NR) for the 5G of wireless communication [54-55].

MIMO, CoMP, and Heterogeneous Networks (HetNets), among others, are a selection of standardized features that have been included into LTE and LTE-A technologies [56-57]. These technologies demonstrate promising outcomes in facilitating extensive networking and delivering high data

transmission rates. Hence, the use of these principles is evident in 5G technology.

**Carrier Aggregation (CA):** CA was implemented in the 4G LTE standard, specifically in accordance with Release 10 of the 3GPP. The system combines a maximum of five component carriers (CCs) of LTE-A, each with a bandwidth of 20 MHz, resulting in a total bandwidth of 100 MHz. This aggregation process effectively increases the overall bandwidth. CA allows for the potential reception of several CCs by a mobile device. Within the framework of wireless communication, it is possible to combine several CCs with varying bandwidths. This aggregation can occur in both the UL and DL directions. However, it is important to note that the number of aggregated CCs in the UL should not exceed the number of aggregated CCs in the DL. The CC can be associated with either intra-band CA, when it belongs to the similar band, or inter-band CA, where it belongs to a separate band. Contiguous and non-contiguous CC aggregation can be implemented in each variant of carrier aggregation. In the context of uplink and downlink communication, it is necessary to designate a principal component carrier (PCC) and designate the remaining component carriers as secondary component carriers (SCCs). There has been a substantial growth in the quantity of Control Channels (QCCs) throughout several versions of the 3GPP.

**Massive-MIMO (M-MIMO) :** MIMO technology is widely regarded as an essential component of LTE-A and is founded upon the principle of spatial multiplexing. The data streams originating from various antennas are combined using multiplexing techniques and subsequently sent over a diverse set of spatially distinct channels. M-MIMO technology plays a crucial role in the architecture of the 5G network. In the mmWave frequency range (mmWFR), a substantial number of antenna components are required in order to generate a highly focused and narrow beam, which serves to mitigate the effects of path-loss. The implementation of high-order multi-user MIMO (MUMIMO) is considered a viable technology for enhancing the capacity of small cells. The 5G RAN relies on the utilization of M-MIMO technology within the context of "macroassisted small cells". In the macro cell, control-plane communication is sent at lower band frequencies by omnidirectional antennas, whereas user-data traffic is conveyed through highly directed M-MIMO beams at mmWFRs [58]. MUMIMO technology enables the implementation of distributed MIMO systems. In this configuration, the base station (BS) may broadcast several narrow beams concurrently to a mobile station located at a separate position. The primary objectives of this approach are to enhance throughput and minimize correlation among the antenna parts. MIMO technology, in its following development, aims to enhance spectrum efficiency by employing arrays of several hundred antennas to service many user devices inside a single time and

frequency slot. Therefore, by utilizing the MIMO technology on a broader scope. In contrast to standard MIMO technology, TDD mode is used in M-MIMO, and the UL and DL channels' reciprocal mechanism is utilized, rather than use pilot waveforms for channel estimation [59]. M-MIMO has demonstrated its advantageous capabilities in enhancing radiation efficiency by up to 100 times, augmenting capacity by an order of 10, bolstering protection against interference and deliberate jamming, significantly reducing latency, and offering a low-power and cost-effective configuration [60].

**Coordinated Multipoint Processing (CoMP) :** The concept of CoMP was initially established and normalized by the 3GPP in Release 10. It was subsequently used in LTE-A networks. The use of CoMP transmission in the DL and reception in the UL has shown to be a very efficient method for improving the throughput of cell-edge users. CoMP use dispersed MIMO techniques to facilitate transmission and reception using antennas that are not necessarily located inside the same cell. This approach aims to mitigate spatial interference in received signals and improve the quality of the received signal. The use of CoMP approach, particularly when implemented with MU-MIMO technology, has proven to be very efficient in enhancing the coverage at the cell edge and mitigating the occurrence of outages resulting from blocking and adverse channel circumstances. Multiple tests were undertaken by NTT Docomo and Ericsson in Stockholm, Sweden, using CoMP with MIMO technology. The purpose of these studies was to determine the efficiency of coordinating distributed MIMO systems and to assess the potential enhancements in user data-rates at mmWFR bands resulting from the integration of both technologies [114-116].

**Heterogeneous Networks (HetNets) :** The network consists of many levels of cells, including femtocells, pico-cells, micro-cells, and macro-cells, as well as multiple Radio Access Technologies (RATs). These networks are comprised of nodes with low power requirements that are necessary for the purpose of data offloading [61]. HetNets, also known as HetNets, contribute to the environmentally friendly element of 5G technology by effectively using the available spectrum and minimizing power transmission in both the UL and DL directions. This approach enhances the spectral and energy efficiency, as stated in reference [49]. The efficient allocation of spectrum in an ultra-dense network (UDN) necessitates the use of an intelligent interference mitigation technology due to the substantial number of user equipment involved. The article [63] presents the HetNet enabled 5G-IoT based solutions.

**D2D Communications :** The HetNet facilitates the synchronization between the macro-cell BS and the low power BS. However, in the context of short-range communication, it does not demonstrate a high level of efficiency. Therefore, the D2D communication has undergone advancements that enable reduced power consumption, improved quality of service, and

load balancing among devices for short-range communication at a distance of less than 200 metres. Given the circumstances, the BS will possess either complete authority or partial authority in distributing resources among the source, destination, and relaying nodes [112-113].

**Centralized Radio Access Network (CRAN)** : The concept of the CRAN is to provide more environmentally friendly and sustainable connection by redistributing the functions of BSs. The allocation of radio duties is limited to the remote radio unit/head of the BS. The baseband unit (BBU), along with other units, is sent to the cloud-based central processor. This facilitates the consolidation of information, collaborative communication between cells, enhanced utilization of cells, and a reduction in complexity and expense at the BS level. Various 5G standards have been created with the purpose of facilitating the extensive interconnectivity of devices in the realm of Cellular IoT. The initial stage involves the implementation of M2M communication is narrowband IoT (NB-IoT), which is a low power wide area technology designed to facilitate the widespread adoption of IoT. This technology is specified in the 3GPP Release 14. Currently, the 3GPP is actively engaged in the process of developing upgrades to meet the increasing demand in the industry.

**Software Defined Wireless Sensor Networking (SDWSN)** : Typically, traditional approaches for implementing cellular technology rely predominantly on hardware-based solutions. The adoption of hardware-based infrastructure imposes constraints on the flexibility of network growth. Therefore, in order to address this constraint, researchers have created SDWSN, a very promising paradigm [64-66]. The SDWSN represents a fusion of SDN within WSNs. The deployment of SDN has been seen in data centres, namely in wired communication networks, as well as for the purpose of Internet connectivity [67]. At now, it is seen as a facilitator of 5G technology [68-69]. The main objective of utilizing this architecture for the implementation of 5G networks is to distribute the control logic layer away from the network device, while simultaneously offering a centralized method for programming the whole network.

**Network Function Virtualization (NFV)** : Virtualization of network functions is made possible by NFV technology. The aforementioned capabilities can afterwards be included into software packages that can thereafter be utilized to fulfill network service needs [70]. NFV and SDN are considered to be distinct and separate concepts within the field of network architecture. The notion of NFV emerged from the idea of virtual computers that may be deployed on several operating systems within a single server. Several anticipated applications associated with NFV include core virtualization and

centralized baseband processing in RANs [71]. The NFV technology has great potential as a viable option for effectively implementing the IoT in the context of 5G networks.

**Cognitive Radios (CRs)** : The existing IoT applications, ranging from extensive to essential IoT, exemplify a substantial increase in connection and subsequent strain on network resources, leading to a shortage of available spectrum. Therefore, it is imperative to utilize the spectrum in an effective and logical manner in order to meet the increasing demand. The issue at hand is effectively addressed by the CR through the strategic utilization and distribution of spectrum resources in an opportunistic way, as evidenced by reference [64]. A CR may be defined as a radio device that has the capability to adapt its transmitter settings in response to the surrounding environment with which it interacts [72,74]. Therefore, this gives rise to the notion of cognitive capacity and reconfigurability. The term "former" pertains to the process of recording spatial and temporal fluctuations in a radio environment while minimizing interference. Following this, a spectrum that has been optimized may be collected for the purpose of transmission. Typically, this refers to an underutilized frequency range known as a "spectrum hole" or "white space." Interference reduction may be achieved through three methods when the system is utilized by a licensed user. Initially, transitioning towards the other end of the spectrum. Additionally, the power level is maintained at a low setting, and the modulation strategy employed is altered [73]. In addition, the CR effectively oversees the spectrum by employing a mechanism to identify and use the most optimal channel, hence facilitating the sharing of spectrum resources. One notable characteristic of CR technology is its ability to exhibit spectrum mobility by vacating the assigned channel upon the arrival of a primary user [74].

