A COMPREHENSIVE SURVEY ON MACHINE LEARNING AND DEEP LEARNING APPLICATIONS IN INTERNET-OF-THINGS: CURRENT DEVELOPMENTS AND FUTURE PROSPECTS

Abstract

Machine learning and deep learning are two distinct subfields within the domain of artificial intelligence that have found extensive applications across diverse disciplines, including but not limited to computer vision, natural language processing, speech recognition, and robotics. Nevertheless, the conventional approaches to machine learning and deep learning frequently encounter difficulties when confronted with the vast data produced by Internet of Things (IoT) devices, including sensors, cameras, smartphones, and wearables. Hence, an increasing demand arises for the creation of novel methodologies and frameworks capable of harnessing the capabilities of machine learning and deep learning in order to facilitate intelligent and efficient IoT applications. This paper presents a comprehensive examination of the present state-of-the-art and forthcoming developments in machine learning and deep learning as applied to IoT applications. In this paper, we commence by presenting a comprehensive overview of the fundamental concepts and principles underlying machine learning and deep learning. Subsequently, we proceed to examine a selection of notable applications of these methodologies within the context of IoT scenarios, encompassing domains such as smart home, smart city, smart health, and smart industry. The primary challenges and outstanding concerns that require attention in this burgeoning industry are also deliberated upon, including but not limited to data quality, security, privacy, scalability, and interoperability. In conclusion, this study emphasises potential avenues and prospects for further investigation and advancement in the

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domain of machine learning and deep learning as applied to IoT applications.

Keywords: Machine Learning, Deep Learning, Convolutional Neural Networks, Internet of Things, Long Short-Term Networks

I. INTRODUCTION

The Internet of Things (IoT) can be described as a worldwide network architecture consisting of interconnected devices that utilize communication, sensory, information processing technologies, and networking. Wireless Sensor Networks (WSN) and these technologies have a multitude of advantages in comparison to traditional networking methods. Some of the important factors include reliability, precision, cost-effectiveness, adaptability, and ease of implementation contribute to the extensive use of these technologies across varied applications.

According to many studies, it is projected that the quantity of interconnected devices would reach a staggering 50 billion by the year 2020 [1]. The proliferation of connected devices is expected to improve network coverage; but, it will also lead to an expansion in the volume of collected data and an increase in processing complexity at the centralized base station. The integration of Wireless Sensor Networks (WSN) with IoT exhibits numerous benefits, such as self-organization, adaptability, expedited implementation, and enhanced computational capabilities. However, the adoption of IoT technology presents numerous problems, as highlighted in previous studies [2, 3]. These challenges encompass various aspects such as hardware design, application design, communication protocols, scalability, heterogeneity, network coverage, energy conservation, communication link failures, decentralized management, quality of service (QoS), as well as security and privacy concerns. WSNs and IoT technologies are required to tackle these issues in order to effectively implement the wide range of anticipated applications and fulfill their respective demands. Hence, it is imperative to develop novel methodologies and approaches to surmount these obstacles.

Artificial Intelligence (AI) is a contemporary scientific field that involves the exploration of patterns and the generation of predictions through the utilization of statistical methods, data mining techniques, pattern recognition algorithms, and predictive analytics [4]. Machine Learning (ML), a discipline closely associated with the study of Artificial Intelligence, encompasses the iterative process of constructing, evaluating, and deploying algorithms with the aim of establishing a methodical framework. Machine learning leverages the vast amount of data known as Big Data to enable machines to effectively address complex challenges. This provides an occasion to examine and emphasize the associations that exist between two or more provided circumstances, and to forecast their diverse ramifications [4]. The intriguing feature of machine learning is in its iterative nature, whereby models possess the ability to freely adjust when they are exposed to novel data. The acquisition of knowledge from past calculations enables individuals to generate reliable and consistent decisions and outcomes [5]. ML endeavors to address challenges in the realms of WSN and IoT by enabling the acquisition of knowledge from experience and constructing models based on an algorithmic core.

II. MACHINE LEARNING METHODS

1. **Linear Regression:** Linear regression [6-8] is a statistical technique employed to demonstrate a correlation between two variables. This method is employed to forecast the numerical value of a particular variable by considering the numerical value of another

variable. Simple linear regression involves the consideration of two variables, namely the independent variable and the dependent variable. The independent variable is the variable utilized for the purpose of forecasting the value of the dependent variable. The dependent variable refers to the variable that is being predicted or influenced by other variables in a research study. Linear regression is a widely utilized statistical technique that finds application in various domains, including finance, economics, biology, and engineering.

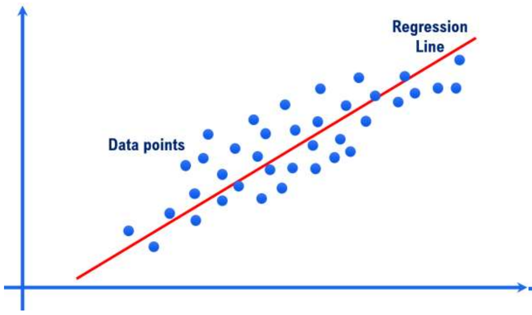

Figure 1: Linear regression

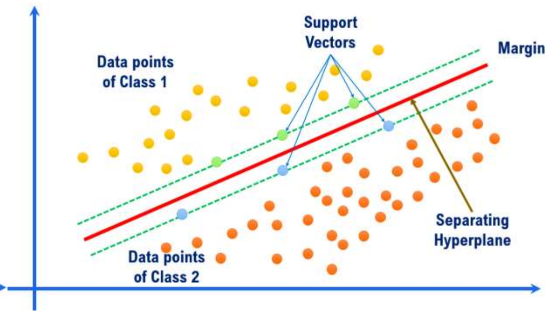

Figure 2: Support Vector Machine

2. **Logistic Regression:** Logistic regression [9, 10] is a statistical technique commonly employed for the purpose of binary classification jobs. This method is employed to estimate the likelihood of an instance being a member of a specific class or not. This statistical procedure examines the correlation between a group of independent factors and a dependent binary variable.

   The idea of the threshold value is employed in logistic regression to determine the probability of either 0 or 1. The sigmoid function is employed to transform the anticipated values into probabilities. The function under consideration is capable of mapping any real number to a value that falls within the interval of 0 and 1. The logistic regression model is constrained to provide output values within the range of 0 to 1, hence exhibiting a sigmoidal curve resembling the shape of the letter "S".