#### IV. DEEP NEURAL NETWORK (DNN)

The DNN is composed of several layers of processing that have the ability to extract hierarchical features from the input information [75]. The operation of DNNs is modelled after the cognitive processes of the brain of a person. The DNN is composed of many layers, with each layer including numerous processing units referred to as neurons. A neuron executes the process of calculating the weighted sum of its inputs ( $X_1, X_2, \dots, X_k$ ) and subsequently transmits this total to an activation function, which then produces the intended output (O). Every individual neuron is composed of a collection of weights ( $W_1, W_2, \dots, W_k$ ) and a bias term (b), which undergoes optimization throughout the training procedure. The operational mechanism of the artificial neuron is illustrated in Figure 6.

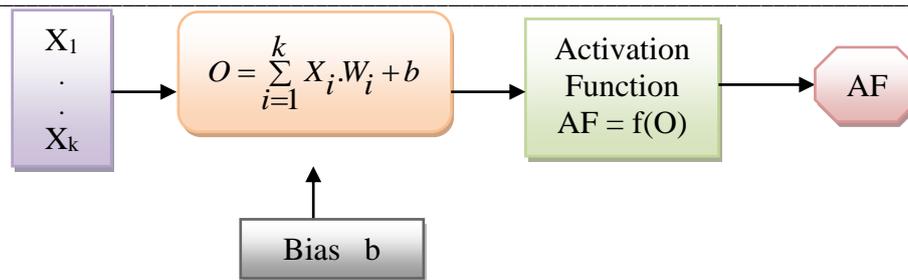


Figure 6. Artificial Neuron

**Convolutional Neural Network (CNN)** : The input to a CNN consists of a 2-D picture or a speech stream. The hierarchical properties of the input data are extracted by CNN through a series of hidden layers (HLs), including convolutional layers (CLs) and pooling layers (PLs) [76]. The CLs are comprised of kernels that possess the same structure as the input data. The process involves the multiplication of the input with the kernel, resulting in the generation of outputs referred to as filter maps. The utilization of PLs serves to decrease the dimensionality of feature maps, hence reducing processing time and mitigating the risk of over-fitting. The output derived from the ultimate PL is subsequently sent via the fully-connected layer in order to produce the intended output. The CNN has demonstrated encouraging outcomes in challenges related to image recognition [77].

**Recurrent Neural Network (RNN)** : In order to address the limitations of traditional feed forward neural networks in modeling time-series issues, researchers developed an extension known as RNNs. RNNs were specifically built to simulate and analyze time-series data, as the standard feed forward neural networks lacked the necessary capabilities for such tasks. The input to a RNN consists of the output at time 'n-1' and the input at time 'n'. The neurons of the RNN possess

an inherent capacity to retain and recall past computations. The training of the RNN involves the utilization of Back Propagation Through Time (BPTT), a type of back propagation. RNNs are not suitable for simulating time-series data with long-term dependencies due to their susceptibility to the vanishing gradient problem in such circumstances. In order to mitigate this occurrence, researchers devised a variant of the RNN known as Long Short Term Memory (LSTM) [78].

**Auto-Encoder (AE)** : The AE belongs to the generative class of DNN models. The neural networks consist of one or more HLs, in addition to the input and output layers [79]. The number of neurons in the output layer is equivalent to the number of neurons in the input layer. The objective of AEs is to reconstruct the input data in order to acquire knowledge about its compressed representation. The system comprises two primary components: an encoder, responsible for converting the input data into a distinct representation known as a code, and a decoder, which reconstructs the original input from the code. The primary objective of training in AEs is to minimize the discrepancy between the input data and the produced output. AEs are commonly employed for the purposes of extracting features and reducing dimensionality in various applications.

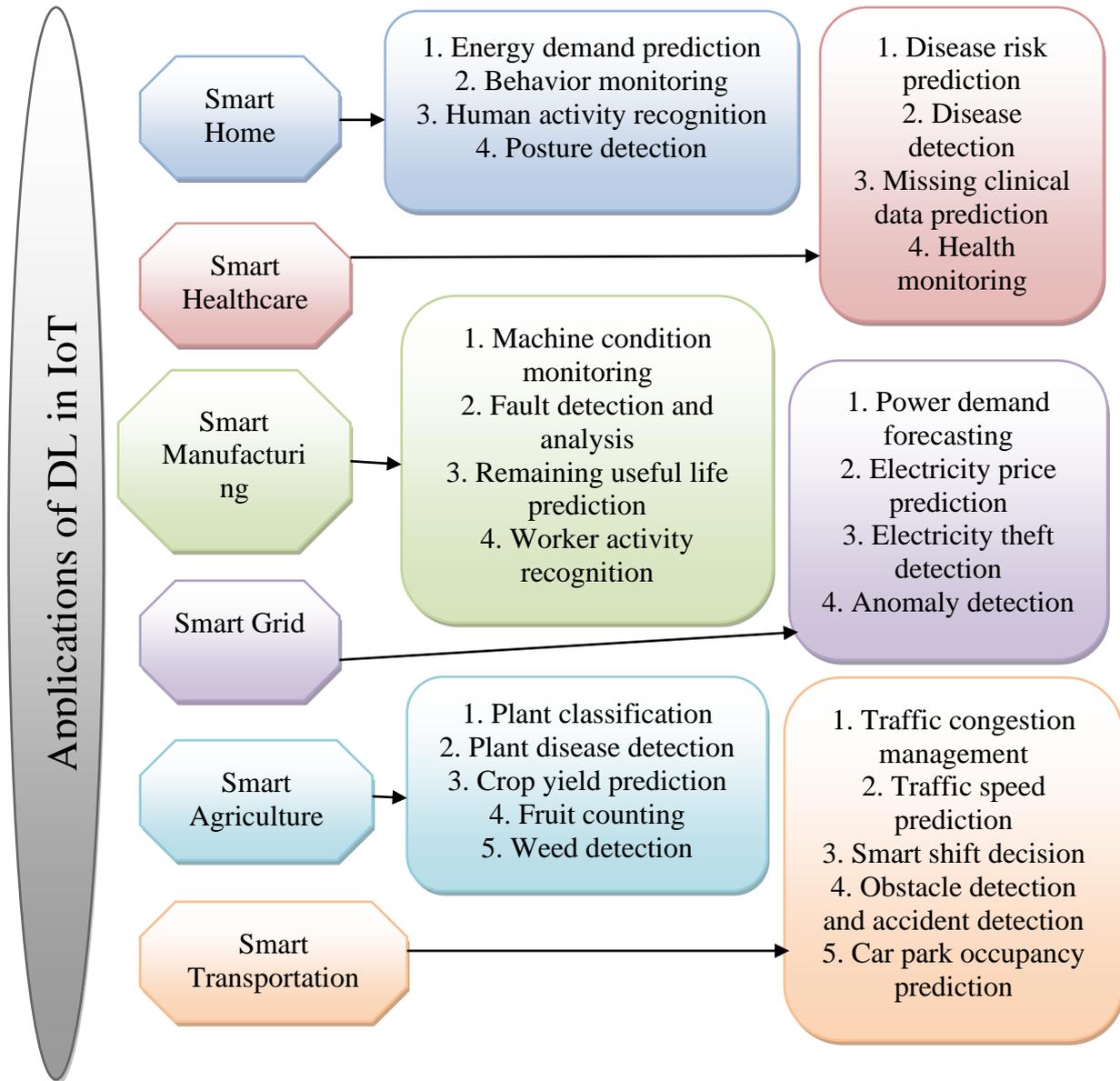


Figure 7 . Applications of DL in IoT

**Generative Adversarial Network (GAN) :** GANs are a type of hybrid DNN architecture including two distinct neural networks, namely the generator and the discriminator [80]. These networks collaborate in order to generate data of superior quality. The generative network (GN) is trained to effectively capture the underlying division of the data and generate new data by leveraging the patterns it has learnt from the existing data. Conversely, the discriminative network is taught with the objective of maximizing the discrepancy between the real data and the data produced by the GN. GANs exhibit a high degree of suitability for circumstances characterized by the presence of noisy data.

**Restricted Boltzmann Machine (RBM) :** The RBM consists of visible layer (VL) and the HL [81]. The input is introduced to the VL, and the HL acquires knowledge of the probability distribution based on the input data. The neurons within the

VL and HLs are interconnected in a manner that results in the formation of a bipartite graph. The utilization of back-propagation and gradient descent techniques is common throughout the training process in order to ascertain the most effective parameters inside the network. The objective of training in the RBM is to enhance the overall value of the probabilities associated with the units residing in the VL. The RBM has the capability to carry out many tasks like as classification, feature extraction, and dimensionality reduction. **Deep Belief Network (DBN) :** DBNs belong to the category of generative DNNs. Neural networks are comprised of one VL, as well as several concealed layers [82]. The individuals possess the ability to extract complex conceptualizations from the provided material. A DBN is composed of a series of stacked RBMs. The training of DBNs is conducted in an USL manner, wherein the model acquires the ability to

probabilistically reconstruct the inputs based on the characteristics retrieved at each layer. In addition to facilitating generative feature discovery, DBNs may also be effectively employed for discriminative prediction tasks.

## V. 5G-IOT NETWORKS BY ARTIFICIAL INTELLIGENCE

The increased data rates offered by 5G-IoT enable the use of data-intensive and computationally demanding AI algorithms for a wide range of consumer applications. The network's high data transfer capacity enables the use of efficient DL algorithms [83], on wireless 5G-IoT nodes. The convergence of 5G, IoT, and AI possesses significant potential to revolutionize the corporate environment through the facilitation of real-time intelligent decision-making. The presence of high-performance hardware in IoT nodes enables the integration of intelligence either on the IoT nodes themselves or on a nearby fog node. This integration leads to reduced latency, enhanced link capacity, and improved network security. It is worth noting that AI techniques have the potential to be utilized in 5G-IoT networks in order to improve their performance across various layers, including application, physical, and network layers. By predicting traffic patterns on the network, AI can optimize data rates and enable the provisioning of user applications that are based on AI. As an illustration, inside the application layer, artificial intelligence techniques may be employed to examine network traffic and analyze capacity trends. This application of AI aims to enable the network to autonomously configure, organize, and adjust itself [84]. AI-based optimization algorithms have the potential to enhance several aspects of the physical and network layers. These algorithms can aid in dynamic spectrum management, organizing large amounts of data, integrating different types of devices, increasing device density, promoting interoperability across IoT nodes, and improving battery life.

The 5G Intelligent IoT possesses the capability to address problems pertaining to the congestion of communication channels and the handling of vast amounts of data. The integration of AI algorithms with 5G technology is the primary aim of the 5G Intelligent IoT. This initiative seeks to intelligently handle vast quantities of data, enhance communication channels, and improve channel utilization in an efficient manner [85]. Furthermore, the incorporation of AI into firmware's core components will create a safe setting in which to deploy software. This, in turn, would facilitate the seamless execution of intelligent decision-making processes without any interruptions.

The integration of 5G wireless technology and AI within the healthcare sector has the potential to improve the quality of life for a substantial number of individuals through the enhancement of the current healthcare infrastructure. In their study, Chen et al. [86] developed a healthcare system that is

tailored to individual emotions and utilizes 5G technology. The system places particular emphasis on providing emotional support for vulnerable populations, such as children, individuals with mental illness, and the elderly. In a previous study [87], the researchers employed both Genetic Algorithm (GA) and Simulated Annealing (SA) techniques to find the optimal placement of 5G drone BSs. This investigation focused on satisfying several requirements related to coverage, energy consumption, and cost.

The applications of AI involves the use of 5G networks. This can be observed in the CogNet project [88], where the discussion revolves on the architecture of an autonomic self-managing network. This network extends the management of NFV by including a decision-making mechanism based on ML. The motivation for implementing a more flexible control mechanism alongside the fundamental NFV capabilities is driven by the objective of minimizing system expenses while maintaining a competitive level of QoS.

The combination of 5G technology with the IoT is facilitating the emergence of vehicles that possess uninterrupted connectivity. The integration of technology has facilitated more efficient access to the internet. Currently, automobile manufacturers have exhibited a keen interest in expanding their reach and investigating various industries to implement this technology inside the realm of transportation systems. Many studies have been conducted on the implementation of internet connectivity in autonomous vehicles. A sophisticated transport system has the capability to establish connectivity between passengers' smartphones and the vehicle. Similar to other IoT devices, a smart transport system has the capability to offer additional functionalities that enhance control [89].

The enormous amount of data produced by the continuous connectivity of IoT devices using 5G technology has the potential to be utilized in the forecasting of accidents and crimes through the correlation of the extensive dataset [90]. Therefore, this process facilitates the generation of novel concepts that have the potential to be developed into large-scale projects for prominent corporations. Additionally, it leads to the accumulation of substantial amounts of data and offers many means of communication, as seen in **Figure 8**. Real-time data extraction can be facilitated by the utilization of IoT technology. This technological advancement has facilitated the remote control of gadgets through diverse means, minimizing the need for extensive human intervention. The use of IoT devices has established a novel infrastructure for the everyday management of traffic. The utilization of wireless network technology has been employed for the purpose of detecting the immediate environment. Furthermore, it can be observed that the IoT has been implemented as a means of facilitating monitoring. The acquisition of high volumes of data from IoT devices has been significant in

facilitating the improvement and enhancement of urban environmental planning.

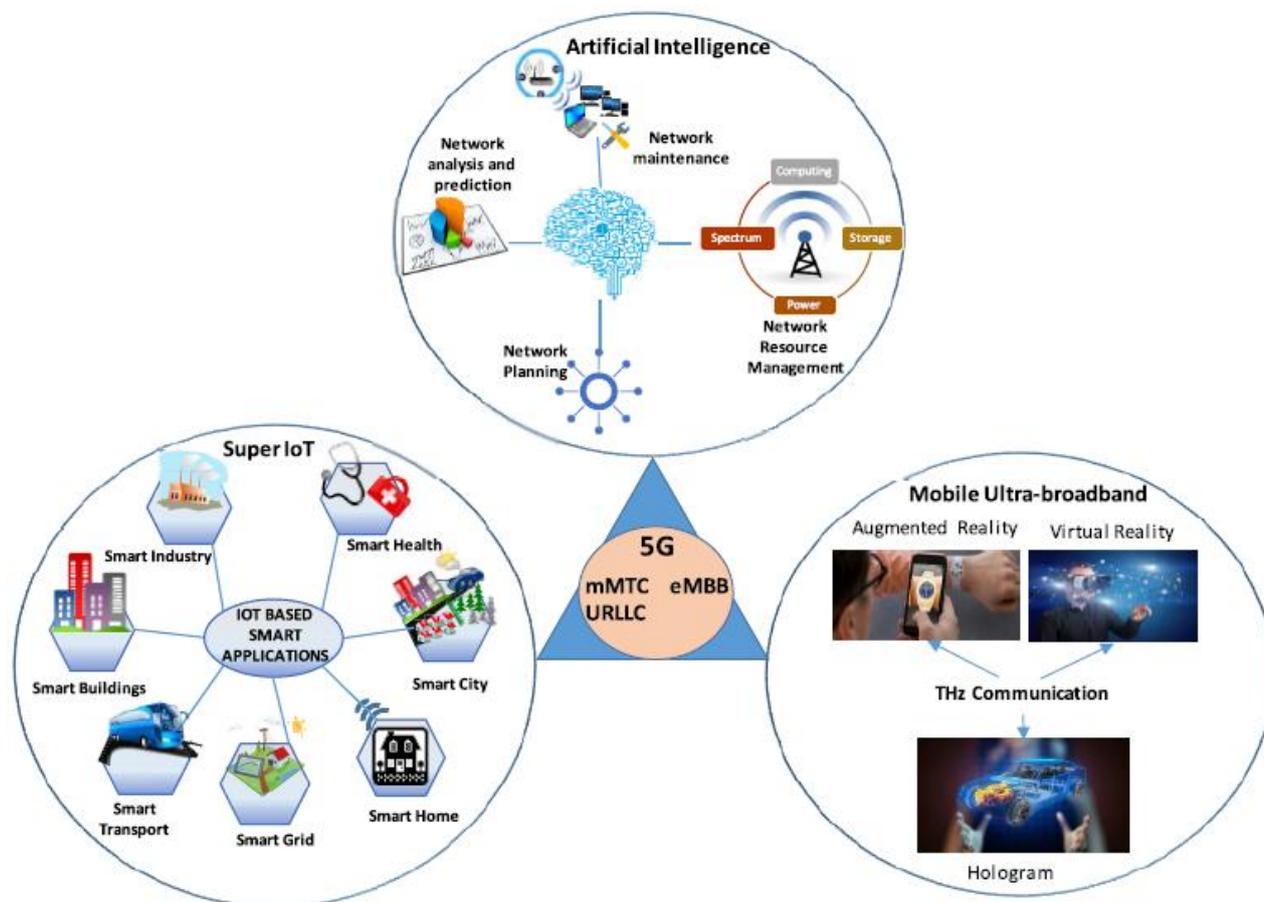


Figure 8. Architecture for 5G and AI [91].