3. **Support Vector Machines (SVM):** Support Vector Machines (SVMs) [11-13] are widely recognized as useful supervised learning models that are commonly employed for both binary and multi-class classification tasks [34, 35, 37]. Support Vector Machines (SVM) utilize a mapping technique to represent the input data as points in a 'n' dimensional space. Subsequently, a $'n-1'$ dimensional hyperplane is constructed to effectively segregate the data points into two distinct groups. The SVM algorithm aims to partition the labeled dataset into two distinct groups using a hyperplane, which, in this context, is represented as a line. The objective is to maximize the separation width between the two groups.

   Support vectors refer to the data points that are in close proximity to the hyperplane, denoted in Fig. 2. The concept of maximum margin was initially put forth by Vapnik in 1963, and subsequently, the support vector machine (SVM) method was introduced in 1992 [14].

4. **Naïve Bayes:** The Naïve Bayes algorithm [15] is a probabilistic form of machine learning that is utilized for classification-related applications. It is based on Bayes' theorem with the idea that predictors can be considered independent of one another. A Naïve Bayes classifier, to put it in more layman's terms, works under the assumption that the existence of one particular characteristic in a class is unrelated to the presence of any other feature. In many different areas, such as text classification, spam filtering, and sentiment analysis, the Naïve Bayes algorithm is utilized as it can manage a high number of features and is computationally efficient while only requiring a small amount of input data.

5. **k-Nearest Neighbors:** The k-Nearest Neighbors (kNN) algorithm [16] is a machine learning technique that can be applied to classification and regression problems. It is a non-parametric algorithm that is used to classify data based on the resemblance of the input data to the training data. This similarity is what determines how well the algorithm performs.

In the kNN method, a test example's classification is predicted based on the k-training instances in the feature space that are most similar to it. Cross-validation is typically used to determine an appropriate value for k.

6. **Decision Trees (DTs):** Decision tree-based approaches primarily classify samples by organizing them based on their feature values. In a tree structure, each vertex, also known as a node, represents a distinct feature. Conversely, each edge, referred to as a branch, signifies a specific value that the corresponding vertex can possess within a given sample, which is subject to classification. The samples are categorized according to their feature values, commencing at the origin vertex. The vertex of the tree that is considered the origin, which is responsible for optimally splitting the training samples, has been identified as the feature [17]. Various methods are employed to determine the most suitable characteristic for dividing the training samples effectively. These methods include information gain [18] and the Gini index [19].

7. **Random Forest (RF):** Random Forests (RFs) are a type of supervised learning algorithms. In an RF setting, several DTs are created and merged together to obtain a highly accurate and resilient prediction model, leading to enhanced overall outcomes [20, 21]. Hence, an RF is comprised of several trees that are generated in a random manner and taught to make collective decisions in classifying data. The class with the highest number of votes is chosen as the ultimate classification result [20]. Although the RF classifier primarily relies on DTs for its construction, it is important to note that these classification techniques exhibit significant differences. Initially, DTs typically generate a set of rules during the training process, wherein the training set is provided as input to the network. These rules are then employed to classify a novel input. DTs are used by RF to create subsets of rules that are then used for classification. As a result, the results from these subsets are averaged to produce the output of the classification process. The resistance of RF to overfitting is one of its notable benefits. Additionally, only a few input parameters are required when using RF, which eliminates the need for feature selection. However, in some real-time applications where a sizable training dataset is required, the use of RF may prove impractical. This is because it is necessary to create multiple DTs in order to implement RF.

8. **Ensemble Learning (EL):** Ensemble learning [22-24] is a robust machine learning paradigm that entails the training of numerous models, referred to as "base learners," and the amalgamation of their predictions to generate a conclusive output. Ensemble learning operates on the fundamental idea that a collective of weak learners can amalgamate to create a robust learner, thereby augmenting the precision of the model.

   Ensemble learning methods encompass a variety of sorts, such as Bagging, Boosting, and Stacking. Bagging is a technique that aids in the reduction of a model's variance. Boosting, on the other hand, is employed to mitigate bias. Lastly, Stacking is a method that enhances prediction accuracy by leveraging the collective capabilities of diverse models.

   Ensemble approaches are widely recognised for their capacity to offer enhanced flexibility and increase the performance of models, particularly in relation to stability and prediction accuracy. They are extensively utilised in several domains, encompassing healthcare, e-commerce, and banking. Nevertheless, these tasks can impose a significant computational burden and necessitate meticulous optimisation. Notwithstanding these issues, ensemble learning continues to be widely utilised in the repertoire of data scientists owing to its efficacy in generating resilient and precise predictions.

III. DEEP LEARNING METHODS

Deep Learning (DL) [25-26] is a subfield within the domain of machine learning that leverages neural networks characterised by numerous layers, hence earning the designation "deep." These neural networks aim to replicate the functioning of the human brain, albeit they fall significantly short of emulating its capabilities, to acquire knowledge from extensive datasets. Although a neural network with a single layer is capable of producing approximation predictions, the inclusion of supplementary hidden layers can significantly enhance the accuracy of the model.

DL plays a pivotal role in advancing various AI applications and services, leading to enhanced automation capabilities that enable the execution of activities without the need for human intervention. AI is widely employed in various sectors, including but not limited to the automotive industry for self-driving vehicles, the consumer electronics industry for voice-activated television remotes, and the financial sector for credit card fraud detection.

One of the primary benefits of DL is its capacity to effectively handle substantial quantities of data. The predictive accuracy of a deep learning model is enhanced when it gains access to a larger volume of data. Nevertheless, the efficient operation of this system necessitates a significant allocation of processing power and resources.

Despite encountering various obstacles, DL is currently positioned as a leading force in the progression of artificial intelligence capabilities, propelling us towards a future in which robots possess the ability to acquire knowledge and autonomously make judgments. Some of the popular DL methods are introduced in the following subsections.

1. **Multilayer Perceptrons (MLPs):** MLPs [27] are a subtype of feedforward artificial neural networks (ANNs). MLPs are the most fundamental type of deep neural network, which consists of a series of completely connected layers. Today, MLP machine learning techniques can be utilised to circumvent the high computing power requirement of contemporary deep learning architectures. Each successive layer is composed of a set of nonlinear functions that are the weighted sum of all outputs (entirely connected) from the previous layer.