## VI. ML TECHNIQUES IN IOT

Data is typically reviewed by humans to classify objects. ML aims to automate this process using the most sophisticated algorithms. ML and DL techniques are widely recognized as AI methodologies that can facilitate the acquisition of knowledge by IoT devices through the analysis of data, enabling them to adapt their behaviour accordingly. The learning models typically consist of a collection of rules, processes, or advanced 'transfer functions' that may be employed to identify significant patterns in IoT data related to security incidents, as well as to detect and forecast behaviour [92]. In the context of the IoT, both ML and DL may function inside dynamic IoT networks without the need for human or user engagement, hence yielding certain outcomes. Figure 9 illustrates the potential use of ML and DL methodologies in the creation of a data-centric framework for enhancing IoT security intelligence. Various ML techniques can be employed to extract insights from IoT security data. These techniques encompass classification and regression analysis, clustering, rule-based methods, feature optimization methods [93], and DL methods that leverage ANNs, and others [94-95].

**Logistic Regression (LR)** : LR is employed for statistical analysis of datasets including several independent factors that result in a binary outcome. The LR model is employed to estimate the posterior probability of K feature classes by fitting data onto a logit function, resulting in a binary output.

**Linear Discriminant Analysis (LDA)** : LDA was developed as a means to tackle several issues encountered by LR. The LDA paradigm is seen more appropriate than the LR paradigm when the distribution of predictors in each class follows a normal distribution and the sample size is relatively modest. Prior to employing LDA, it is important to establish an assumption regarding the dataset to be processed, namely that each of the predictors adheres to a normal distribution. In cases where the data deviates significantly from a linear assumption and may be readily characterized, LDA may be inadequate [97].

**Linear Support Vector Machine (LSVM)** : The primary objective of the SVM is to identify an optimal hyperplane for K-feature classes. In K-dimensional space, the process involves mapping input data characteristics to target classes with the objective of identifying the optimal hyperplane. When

the hyperplane reaches the maximum distance between the data points in the class, as indicated by reference [98].

**Ridge Classifier (RC) :** The RC is commonly employed as a regression approach for the purpose of mapping label data in the majority of situations. Consequently, the problem's resolution is approached using a regression-based framework. The prediction with the greatest value is allocated to the target class, with the exception of multiclass scenarios when multi-output regression is employed [99].

**Gaussian Naive Bayes (GNB) :** In general, the Naive Bayes (NB) classifier exhibits nonlinearity. The NB classifier is considered a linear classifier when the likelihood factors are dependent on exponential families. In the case of features that possess continuous values, a specific variant of the NB method, referred to as the Gaussian algorithm, is employed. In a more precise manner, it is anticipated that the features would conform to a supervised Gaussian distribution, as stated in [100]. The GNB is a probabilistic model that makes predictions by considering the likelihood of each class's existence.

**AdaBoost (AB) :** AB is a machine learning algorithm that use adaptive boosting to iteratively train weak classifiers on dynamically changing datasets. These weak classifiers are then combined to form a stronger classifier by a weighted majority voting scheme. The AB method assigns greater weight to items that are more challenging to categorize, while assigning lesser weight to those that are easier to manage. The first assignment of observation weights is performed by AB in the initial stage [101]. The classifier is subsequently trained on the training data utilizing the assigned weights. Following the computation of the weighted error rate, the classifier is assigned a new weight to aid in its ultimate decision-making process.

**K-Nearest Neighbors (KNN) :** The KNN algorithm is a classification method that assigns a given input to the majority class among its KNN in a given space. In this context, we will illustrate the application of the KNN algorithm using the example provided in [102]. When the value of k is set to 1, the KNN algorithm is expected to provide the smallest KNN. This is because the model becomes more susceptible to being excessively influenced by noise or outliers.

**CatBoost Classifier (CB) :** The CB algorithm employs a specific variant of depth-first expansion called oblivious trees. The classification algorithm employs a vectorized representation of the tree, in which each level utilizes a binary splitting technique. As a consequence, it leads to rapid convergence and expedited review. In contrast, it has been argued by [103] that the CB does not offer any benefits when employed with low false-positive rates.

**Rule-based Techniques :** A rule-based system that extracts rules from data has the ability to imitate human intelligence. This system operates by applying rules in order to arrive at

intelligent decisions [104]. Therefore, it is evident that rule-based systems have the potential to make a substantial contribution to the field of IoT security by acquiring security or policy rules from data sources [105]. Association rule learning is a widely utilized technique in the domain of ML [106] with the purpose of identifying relationships or rules within a given collection of characteristics in a security dataset. The use of a rule-based method, while straightforward, presents a significant drawback in terms of temporal complexity. This is due to the generation of a large number of associations or frequent patterns, which is dependent on the support and confidence values. As a result, the model becomes more complicated [107-108]. The use of an efficient association model has the potential to mitigate this problem. Various forms of association rules have been presented within the field, including frequent pattern-based, tree-based, logic-based, fuzzy-rules, and belief rule approaches. There are several rule learning approaches available for addressing IoT security issues and facilitating intelligent decision making. These techniques include AIS, Apriori, Apriori-TID, Apriori-Hybrid, FP-Tree, Eclat, and RARM. An article by [109] introduces a network IDS that utilizes an association rule-mining technique. Furthermore, the use of fuzzy association rules is employed in the construction of a rule-based IDS. A research was undertaken in [110] to examine the actions of IoT malware by the utilization of an FP-tree association rule-based analysis.

**ML model evaluation parameters :** The below metrics are frequently employed to assess the performance of ML models. Various ML models have been created and assessed for the purpose of enhancing security in IoT-based SS.

$$Accuracy = \frac{\sum_{m=1}^n I(T_m = Y_m)}{n}$$

$$Accuracy = \frac{T_p + T_N}{n}$$

$$F1 - score = \frac{T_p}{T_p + 0.5(F_p + F_N)}$$

$$Cohen Kappa score k = \frac{2 * (T_p * T_N - F_p * F_N)}{(T_p + F_p) * (T_p + F_N) * (T_N + F_p) * (T_N + F_N)}$$

$$Matthews Correlation Coefficient MCC = \frac{(T_p * T_N - F_p * F_N)}{\left[ (T_p + F_p) * (T_p + F_N) * (T_N + F_p) * (T_N + F_N) \right]^{\frac{1}{2}}}$$

$$\text{Intersection Over Union (IOU)} = \frac{A \cap B}{A \cup B}$$

where  $n$  is number of predictions,  $T_m$  is predicted target,  $I$  is indicator function,  $Y_m$  target of the class,  $T_P$  is true positive,  $T_N$  is true negative,  $F_P$  is false positive,  $F_N$  is false negative,  $A$  is predicted label set and  $B$  is true label set.

$$\text{True Positive Rate TPR} = \frac{T_P}{T_P + F_N}$$

$$\text{False Positive Rate FPR} = \frac{F_P}{F_P + T_N}$$

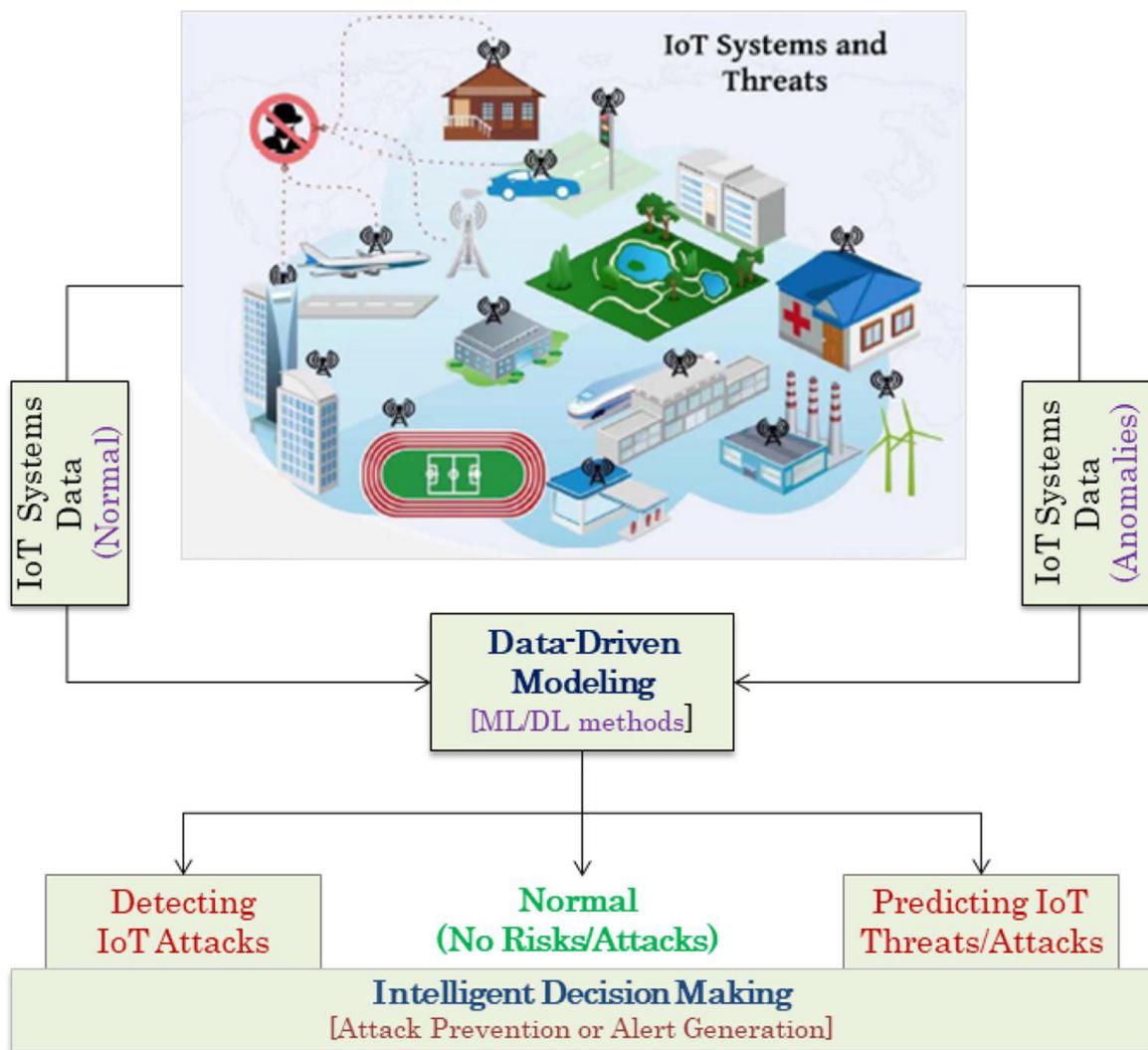


Figure 9. The promise of ML and DL in constructing data-driven IoT security intelligence models [96]

## VII. CONCLUSION

The IoT has emerged as a prominent area of research in recent times due to its wide range of uses that transcend specific fields. This study effort aims to acquire previous knowledge by discussing an overview of numerous IoT systems, since IoT has been extensively accepted due to its diverse properties. The study is conducted by considering many factors such as domain, applications, and environmental characteristics. This study also provides a comprehensive analysis of the 5G wireless technologies that have emerged as crucial facilitators

for the widespread implementation of the IoT technology. The survey provided an analysis of the progression of cellular wireless technologies, highlighting the advancements made by 5G wireless technology in comparison to its predecessors. This advancement has facilitated the widespread use of the IoT. The process of deriving practical and implementable knowledge from unprocessed IoT data is a significant challenge that beyond the capabilities of conventional data analysis frameworks. DL offers an optimal solution for a range of categorization and prediction problems inside the IoT due to its ability to acquire hierarchical representations from the input

data. Additionally, DL is well-suited for representing complex patterns and behaviours throughout diverse datasets. The system comprises many architectures that serve a range of purposes. CNNs provide exceptional performance when used to both picture and audio data. The RNN and the LSTM model are employed for the purpose of forecasting time series data. AEs are employed for the purpose of reducing the dimensionality of data that exists in high-dimensional spaces. GANs demonstrate suitability in the context of noisy settings. The RBM and the DBN are capable of capturing intricate data representations using an unsupervised learning approach. The wide range of applications for DL models renders them very appropriate for IoT situations. While DL models demonstrate superior performance compared to traditional ML methods. The present study offers a complete overview that aims to facilitate more collaborative endeavours between industry and academics in order to drive advancements in 5G-IoT technology.

#### REFERENCES

- [1] Wang, M., Zhang, G., Zhang, C., Zhang, J., & Li, C. (2013) An IoT-based appliance control system for smart homes. In 2013 fourth international conference on intelligent control and information processing, pp. 744-747.
- [2] Zhai, S. L., Zhao, D. S., Wang, Z., & Zhang, Y. (2012). Research of communication technology on IoT for high-voltage transmission line. *International Journal of Smart Grid and Clean Energy*, 1(1): 85-90.
- [3] Soliman, M., Abiodun, T., Hamouda, T., Zhou, J., & Lung, C. H. (2013, December). Smart home: Integrating internet of things with web services and cloud computing. In 2013 IEEE 5th international conference on cloud computing technology and science, 2: 317-320.
- [4] Singh, D., Tripathi, G., & Jara, A. J. (2014). A survey of Internet-of-Things: Future vision, architecture, challenges and services. In 2014 IEEE world forum on Internet of Things (WF-IoT), 287-292.
- [5] Karthik Kumar Vaigandla , Radha Krishna Karne , Allanki Sanyasi Rao, " A Study on IoT Technologies, Standards and Protocols", IBM RD's Journal of Management & Research, Volume 10, Issue 2, September 2021, Print ISSN : 2277-7830, Online ISSN: 2348- 5922, DOI: 10.17697/ibmrd/2021/v10i2/166798
- [6] Yashiro, T., Kobayashi, S., Koshizuka, N. and Sakamura, K. (2013) An Internet of Things (IoT) architecture for embedded appliances, 2013 IEEE Region 10 Humanitarian Technology Conference, Sendai, 2013, 314-319, doi: 10.1109/R10-HTC.2013.6669062
- [7] Rathore, M. M., Paul, A., Ahmad, A., & Jeon, G. (2017). IoT-based big data: from smart city towards next generation super city planning. *International Journal on Semantic Web and Information Systems (IJSWIS)*, 13(1), 28-47.
- [8] K. K. Vaigandla, "Communication Technologies and Challenges on 6G Networks for the Internet: Internet of Things (IoT) Based Analysis," 2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM), 2022, pp. 27-31, doi: 10.1109/ICIPTM54933.2022.9753990.
- [9] L. Roselli, N. B. Carvalho, F. Alimenti, P. Mezzanotte, G. Orecchini, M. Virili, C. Mariotti, R. Goncalves, and P. Pinho, "Smart surfaces: Large area electronics systems for Internet of Things enabled by energy harvesting," *Proc. IEEE*, vol. 102, no. 11, pp. 1723\_1746, Nov. 2014.
- [10] A. Costanzo and D. Masotti, "Energizing 5G: Near- and far-field wireless energy and data transfer as an enabling technology for the 5G IoT," *IEEE Microw.*, vol. 18, no. 3, pp. 125\_136, May 2017.
- [11] L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," *Comput. Netw.*, vol. 54, no. 15, pp. 2787\_2805, Oct. 2010.
- [12] A. Osseiran, F. Boccardi, V. Braun, K. Kusume, P. Marsch, M. Maternia, O. Queseth, M. Schellmann, H. Schotten, H. Taoka, H. Tullberg, M. A. Uusitalo, B. Timus, and M. Fallgren, "Scenarios for 5G mobile and wireless communications: The vision of the METIS project," *IEEE Commun. Mag.*, vol. 52, no. 5, pp. 26\_35, May 2014.
- [13] Vaigandla, K. K., Thatipamula, S. & Karne, R. K. (2022). Investigation on Unmanned Aerial Vehicle (UAV): An Overview. *IRO Journal on Sustainable Wireless Systems*, 4(3), 130-148. doi:10.36548/jsws.2022.3.001
- [14] M. R. Manesh, J. Kenney, W. C. Hu, V. K. Devabhaktuni, and N. Kaabouch, "Detection of GPS spoofing attacks on unmanned aerial systems," in *Proc. 16th IEEE Annu. Consum. Commun. Netw. Conf. (CCNC)*, Jan. 2019, pp. 1-6.
- [15] A. Uprety, D. B. Rawat, and J. Li, "Privacy preserving misbehavior detection in IoV using federated machine learning," in *Proc. IEEE 18th Annu. Consum. Commun. Netw. Conf. (CCNC)*, Jan. 2021, pp. 1-6.
- [16] G. Cremen, C. Galasso, and E. Zuccolo, "Investigating the potential effectiveness of earthquake early warning across Europe," *Nature Commun.*, vol. 13, no. 1, pp. 1-10, Feb. 2022.
- [17] M. Elhadidy, M. S. Abdalzaher, and H. Gaber, "Up-to-date PSHA along the Gulf of aqaba-dead sea transform fault," *Soil Dyn. Earthq. Eng.*, vol. 148, Sep. 2021, Art. no. 106835.
- [18] M. S. Abdalzaher, M. El-Hadidy, H. Gaber, and A. Badawy, "Seismic hazard maps of Egypt based on spatially smoothed seismicity model and recent seismotectonic models," *J. Afr. Earth Sci.*, vol. 170, Oct. 2020, Art. no. 103894.
- [19] S. S. Moustafa, M. S. Abdalzaher, F. Khan, M. Metwaly, E. A. Elawadi, and N. S. Al-Arifi, "A quantitative site-specific classification approach based on affinity propagation clustering," *IEEE Access*, vol. 9, pp. 155297-155313, 2021.
- [20] M. S. Abdalzaher, S. S. R. Moustafa, H. E. A. Hafiez, and W. F. Ahmed, "An optimized learning model augment analyst decisions for seismic source discrimination," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, pp. 1-12, 2022.
- [21] T. Perol, M. Gharbi, and M. Denolle, "Convolutional neural network for earthquake detection and location," *Sci. Adv.*, vol. 4, no. 2, Feb. 2018, Art. no. e1700578.
- [22] M. S. Abdalzaher, M. S. Soliman, S. M. El-Hady, A. Benslimane, and M. Elwekeil, "A deep learning model for earthquake parameters observation in IoT system-based