2. **Convolutional Neural Networks (CNNs):** CNN [28] is a deep neural networks that are utilised most frequently in computer vision applications. With the aid of CNN and a collection of images or videos from the real world, the AI system learns to automatically extract the features of these inputs in order to complete a specific task, such as image classification, face authentication, and image semantic segmentation. In contrast to the completely connected layers of MLPs, CNN models use one or multiple convolution layers to extract simple features from the input using convolution operations. Each layer is comprised of a set of nonlinear functions of weighted sums at various coordinates of spatially adjacent subsets of outputs from the previous layer, allowing the weights to be reused.

   CNN uses a variety of convolutional filters, and CNN machine learning models can capture the high-level representation of input data, making CNN techniques widely used in computer vision tasks like image classification (e.g., AlexNet, VGG network, ResNet, MobileNet) and object detection (e.g., Fast R-CNN, Mask R-CNN, YOLO, SSD).

   - **The AlexNet network:** AlexNet [29], the first CNN neural network to win the ImageNet Challenge in 2012, consists of five convolution layers and three completely connected layers for image classification. AlexNet thus requires 61 million weights and 724 million MACs (multiply-add computation) to classify the 227x227 pixel image.

   - **VGG-16:** VGG-16 [30] is trained to a deeper structure of 16 layers consisting of 13 convolution layers and three fully connected layers, requiring 138 million weights and 15.5G MACs to classify an image of size 224x224 in order to attain higher accuracy.

   - **The GoogleNet:** GoogleNet [31] introduces an inception module comprised of filters of varying sizes to increase accuracy while reducing the computation of DNN inference. GoogleNet obtains a higher level of accuracy than VGG-16 despite requiring only seven million weights and 1.43G MACs to process an image of the same size.

   - **The ResNet**: ResNet [32], the state-of-the-art system, employs a "shortcut" structure to achieve human-level accuracy with a top-5 error rate of less than 5%. In addition, the "shortcut" module is used to address the gradient vanishing problem during training, allowing a DNN model with a deeper structure to be trained.

- **MobileNet** MobileNet [33] is a category of computationally efficient DL models specifically developed for the purpose of mobile and embedded vision applications. Depth-wise separable convolutions are employed in order to construct deep neural networks that are lightweight in nature. The proposed architectural design effectively mitigates the parameter count in comparison to alternative network structures, hence yielding a deep neural network that is characterised by its lightweight nature.

  The MobileNet architecture has two straightforward global hyper-parameters that effectively balance the trade-off between computational delay and model accuracy. The utilisation of hyper-parameters enables the model developer to select an appropriately sized model for their specific application, taking into consideration the limitations imposed by the task at hand.

  MobileNets have demonstrated robust performance in comparison to other widely-used models in the context of ImageNet categorization. Furthermore, these models have exhibited efficacy in several domains and scenarios, encompassing item identification, precise categorization, facial features analysis, and extensive geographical localisation. MobileNets are often regarded as very effective deep learning models for deployment on mobile devices because to their compact size and minimal latency.

3. **Recurrent Neural Networks (RNNs):** The recurrent neural network (RNN) [34] is a type of artificial neural network that employs sequential data input and have been devised as a solution to tackle the challenge of sequential input data in time-series problems. The input of a RNN is comprised of the current input as well as the preceding samples. Hence, the interconnections among the nodes give rise to a directed graph that follows a time sequence. Additionally, it should be noted that every individual neuron inside a RNN possesses an internal memory component that retains the information obtained from previous samples during the computing process. The concept of a RNN refers to a type of artificial neural network that is designed to process sequential data by utilising feedback connections. Unlike traditional feedforward neural networks, RNNs include internal memory, allowing them to retain information about previous inputs and utilise it in the processing of subsequent inputs. This characteristic of RNN models are extensively employed in the field of Natural Language Processing (NLP) owing to their ability to effectively handle data with variable input lengths. RNN consists of many layers, where each following layer is comprised of a set of nonlinear functions that operate on weighted sums of outputs and the prior state. The fundamental component of a RNN is referred to as a "cell". Each cell is composed of layers and a sequence of cells, facilitating the sequential processing of RNN models.

4. **Long Short-Term Memory (LSTM) Networks:** The Long Short-Term Memory (LSTM) [35] is a recurrent neural network (RNN) architecture specifically developed to effectively capture temporal sequences and their extensive relationships, surpassing the capabilities of traditional RNNs. Long Short-Term Memory (LSTM) networks demonstrate a high degree of suitability for the tasks of categorising, processing, and predicting time series data, particularly when confronted with time lags of indeterminate duration. In contrast to conventional feedforward neural networks, Long Short-Term

Memory (LSTM) networks possess feedback connections, rendering them capable of functioning as a "universal computer" capable of executing computations equivalent to those of a Turing machine.

Long Short-Term Memory (LSTM) networks exhibit a sequential arrangement, wherein the recurrent module possesses a distinct structural composition. Instead of employing a singular neural network layer, the system has four distinct layers that interact in a unique and intricate manner. The fundamental aspect of Long Short-Term Memory (LSTM) networks is in the cell state, which is represented by a horizontal line traversing the top of the picture. The cellular state can be analogously compared to a conveyor belt. The phenomenon exhibits a predominantly linear progression throughout the whole chain, with occasional slight interactions.

The efficacy of Long Short-Term Memory (LSTM) models in acquiring knowledge from extended sequences renders them valuable in real-world scenarios, including but not limited to speech recognition, music composition, and text production endeavours. Although LSTMs have demonstrated their efficacy, training them effectively can pose difficulties owing to their intricate nature and resource demands.

5. **Gated Recurrent Unit (GRU) Networks:** Gated Recurrent Units (GRUs) [36] have emerged as a notable variation of RNNs for their notable efficacy in processing sequential input. The proposed networks were introduced as a more efficient alternative to Long Short-Term Memory (LSTM) networks, as they possess a reduced computational complexity owing to a smaller number of parameters.

   In contrast to the LSTM, the GRU does not necessitate the inclusion of a memory unit for regulating the transmission of information. The process reveals the entirety of concealed information without any form of restriction, thereby streamlining its framework and rendering it more adaptable to alterations.

   GRUs are equipped with two distinct gates, namely an update gate and a reset gate. The update gate is responsible for determining the degree to which the prior state should be preserved, while the reset gate specifies the amount of the previous state that should be disregarded. The utilisation of this gating mechanism serves to address the challenges associated with the occurrence of vanishing or exploding gradients, which are frequently observed in conventional RNNs.

   Although GRUs are relatively simple, they have shown comparable performance to LSTMs in a wide range of tasks. As a result, these models are often favoured for tasks that require the analysis and processing of sequential data, such as natural language processing, speech recognition, and time series prediction.

6. **Autoencoders (AE) :** Autoencoders [37] are a distinct category of feedforward neural networks in which the input and output are identical. The input is compressed into a code with lower dimensions, and afterwards, the output is reconstructed based on this representation. The code refers to a condensed form of the input, commonly known as the

latent-space representation, which serves as a summary or compression of the original data.

The autoencoder is comprised of three fundamental components: an encoder, a code, and a decoder. The process of encoding involves compressing the given input data to generate a corresponding code, whereas the subsequent process of decoding entails reconstructing the original input data only based on this code.

In order to construct an autoencoder, three essential components are required: an encoding technique, a decoding technique, and a loss function, which quantifies the disparity between the initial input and the reconstructed output.

Autoencoders are a type of machine learning models that fall under the category of unsupervised learning. The primary application of these methods is to reconstruct inputs that are affected by noise and to reduce the dimensionality of data for the purpose of visualisation. By imposing suitable dimensionality and sparsity constraints, autoencoders have the capability to acquire data projections that exhibit greater complexity and novelty compared to conventional techniques such as Principal Component Analysis (PCA).

7. **Generative and Adversarial Networks (GAN):** Generative Adversarial Networks (GANs) [38] refer to a category of artificial intelligence algorithms employed in the domain of unsupervised machine learning. These algorithms operate through a framework consisting of two neural networks engaged in a competitive interaction, forming a zero-sum game. Ian Goodfellow and a team of researchers from the University of Montreal, which included Yoshua Bengio, introduced the idea in 2014.

   There are two networks at play in this scenario: the "Generator" network, which aims to produce data, and the "Discriminator" network, which assesses the authenticity of the data by determining whether it originates from the real dataset or was generated by the Generator. The performance of the Generator is enhanced through the utilisation of feedback received from the Discriminator.

   GANs have been employed in several applications to generate samples of photorealistic images. These applications include synthesising images of fashion products, generating realistic human faces, and making "paintings" that bear resemblance to renowned works of art.

   Despite their considerable potential, GANs are widely recognised as challenging to train, with model collapse frequently posing a significant issue. Nevertheless, their contributions to the domain of artificial intelligence image synthesis have been substantial.

8. **Hybrid Deep Learning Networks**: Hybrid Deep Learning models [39-42] represent a sophisticated iteration of artificial intelligence models, wherein various neural networks are integrated to harness their respective capabilities and yield enhanced outcomes. These models incorporate a range of deep learning architectures, including Convolutional

Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRUs), and other similar structures.

One of the key benefits of hybrid models is in their capacity to effectively manage heterogeneous data types and execute intricate operations with enhanced efficiency. An example of a hybrid model that combines Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) demonstrates the capability to efficiently analyse and generate predictions from data that possesses both spatial and temporal dimensions.

Hybrid models exhibit significant utility in fields such as healthcare, wherein data exhibits heterogeneity, encompassing diverse forms such as patient records, medical imaging, and time-series data derived from monitoring equipment. Hybrid models have the ability to grasp intricate patterns in data by efficiently integrating various neural network topologies, hence resulting in enhanced predictive accuracy.

Although hybrid models have the potential to achieve high performance, they can impose a significant computational burden and necessitate the utilisation of advanced training methodologies. Nevertheless, the relentless progress in processing capacity and deep learning algorithms persists in pushing the limits of AI capabilities.

IV. IOT ARCHITECTURE

The concept of the IoT refers to the interconnectedness of various objects, systems, and services that possess the capability to gather, analyse, and share data across networks. The IoT finds utility in several sectors, including but not limited to smart homes, industrial automation, healthcare, and environmental monitoring. Nevertheless, the IoT presents various issues in relation to security, privacy, scalability, and interoperability. Hence, comprehending the structure and functioning of the IoT holds significant importance.

The three-layer architecture shown in Fig.3 is a widely employed and fundamental concept within the realm of IoT architecture. This model encompasses three distinct layers: the sensor layer, the network layer, and the application layer. Each layer inside the IoT system possesses distinct functions and roles.

The sensing layer, situated at the base of the IoT architecture, assumes the crucial role of gathering data from the tangible surroundings. This layer comprises of sensors and actuators capable of measuring various characteristics, including but not limited to temperature, humidity, light, sound, and motion. Typically, these devices are integrated within various objects or affixed to them, enabling intercommunication either amongst themselves or with the network layer via wired or wireless protocols.

The network layer occupies a central position within the IoT architecture, facilitating the establishment of connectivity and enabling communication among the many devices comprising the IoT system. This layer encompasses a range of technologies and protocols that facilitate the exchange of data via networks, including but not limited to WiFi, Bluetooth, Zigbee, and cellular networks. The network layer may encompass gateways and routers, which serve as middlemen between devices and the internet or other networks. The network layer has the capability to offer security functionalities, like encryption and authentication, in order to safeguard data from unauthorised access or alteration.