- earthquake early warning," *IEEE Internet Things J.*, vol. 9, no. 11, pp. 8412–8424, Jun. 2022.
- [23] B. Pradhan, "A comparative study on the predictive ability of the decision tree, support vector machine and neuro-fuzzy models in landslide susceptibility mapping using GIS," *Comput. Geosci.*, vol. 51, pp. 350–365, Feb. 2013.
- [24] M. S. Abdalzaher, S. S. R. Moustafa, M. Abd-Elnaby, and M. Elwekeil, "Comparative performance assessments of machine-learning methods for artificial seismic sources discrimination," *IEEE Access*, vol. 9, pp. 65524–65535, 2021.
- [25] S. S. R. Moustafa, M. S. Abdalzaher, M. H. Yassien, T. Wang, M. Elwekeil, and H. E. A. Hafiez, "Development of an optimized regression model to predict blast-driven ground vibrations," *IEEE Access*, vol. 9, pp. 31826–31841, 2021.
- [26] Disruptive Civil Technologies\_Six Technologies with Potential Impacts on US Interests Out to 2025-Conference Report CR 2008-07, Nat. Intell. Council, Washington, DC, USA, Apr. 2008.
- [27] I.Yaqoob, E. Ahmed, I. A. T. Hashem, A. I. A. Ahmed, A. Gani, M. Imran, and M. Guizani, "Internet of Things architecture: Recent advances, taxonomy, requirements, and open challenges," *IEEE Wireless Commun.*, vol. 24, no. 3, pp. 10\_16, Jun. 2017.
- [28] X. Krasniqi and E. Hajrizi, "Use of IoT technology to drive the automotive industry from connected to full autonomous vehicles," *IFAC-PapersOnLine*, vol. 49, no. 29, pp. 269\_274, 2016.
- [29] Gartner Inc. (2012). *Gartner's Hype Cycle Special Report for 2011*. Available: <http://www.gartner.com/technology/research/hype-cycles/>
- [30] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," *Future Gener. Comput. Syst.*, vol. 29, no. 7, pp. 1645\_1660, Sep. 2013.
- [31] M. Feldhofer, S. Dominikus, and J. Wolkerstorfer, "Strong authentication for RFID systems using the AES algorithm," in *Cryptographic Hardware and Embedded Systems\_CHES*, vol. 3156, M. Joye and J.-J. Quisquater, Eds. Berlin, Germany: Springer, 2004, pp. 357\_370.
- [32] B. Calmels, S. Canard, M. Girault, and H. Sibert, "Low-cost cryptography for privacy in RFID systems," in *Smart Card Research and Advanced Applications*, vol. 3928, J. Domingo-Ferrer, J. Posegga, and D. Schreckling, Eds. Berlin, Germany: Springer, 2006, pp. 237\_251.
- [33] M. Weiser, "The computer for the 21st century," *ACM SIGMOBILE Mobile Comput. Commun. Rev.*, vol. 3, no. 3, pp. 3\_11, Jul. 1999.
- [34] N. Kaur and S. K. Sood, "An energy-efficient architecture for the Internet of Things (IoT)," *IEEE Syst. J.*, vol. 11, no. 2, pp. 796\_805, Jun. 2017.
- [35] K. Shafique, B. A. Khawaja, F. Sabir, S. Qazi, and M. Mustaqim, "Internet of Things (IoT) for next-generation smart systems: A review of current challenges, future trends and prospects for emerging 5G-IoT scenarios," *IEEE Access*, vol. 8, pp. 23022–23040, 2020.
- [36] Karthik Kumar Vaigandla, Radhakrishna Karne, Allanki Sanyasi Rao, "Analysis of MIMO-OFDM: Effect of Mutual Coupling, Frequency Response, SNR and Channel Capacity", *YMER Digital - ISSN:0044-0477*, vol.20, no.10 - 2021, pp.118-126, 2021.
- [37] Karthik Kumar Vaigandla, Dr.N.Venu, "Survey on Massive MIMO: Technology, Challenges, Opportunities and Benefits," vol. 20, no. 11 (Nov) - 2021, pp.271-282, 2021.
- [38] L. Xiao, X. Wan, X. Lu, Y. Zhang, and D. Wu, "IoT security techniques based on machine learning: How do IoT devices use AI to enhance security?" *IEEE Signal Process. Mag.*, vol. 35, no. 5, pp. 41–49, Sep. 2018.
- [39] F. Hussain, R. Hussain, S. A. Hassan, and E. Hossain, "Machine learning in IoT security: Current solutions and future challenges," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 3, pp. 1686–1721, 3rd Quart., 2020.
- [40] S. M. Tahsien, H. Karimpour, and P. Spachos, "Machine learning based solutions for security of Internet of Things (IoT): A survey," *J. Netw. Comput. Appl.*, vol. 161, Jul. 2020, Art. no. 102630.
- [41] R. Ahmad and I. Alsmadi, "Machine learning approaches to IoT security: A systematic literature review," *Internet Things*, vol. 14, Jun. 2021, Art. no. 100365.
- [42] M. Bagaa, T. Taleb, J. B. Bernabe, and A. Skarmeta, "A machine learning security framework for IoT systems," *IEEE Access*, vol. 8, pp. 114066–114077, 2020.
- [43] F. Liang, W. G. Hatcher, W. Liao, W. Gao, and W. Yu, "Machine learning for security and the Internet of Things: The good, the bad, and the ugly," *IEEE Access*, vol. 7, pp. 158126–158147, 2019.
- [44] A. Thakkar and R. Lohiya, "A review on machine learning and deep learning perspectives of IDS for IoT: Recent updates, security issues, and challenges," *Arch. Comput. Methods Eng.*, vol. 28, no. 4, pp. 3211–3243, Jun. 2021.
- [45] L. Cui, S. Yang, F. Chen, Z. Ming, N. Lu, and J. Qin, "A survey on application of machine learning for Internet of Things," *Int. J. Mach. Learn. Cybern.*, vol. 9, no. 8, pp. 1399–1417, Aug. 2018.
- [46] Dr.Nookala Venu, Dr.A.Arunkumar, Karthik Kumar Vaigandla, "Investigation on Internet of Things(IoT) : Technologies, Challenges and Applications in Healthcare," *International Journal of Research*, Volume XI, Issue II, February/2022, pp.143-153
- [47] R. Chávez-Santiago, M. Szydelko, A. Kliks, F. Foukalas, Y. Haddad, K. E. Nolan, M. Y. Kelly, M. T. Masonta, and I. Balasingham, "5G: The convergence of wireless communications," *Wireless Pers. Commun.*, vol. 83, no. 3, pp. 1617\_1642, Aug. 2015.
- [48] Karthik Kumar Vaigandla, J.Benita, "PRNGN - PAPR Reduction using Noise Validation and Genetic System on 5G Wireless Network," *International Journal of Engineering Trends and Technology*, vol. 70, no. 8, pp. 224-232, 2022. <https://doi.org/10.14445/22315381/IJETT-V70I8P223>
- [49] M. Jaber, M. A. Imran, R. Tafazolli, and A. Tukmanov, "5G backhaul challenges and emerging research directions: A survey," *IEEE Access*, vol. 4, pp. 1743\_1766, 2016.
- [50] 3GPP TSG-RAN. *5G: From Myth to Reality*. Accessed: Feb. 13, 2019. Available: <http://www.3gpp.org/specifications-groups/ranplenary>

- [51] Working Party 5D (WP 5D) IMT Systems. *ITU Towards IMT for 2020 and Beyond*. : <http://www.itu.int/en/ITU-R>
- [52] Dr.Nookala Venu, Dr.A.ArunKumar and Karthik Kumar Vaigandla. Review of Internet of Things (IoT) for Future Generation Wireless Communications. *International Journal for Modern Trends in Science and Technology* 2022, 8(03), pp. 01-08. <https://doi.org/10.46501/IJMTST0803001>
- [53] *5G Spectrum Vision, 5G Americas White Paper-5G Spectrum Vision*, Feb. 2019.
- [54] Vaigandla, K. K. ., & Benita, J. (2023). A Novel PAPR Reduction in Filter Bank Multi-Carrier (FBMC) with Offset Quadrature Amplitude Modulation (OQAM) Based VLC Systems. *International Journal on Recent and Innovation Trends in Computing and Communication*, 11(5), 288–299. <https://doi.org/10.17762/ijritcc.v11i5.6616>
- [55] R. Yadav, Ritambhara, K. K. Vaigandla, G. S. P. Ghantasala, R. Singh and D. Gangodkar, "The Block Chain Technology to protect Data Access using Intelligent Contracts Mechanism Security Framework for 5G Networks," 2022 5th *International Conference on Contemporary Computing and Informatics (IC3I)*, Uttar Pradesh, India, 2022, pp. 108-112, doi: 10.1109/IC3I56241.2022.10072740.
- [56] Karthik Kumar Vaigandla and Dr.N.Venu, "A Survey on Future Generation Wireless Communications - 5G : Multiple Access Techniques, Physical Layer Security, Beamforming Approach", *Journal of Information and Computational Science*, Volume 11 Issue 9,2021, pp. 449-474. DOI:10.12733/JICS.2021.V11I9.535569.36347
- [57] Karthik Kumar Vaigandla, SandyaRani Bolla , RadhaKrishna Karne, "A Survey on Future Generation Wireless Communications-6G: Requirements, Technologies, Challenges and Applications", *International Journal of Advanced Trends in Computer Science and Engineering*, Volume 10, No.5, September - October 2021, pp.3067-3076, <https://doi.org/10.30534/ijatcse/2021/211052021>
- [58] Karthik Kumar Vaigandla, Bolla Sandhya Rani, Kallepelli Srikanth, Thippani Mounika, RadhaKrishna Karne, "Millimeter Wave Communications: Propagation Characteristics, Beamforming, Architecture, Standardization, Challenges and Applications". *Design Engineering*, Dec. 2021, pp. 10144-69, <http://thedesigengineering.com/index.php/DE/article/view/8133>
- [59] A. Gupta and R. K. Jha, "A survey of 5G network: Architecture and emerging technologies," *IEEE Access*, vol. 3, pp. 1206\_1232, 2015.
- [60] *Intel and Ericsson Develop 5G Platform*, Corinne Reichert, Feb. 2019.
- [61] A. Aijaz, H. Aghvami, and M. Amani, "A survey on mobile data offloading: Technical and business perspectives," *IEEE Wireless Commun.*, vol. 20, no. 2, pp. 104\_112, Apr. 2013.
- [62] J. G. Andrews, A. Ghosh, and R. Muhamed, *Fundamentals of WiMAX*. Englewood Cliffs, NJ, USA: Prentice-Hall, 2007.
- [63] S. Li, L. Da Xu, and S. Zhao, "5G Internet of Things: A survey," *J. Ind. Inf. Integr.*, vol. 10, pp. 1\_9, Jun. 2018.
- [64] G. A. Akpakwu, B. J. Silva, G. P. Hancke, and A. M. Abu-Mahfouz, "A survey on 5G networks for the Internet of Things: Communication technologies and challenges," *IEEE Access*, vol. 6, pp. 3619\_3647, 2018.
- [65] H. I. Kobo, A. M. Abu-Mahfouz, and G. P. Hancke, "A survey on software-defined wireless sensor networks: Challenges and design requirements," *IEEE Access*, vol. 5, pp. 1872\_1899, 2017.
- [66] M. Ndiaye, G. Hancke, and A. Abu-Mahfouz, "Software defined networking for improved wireless sensor network management: A survey," *Sensors*, vol. 17, no. 5, p. 1031, May 2017.
- [67] W. Xia, Y.Wen, C. H. Foh, D. Niyato, and H. Xie, "A survey on software defined networking," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 1, pp. 27\_51, 1st Quart., 2015.
- [68] A. Hakiri and P. Berthou, "Leveraging SDN for the 5G networks: Trends, prospects, and challenges," in *Software Defined Mobile Networks (SDMN): Beyond LTE Network Architecture*, M. Liyanage, A. Gurtov, and M. Ylianttila, Eds. Chichester, U.K.: Wiley, 2015, pp. 61\_80.
- [69] I. F. Akyildiz, P. Wang, and S.-C. Lin, "SoftAir: A software defined networking architecture for 5G wireless systems," *Comput. Netw.*, vol. 85, pp. 1\_18, Jul. 2015.
- [70] I. F. Akyildiz, S.-C. Lin, and P. Wang, "Wireless software-defined networks (W-SDNs) and network function virtualization (NFV) for 5G cellular systems: An overview and qualitative evaluation," *Comput. Netw.*, vol. 93, pp. 66\_79, Dec. 2015.
- [71] *Cloud RAN. The Benefits of Virtualization, Centralization and Coordination*, Ericsson, Stockholm, Sweden, 2015.
- [72] *ET Docket No. 03\_222, Notice of Proposed Rule Making and Order*, FCC, Washington, DC, USA, Dec. 2003.
- [73] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey," *Comput. Netw.*, vol. 50, no. 13, pp. 2127\_2159, Sep. 2006.
- [74] Karthik Kumar Vaigandla, Thippani Mounika, Uzma Urooj, Nilofar Azmi, RadhaKrishna Karne, "Investigation on Cognitive Radio Networks: Introduction, Spectrum Sensing, IEEE Standards, Challenges, Applications," *International Journal of Engineering Applied Sciences and Technology*, Vol. 6, Issue 9, 2022, pp.91-103, DOI: 10.33564/IJEAST.2022.v06i09.011
- [75] T.J. Saleem, M.A. Chishti, Data analytics in the internet of things: a survey, *Scalable Computing, Practice and Experience* 20 (4) (2019) 607–630.
- [76] S. Srinivas, R.K. Sarvadevabhatla, K.R. Mopuri, N. Prabhu, S.S. Kruthiventi, R.V. Babu, A taxonomy of deep convolutional neural nets for computer vision, *Frontiers in Robotics and AI* 2 (2016) 36.
- [77] Karne, Ms Archana, et al. "Convolutional Neural Networks for Object Detection and Recognition." *Journal of Artificial Intelligence, Machine Learning and Neural Network (JAIMLNN)* ISSN: 2799-1172 3.02 (2023): 1-13.
- [78] A. Sherstinsky, Fundamentals of Recurrent Neural Network (Rnn) and Long Short- Term Memory (Lstm) Network, arXiv preprint arXiv:1808.03314.