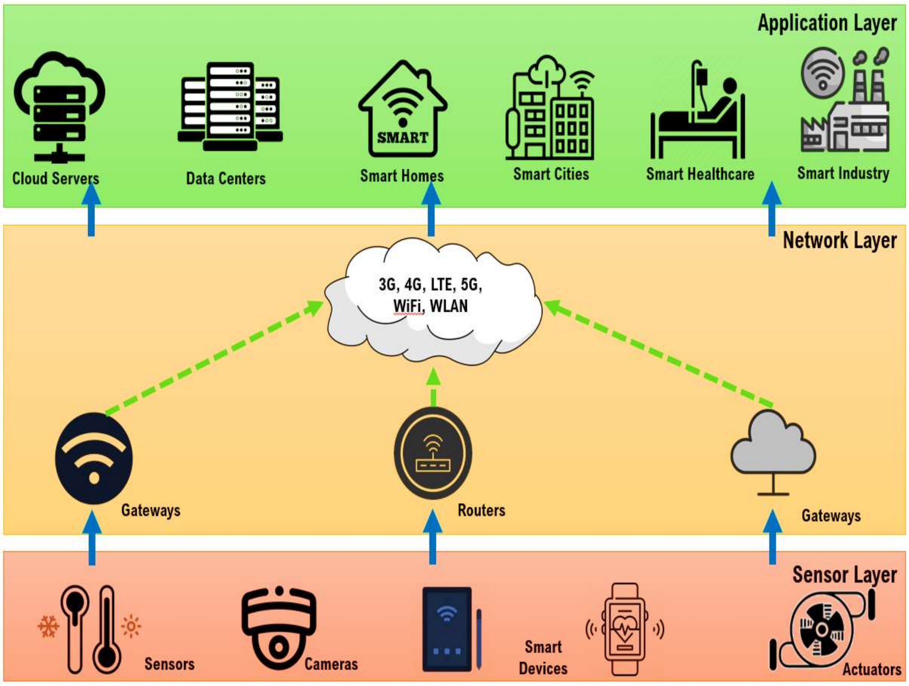

Figure 3: IoT Architecture

The application layer, situated at the topmost level of the IoT architecture, assumes the crucial role of facilitating user interfaces and functions that empower people to interact with and manage IoT devices. This layer encompasses a diverse range of software applications and platforms that are specifically engineered to engage with the foundational IoT infrastructure. Their primary function is to deliver a multitude of services, including but not limited to data analysis, visualisation, decision-making, and automation. The application layer may also encompass the utilisation of cloud computing or edge computing technologies for the purpose of storing, processing, and managing substantial volumes of data generated by IoT devices.

The three-tier architecture of the IoT is a straightforward and versatile framework that may be implemented across various contexts and fields. Nevertheless, it is plausible that this approach may not adequately tackle the myriad intricacies and obstacles inherent in the IoT. Hence, several models of IoT architecture have been proposed, incorporating additional layers or stages to enhance usefulness and adaptability. For instance, certain architectures incorporate an intermediary layer positioned between the network layer and the application layer, with the purpose of delivering data processing, administration, integration, and abstraction functionalities. Certain models incorporate an additional layer known as the edge layer, which is positioned between the sensing layer and the network layer. This additional layer facilitates localised processing and storage at the network's edge.

V. APPLICATION DOMAINS

1. **Smart Agriculture:** Deep learning algorithms are currently being employed in the field of smart agriculture to effectively monitor and observe a range of interconnected characteristics, enabling remote access and analysis from any location throughout the globe. Recent surveys have focused mostly on examining the advantages of deep learning within various agricultural applications.

   There has been a noticeable rise in researchers' inclination towards utilising the CNN method for the purpose of detecting and classifying plant diseases in various applications. Deep learning algorithms are currently being employed in the field of smart agriculture to effectively monitor and study a range of interconnected characteristics, enabling remote access and observation from any location throughout the globe. Recent surveys have focused mostly on examining the advantages of deep learning within various agricultural applications. This report provides an overview of the contributions of deep learning in various applications of smart agriculture. We conducted an analysis to determine the suitability of several deep learning models for different applications, as well as their relative efficiency and effectiveness. There is a growing interest among researchers in utilising the DL algorithms for the purpose of plant disease detection and classification applications. This approach has yielded significant and noteworthy outcomes.

   Disease fungi, germs, and bacteria feed on plants, reducing crop output. Not detected in time can result in considerable economic losses for farms. Pesticides that kill diseases and restore crop function cost farmers a lot. Excessive pesticide use degrades the ecosystem and impacts agricultural water and soil cycles [43]. Early diagnosis of plant diseases is crucial as they affect species growth. Many deep learning models (DL) have been used to categorise plant diseases. Deep learning has great promise for improving accuracy over time. New DL architectures and changes to current ones are proposed. Modern visualisation techniques are utilised to classify plant sickness symptoms using various methods [44].

   The author [45] introduced a CNN model-based method for finding and classifying banana illnesses. It can help farmers diagnose diseases quickly, affordably, and efficiently. This method detects two banana illnesses, Sigatoka and speckle, using a deep neural network model and a snapshot of an infected leaf. The authors of [46] utilised AlexNet, a deep learning model, to accurately classify plant diseases using leaf images. A hybrid deep learning model [47] classifies sunflower diseases such as Alternaria leaf rot, Downy mildew, phoma rot, and verticillium wilt. The author developed a hybrid model of H.VGG-16 and MobileNet using stacking ensemble learning. The dataset was created using Google Photos, and their suggested model achieved an impressive 89.2% accuracy, surpassing other models.

   The research in [48] examined five deep learning models, including H. Vgg16, Vgg19, ResNet50, ResNet50V2, and ResNet101V2, using simulated data and rice field photos from Gujranwala, Pakistan. The ResNet50 model had a 75% accuracy on a simulated dataset, while the ResNet101V2 model had an 86.799 accuracy on the actual dataset.

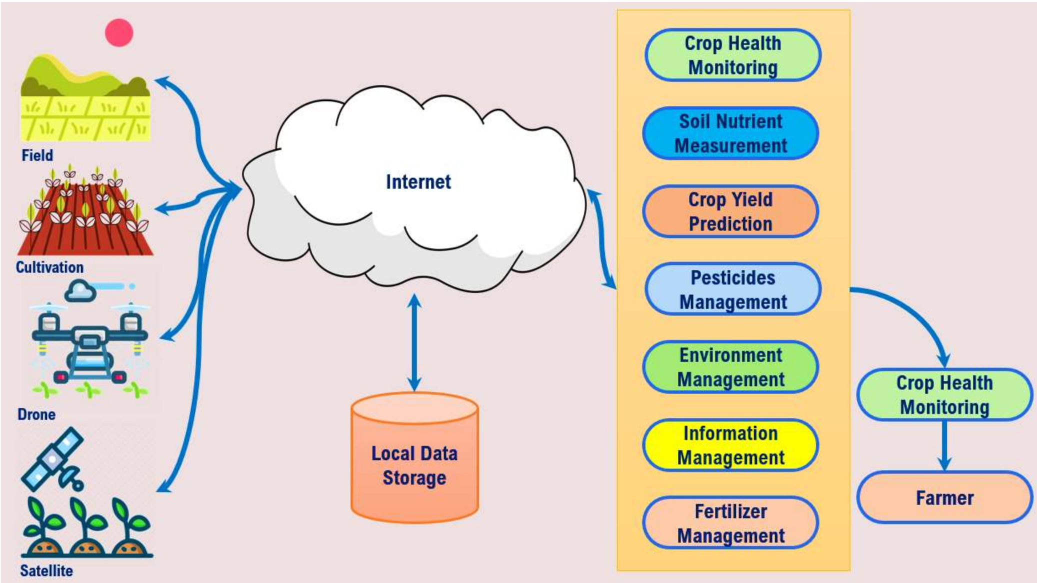

Figure 4: IoT Applications in Agriculture

The author of [49] created a mobile gadget that uses machine learning to automate plant leaf disease diagnostics. The system uses CNNs as the deep learning engine to classify 38 types of illnesses. The researchers collected 96,206 pictures of healthy and diseased plant leaves for CNN model training, validation, and testing. The Android app was designed for farmers to picture ill plant leaves. The illness category and 90% confidence were displayed. This strategy aims to help farmers maintain healthy crops and reduce harmful fertiliser use.

A transfer learning pre-trained deep neural network model was utilised in [50] to detect agricultural diseases by immediately learning leaf attributes from input data. The study examined CNN topologies (ResNet, MobileNet, WideNet, and DenseNet) and deep learning methods. The results show that the suggested strategy beats previous methods in memory and precision.

Another CNN method for detecting, classifying, and identifying plant diseases is provided in [51] where the system has achieved output accuracy of 91-98% and an average of 96.3% for thirteen plant diseases. In addition, it can detect good and sick leaves from their surroundings. The author of [52] obtained 99.58 % accuracy in recognising and classifying plant photos using a CNN model in agriculture. They evaluated maize crop growth using off-the-shelf ConvNet representations.

In [53], an SVM classifier is presented for autonomous plant disease identification using image analysis, achieving 94% accuracy. The experiment used 500 plant leaf photos from 30 natural plant types. Other deep learning studies [54-64] created automatic plant detection and recognition systems to classify nine diseases into a single healthy class. All experiments used the PlanVillage dataset for training and testing, achieving an accuracy of more than 91%.

2. **Smart Transportation:** The importance of the IoT in improving traffic solutions for customers through its interconnected and intelligent gadgets exceeds current observations. Urban mobility is of paramount importance in the successful deployment of intelligent traffic and transport solutions, as it simultaneously enhances the availability of diverse services to individuals. Urban regions around the world are seeing substantial growth and expansion. Urban areas encounter a myriad of intricate issues, encompassing, though not restricted to, the predicaments of traffic congestion, escalated pollution levels, and significant economic consequences arising from traffic disruptions and vehicular incidents. The incorporation of machine learning within the framework of the IoT strategy offers a potentially advantageous pathway for creating value by means of analysing networked data. The aforementioned technique possesses the capacity to improve services and accelerate the process of innovation [65, 66].

   Developed countries exhibit a notable level of complexity and efficient maintenance in their road infrastructure. On the other hand, road infrastructure in emerging countries is confronted with persistent maintenance difficulties. Roadway surface disruptions and obstacles (RSDOs) are commonly observed, resulting in mishaps, difficulties in driving, interruptions in travel, and delays in transportation. In the work conducted by Gónzalez and colleagues [67], acceleration sensor data was utilised to classify patterns related to speed bumps, potholes, metal humps, and uneven roadways. The categorization challenge was successfully completed by employing logistic regression and artificial neural network machine learning methods. A other research project [68], investigates the identical issue through the utilisation of a hybrid methodology that integrates supervised and unsupervised machine learning approaches. This strategy incorporates the use of data collected via the Street Bump smartphone application. The surveillance of vehicular movement plays a pivotal role in the effective administration of traffic congestion. The achievement of this objective is facilitated through the process of identifying traffic patterns by analysing the movements of cars. This is achieved by applying a comprehensive categorization method, as outlined in reference [69], and utilising regression analysis techniques, as explained in reference [70]. Machine learning has been applied in various domains, one of which is the development and deployment of intelligent traffic light control systems. The achievement of this has been facilitated by the application of Q-learning [71], in conjunction with artificial neural networks (ANNs) and reinforcement learning [72].

   Autonomous vehicles (AVs) possess the capacity to profoundly alter the landscape of the transportation industry and depend heavily on ML algorithms, which gradually evolve towards attaining AI capabilities for autonomous driving. Machine learning algorithms are utilised to monitor and distinguish the motions and locations of both mobile and stationary items. The approach proposed by Alam et al. [73] entails the amalgamation of deep learning and decision fusion techniques to achieve object recognition in driving environments. Tesla and Google, two important businesses in the technology industry, utilise ANN and DL methodologies in their AVs to accurately detect and comprehend objects inside the driving environment.

3. **Smart healthcare:** In the past few years, there has been a notable increase in the utilisation of IoT devices within the domain of health-related applications. The significance of the IoT system in the healthcare sector is progressively gaining recognition [74]. The healthcare business effectively use IoT devices to conscientiously observe and record patient situations. Furthermore, these gadgets possess the capacity to communicate notifications to the appropriate healthcare system in critical circumstances, so enabling expeditious and punctual medical intervention for patients. According to a study, almost 60% of the healthcare industry has adopted the integration of Internet of Medical Things (IoMT) devices. The global internet of medical things (IoMT) market is projected to grow from $30.79 billion in 2021 to $187.60 billion in 2028 at a CAGR of 29.5% [75].

   The IoMT is widely acknowledged for its significant contribution to the transformation of the healthcare business. It enables the transition from fragmented healthcare systems to integrated and coordinated healthcare practises. In 2015, almost 30.3% of the total 4.5 billion IoT devices were categorised as IoMT devices. According to projections, it is anticipated that the quantity of IoMT devices would witness a substantial growth, reaching an estimated range of 20-30 billion by the year 2020.

   In comparison to alternative applications, it is of utmost importance to prioritise the safeguarding of IoT in healthcare systems, while concurrently facilitating adaptable accessibility to equipment, with the ultimate objective of efficiently preserving lives during critical circumstances [76]. To provide an example, consider an individual who possesses a medical device implanted within their body that operates on the principles of the IoT. This person has met a significant situation where they unexpectedly require hospitalisation instead of merely engaging in routine visits. In this particular situation, it is of utmost importance that the staff members at the newly established healthcare facility possess the ability to promptly access the implanted medical devices that function on the IoT framework. Therefore, it is conceivable that a complex security requirement may not be considered satisfactory, therefore requiring a security strategy that meticulously evaluates and harmonises both security measures and the facilitation of adaptable access during emergency situations.