- [79] P. Baldi, Autoencoders, unsupervised learning, and deep architectures, in: Proceedings of ICML Workshop on Unsupervised and Transfer Learning, 2012, pp. 37–49.
- [80] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative adversarial nets, in: Advances in Neural Information Processing Systems, 2014, pp. 2672–2680.
- [81] A. Fischer, C. Igel, An introduction to restricted Boltzmann machines, in: Iberoamerican Congress on Pattern Recognition, Springer, 2012, pp. 14–36.
- [82] N. Lopes, B. Ribeiro, Machine Learning for Adaptive Many-Core Machines: A Practical Approach.
- [83] X. Xu, D. Li, Z. Dai, S. Li, and X. Chen, "A heuristic offloading method for deep learning edge services in 5G networks," *IEEE Access*, vol. 7, pp. 67734–67744, 2019.
- [84] N. Javaid, A. Sher, H. Nasir, and N. Guizani, "Intelligence in IoT-based 5G networks: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 56, no. 10, pp. 94–100, Oct. 2018.
- [85] D. Wang, D. Chen, B. Song, N. Guizani, X. Yu, and X. Du, "From IoT to 5G I-IoT: The next generation IoT-based intelligent algorithms and 5G technologies," *IEEE Commun. Mag.*, vol. 56, no. 10, pp. 114–120, Oct. 2018.
- [86] M. Chen, J. Yang, Y. Hao, S. Mao, and K. Hwang, "A 5G cognitive system for healthcare," *Big Data Cogn. Comput.*, vol. 1, no. 1, p. 2, Mar. 2017.
- [87] F. Al-Turjman, J. P. Lemayian, S. Alturjman, and L. Mostarda, "Enhanced deployment strategy for the 5G Drone-BS using artificial intelligence," *IEEE Access*, vol. 7, pp. 75999–76008, 2019.
- [88] P. Kiss, A. Reale, C. J. Ferrari, and Z. Istenes, "Deployment of IoT applications on 5G edge," in *Proc. IEEE Int. Conf. Future IoT Technol. (Future IoT)*, Eger, Hungary, Jan. 2018, pp. 1–9.
- [89] H. Uddin, "IoT for 5G/B5G applications in smart homes, smart cities, wearables and connected cars," in *Proc. IEEE 24th Int. Workshop Comput. Aided Model. Design Commun. Links Netw. (CAMAD)*, Limassol, Cyprus, Sep. 2019, pp. 1–5.
- [90] R. Arridha, S. Sukaridhoto, D. Pramadihanto, and N. Funabiki, "Classification extension based on IoT-big data analytic for smart environment monitoring and analytic in real-time system," *Int. J. Space-Based Situated Comput.*, vol. 7, no. 2, p. 82, 2017.
- [91] K. Shafique, B. A. Khawaja, F. Sabir, S. Qazi and M. Mustaqim, "Internet of Things (IoT) for Next-Generation Smart Systems: A Review of Current Challenges, Future Trends and Prospects for Emerging 5G-IoT Scenarios," in *IEEE Access*, vol. 8, pp. 23022–23040, 2020, doi: 10.1109/ACCESS.2020.2970118.
- [92] Dua S, Du X (2016) Data mining and machine learning in cybersecurity. CRC Press, Boca Raton.
- [93] Sarker IH (2021) Machine learning: Algorithms, real-world applications and research directions. SN Computer Science 2(3):1–21
- [94] Sarker IH (2021) Deep cybersecurity: a comprehensive overview from neural network and deep learning perspective. SN Computer Science 2(3):1–16
- [95] Sarker IH (2021) Deep learning: A comprehensive overview on techniques, taxonomy, applications and research directions. SN Comput Sci.
- [96] Sarker, I.H., Khan, A.I., Abushark, Y.B. et al. Internet of Things (IoT) Security Intelligence: A Comprehensive Overview, Machine Learning Solutions and Research Directions. *Mobile Netw Appl* 28, 296–312 (2023). <https://doi.org/10.1007/s11036-022-01937-3>
- [97] G. James, D. Witten, T. Hastie, and R. Tibshirani, *An Introduction to Statistical Learning*, vol. 112. Cham, Switzerland: Springer, 2013.
- [98] Y.-W. Chang and C.-J. Lin, "Feature ranking using linear SVM," in *Proc. Causation Predict. Challenge*, 2008, pp. 53–64.
- [99] J. Staal, M. D. Abramoff, M. Niemeijer, M. A. Viergever, and B. van Ginneken, "Ridge-based vessel segmentation in color images of the retina," *IEEE Trans. Med. Imag.*, vol. 23, no. 4, pp. 501–509, Apr. 2004.
- [100] A. Pérez, P. Larrañaga, and I. Inza, "Supervised classification with conditional Gaussian networks: Increasing the structure complexity from naive Bayes," *Int. J. Approx. Reasoning*, vol. 43, no. 1, pp. 1–25, Sep. 2006.
- [101] J. Zhu, H. Zou, S. Rosset, and T. Hastie, "Multi-class AdaBoost," *Statist. Interface*, vol. 2, no. 3, pp. 349–360, 2009.
- [102] S. Tan, "An effective refinement strategy for KNN text classifier," *Exp. Syst. Appl.*, vol. 30, no. 2, pp. 290–298, Feb. 2006.
- [103] R. Punmiya and S. Choe, "Energy theft detection using gradient boosting theft detector with feature engineering-based preprocessing," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 2326–2329, Mar. 2019.
- [104] Sarker IH (2021) Data science and analytics: An overview from data-driven smart computing, decision-making and applications perspective. SN Comput Sci.
- [105] Sarker IH, Furchad MdH, Nowrozy R (2021) Ai-driven cybersecurity: an overview, security intelligence modeling and research directions. SN Computer Science 2(3):1–18
- [106] Agrawal R, Imieliński T, Swami A (1993) Mining association rules between sets of items in large databases. In: ACM SIGMOD record, vol 22. ACM, pp 207–216.
- [107] Agrawal R, Srikant R, et al. (1994) Fast algorithms for mining association rules. In: Proc. 20th int. conf. very large data bases, VLDB, vol 1215. pp 487–499.
- [108] Tahsien SM, Karimpour H, Spachos P (2020) Machine learning based solutions for security of internet of things (IoT): A survey. *Journal of Network and Computer Applications* 161:102630.
- [109] Sellappan D, Srinivasan R (2020) Association rule-mining-based intrusion detection system with entropy-based feature selection: Intrusion detection system. In: Handbook of research on intelligent data processing and information security systems. IGI Global, pp 1–24
- [110] Ozawa S, Ban T, Hashimoto N, Nakazato J, Shimamura J (2020) A study of IoT malware activities using association rule learning for darknet sensor data. *International Journal of Information Security* 19(1):83–92

- [111] KarthikKumar Vaigandla, Nilofar Azmi, RadhaKrishna Karne, "Investigation on Intrusion Detection Systems (IDSs) in IoT," *International Journal of Emerging Trends in Engineering Research*, Volume 10. No.3, March 2022, <https://doi.org/10.30534/ijeter/2022/041032022>
- [112] Radha Krishna Karne and Dr. T. K. Sreeja (2022), A Novel Approach for Dynamic Stable Clustering in VANET Using Deep Learning (LSTM) Model. *IJEER* 10(4), 1092-1098. DOI: 10.37391/IJEER.100454.
- [113] Karne, R. K. ., & Sreeja, T. K. . (2023). PMLC- Predictions of Mobility and Transmission in a Lane-Based Cluster VANET Validated on Machine Learning. *International Journal on Recent and Innovation Trends in Computing and Communication*, 11(5s), 477–483. <https://doi.org/10.17762/ijritcc.v11i5s.7109>
- [114] Karthik Kumar Vaigandla and J.Benita (2022), Novel Algorithm for Nonlinear Distortion Reduction Based on Clipping and Compressive Sensing in OFDM/OQAM System. *IJEER* 10(3), 620-626. <https://doi.org/10.37391/IJEER.100334>.
- [115] Vaigandla, Karthik Kumar and Benita, J. 'Selective Mapping Scheme Based on Modified Forest Optimization Algorithm for PAPR Reduction in FBMC System'. *Journal of Intelligent & Fuzzy Systems*, vol. 45, no. 4, pp. 5367-5381, October 2023, DOI: 10.3233/JIFS-222090.
- [116] Karthik Kumar Vaigandla and B. J, Study and analysis of multi carrier modulation techniques – FBMC and OFDM, *Materials Today: Proceedings*, Volume 58, Part 1, 2022, Pages 52-56, <https://doi.org/10.1016/j.matpr.2021.12.584>