   Furthermore, the utilisation of IoT sensors is widely prevalent in the monitoring of diverse health-related activities on a daily basis. A smartphone is frequently employed for the aim of monitoring health-related activities, encompassing several aspects such as daily physical activity, including step count, distance travelled by walking, jogging, and cycling, as well as sleep analysis. The IoT offers considerable potential for strengthening healthcare systems and a wide range of applications [77]. The advancement of traditional medical devices towards interactive environment medical devices can be augmented by using an IoT framework. The integration of implanted, wearable, and environmental sensors in a cooperative manner within the IoT framework enables the realisation of this objective. The primary objective of this integration is to efficiently oversee the well-being of users and offer immediate health assistance in real-time [74]. However, the matter of guaranteeing the security of IoT systems remains highly significant [79, 80], requiring further investigation to successfully and securely incorporate IoT devices into the healthcare industry.

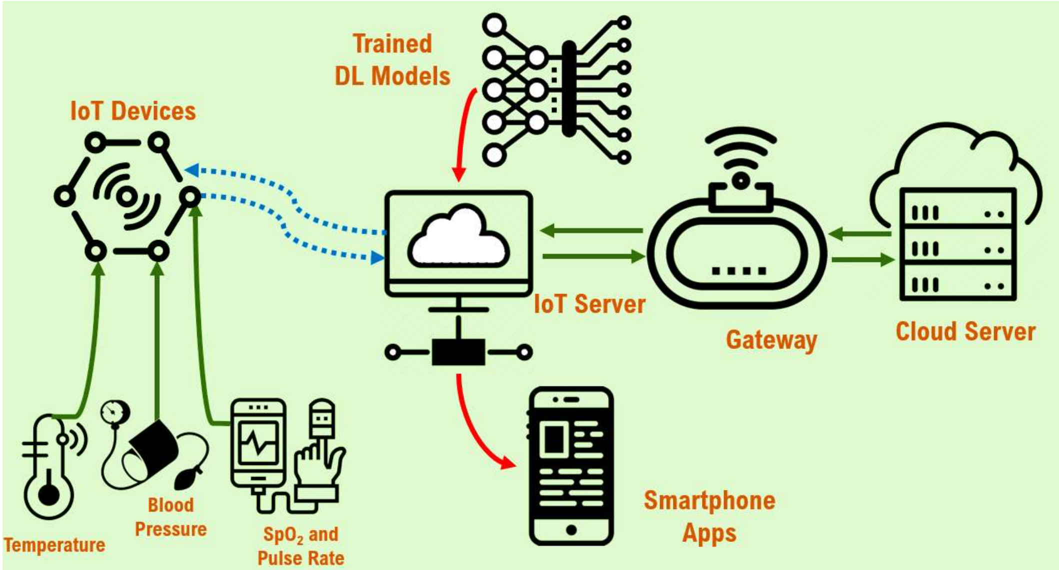

Figure 5: IoT Implementation in Healthcare

4. **Smart Homes:** The concept of IoT-enabled smart homes (SHs) refers to a technical framework that facilitates the complete automation of household devices and home appliances by utilising internet connectivity. The integration of context awareness into SHs yields a notable result in terms of improving user comfort and safety. However, there is a decrease in the extent of direct interaction between the user and the surrounding environment. The MavHome project, referred to as Managing an Intelligent Versatile residential, employs a fusion of multiagent systems and probabilistic ML algorithms to develop a rational agent that maximises inhabitant comfort while minimising operational expenses within a residential setting [80].

   A more advanced context-aware model integrates a back-propagation ANN to facilitate service selection. Furthermore, it utilises a reinforcement learning technique that falls under the category of temporal differential to offer adaptive context awareness. This is crucial due to the fact that user preferences are susceptible to alteration throughout the course of time. Some notable advantage can be added by using a context-aware system that does not require a preexisting model [81]. The modelling process is executed in an automated manner, making use of the input provided by the user on the service.

   Humans who are social in nature possess the cognitive ability to make rational and well-thought-out decisions pertaining to the integration of technology. The achievement of this goal is helped by monitoring and anticipating the mobility patterns and device usage of individuals dwelling in the specified area. This study presents the LeZi prediction method, which is an active strategy that use the Markov chain, as described in reference [82]. The objective of this algorithm is to understand and analyse patterns of future events. The automation of smart homes (SHs) has prompted significant attention towards human activity recognition (HAR) as a key research field. Some studies have examined the application of deep learning algorithms in predicting human behaviour through activity recognition [83].

Previous studies have conducted comparative analyses to evaluate the effectiveness of different machine learning algorithms in the context of HAR utilising data obtained from IoT sensors. Fahad et al. conducted a comparison research to evaluate the accuracy of five machine learning algorithms (MLAs) in effectively detecting smart home behaviours. In the domain of human activity recognition (HAR), the support vector machine (SVM) and evidence-theoretic kNN algorithms have exhibited higher levels of accuracy when compared to the probabilistic ANN, kNN, and NB approaches [84]. In contrast, the study conducted by Alam et al. [74] involved a comparative comparison of eight machine learning algorithms, revealing that deep learning has greater performance in terms of prediction accuracy. Taiwo et al. [85] conducted a study whereby they introduced a deep-learning model that specifically targets motion categorization by analysing patterns of movement. The main aim of this model is to optimise electricity efficiency in residential environments. However, it is important to note that the utilisation of deep learning methods incurs a significant computational burden. Furthermore, a study conducted by researchers [86] has demonstrated that the C5.0 algorithm demonstrates a performance level that is closely comparable to that of the DL approach.

The notion of HAR can be delineated into two discrete elements. There are two primary factors that need consideration: the clustering of activity patterns and the decision-making process associated with activity kinds. Nevertheless, it is important to acknowledge that a multitude of literary sources often focus on a certain facet, resulting in a decrease in overall efficacy. In order to tackle this issue, a sophisticated user behaviour classification is conducted utilising an unsupervised machine learning algorithm known as K-pattern along with ANNs have been utilised for the purpose of training and predicting user actions [87]. The use of K-pattern ML exhibits improved accuracy in managing substantial volumes of IoT data, specifically with temporal complexity and flexibility of cluster sets. The utilisation of HAR technology offers advanced control and automation functionalities to intelligent residential buildings like the implementation of on/off mechanisms for lights, fans, and home appliances can lead to improved power optimisation, emergency health problems can be identified, and alerting others can help mitigate the risk of fatalities.

VI. ISSUES

The employment of data sources plays a pivotal role in determining the effectiveness of deep learning approaches. The utilisation of DL in the context of IoT poses a significant problem owing to the constrained accessibility of extensive datasets. To improve the precision of deep learning models, it is crucial to obtain a larger quantity of data. An additional problem that arises in the context of IoT applications pertains to the creation of raw data that conforms to the suitable format for input into DL models. The improvement of accuracy in the produced discoveries often requires the preparation of data for many deep learning techniques. In the realm of IoT applications, the preprocessing stage gets increasingly complex as the system deals with data that originates from several sources. These sources may have different formats, distributions, and cases where data is missing. The utilisation of data collection systems is a pivotal domain of investigation.

The number and strategic placement of sensors have a substantial influence on the quality of the data gathered. To ensure the efficacy of the model design, it is important to construct a comprehensive data acquisition module that encompasses the entirety of the IoT system. The model ought to demonstrate enhanced reliability, cost-efficiency, and credibility.

The main challenge within the domain of IoT revolves around security, owing to the vast accumulation of data from multiple origins. The preservation of data privacy and confidentiality poses a substantial obstacle in various applications of the IoT. The primary reason for this phenomenon can be attributed to the widespread dissemination of large quantities of IoT data for worldwide accessibility. Anonymization techniques are frequently utilised in diverse applications. However, it is crucial to acknowledge that these methods are vulnerable to exploitation and subsequent re-identification of the anonymized data. Deep learning models have the capacity to acquire information regarding the intrinsic characteristics of raw data, hence allowing them to leverage imperfect data streams for their benefit. In this particular circumstance, it is crucial to utilise precise approaches for the purpose of recognising and rectifying irregular or erroneous data when updating deep learning models.

The task of developing deep learning (DL) models poses a substantial challenge for designers of IoT systems, as they must address the need to effectively deploy DNNs on devices that have limited resources. It is projected that the expected expansion of data sets and the incorporation of novel algorithms into IoT solutions based on deep learning would likely result in an increase in this phenomenon. DL also has various limitations. Another constraint lies in the fact that deep learning models predominantly prioritise classification tasks, but certain IoT applications necessitate regression analysis as their fundamental component. The integration of regression skills into DNNs has been a focus of study for a select group of scientists.

The efficacy of digital monitoring for off-road vehicles is impeded by the utilisation of sophisticated and expensive IoT sensor technology. The substantial reliance on cloud/fog computing, network connectivity, and specialised knowledge presents a notable obstacle in remote off-network regions. The solution that has not yet been brought to market involves the usage of edge devices, such as smartphones, which possess computing capability. The authors put out a computational intelligence approach that integrates many techniques to create an artificial intelligence system with the ability to monitor and diagnose the condition of off-road vehicles. The technology is specifically developed for deployment on edge devices and employs cost-effective microphones as sensory components.

DL is a highly effective methodology for handling large volumes of data within the framework of the IoT, hence requiring the utilisation of sophisticated hardware resources. The challenge of designing a deep learning model for an embedded device with restricted resources remains a prominent issue. There exists a potential for network failure and data disclosure during the various stages of data collection, transmission, and analysis on the servers. There is an increasing inclination towards the implementation of a cloud-based educational framework that incorporates important devices and cloud technology. Cloud-based devices utilise edge computing to cut latency and optimise security and safeguarding protocols. In the domain of electronics, it is advisable to utilise intelligent approaches in order to ensure the preservation of data. In addition, the use of cloud computing can enable the smooth exchange of information related to state-of-the-art developments, along with the refinement of high-quality computational models.

VII. FUTURE TRENDS

1. **Agriculture:** Agriculture is a multifaceted field that has inherent complexities due to the unique climatic circumstances, natural characteristics, and distinct traits that vary across different regions. Hence, there exists a pressing necessity for technological advancements that can effectively differentiate the aspects of significance and conduct thorough analysis of the accumulated data. Exploring this phenomenon necessitates a substantial volume of data, given the need to account for real-time fluctuations. Hence, deep learning emerges as a pivotal technology capable of executing these tasks through the use of suitable algorithms like CNN and RNN.

   When an algorithm is provided with field data, encompassing climate parameters, soil types, weather patterns, and other relevant aspects, it constructs a probabilistic model prior to executing any decision-making process.

   The timely and precise diagnosis of illnesses is crucial for effectively monitoring and mitigating any food or financial losses. By analysing a collection of photos depicting diseased plants over a period of ten years, this system is capable of accurately identifying the specific type and level of severity of the disease. The aforementioned principle also holds true for the progression of atmospheric conditions. One primary benefit of employing a deep learning model is its ability to autonomously generate the desired feature without explicit guidance or provision from external sources. Unsupervised learning enhances our ability to effectively navigate and adapt to the dynamic and uncertain nature of real-time environments. The importance of the IoT is increasingly recognised due to its expanding significance. A substantial portion of the data produced by both humans and machines is characterised by its lack of structure and classification. Deep learning has been found to exhibit superior performance compared to older methods, including ANN, SVM, RFs, and others. The efficiency of automatic feature extraction using deep learning models is aimed to surpass that of conventional feature extraction methods in future.

2. **Healthcare:** Several emerging trends in the field of smart healthcare, which are propelled by advancements in machine learning and deep learning, include:

   - **Medical image analysis:** Medical image analysis involves the utilisation of machine learning and deep learning techniques to examine many types of medical images, including X-rays, CT scans, MRI scans, ultrasound images, and histopathological images. These advanced computational methods aid in the identification, diagnosis, and monitoring of a wide range of diseases, encompassing cancer, cardiovascular diseases, neurological disorders, and the ongoing COVID-19 pandemic. Machine learning and deep learning techniques have the potential to generate synthetic medical images, which can be utilised for data augmentation, simulation, and visualisation objectives.

- **Electronic Health Records:** The utilisation of machine learning and deep learning techniques in the mining of electronic health records (EHRs) enables the extraction of significant insights. EHRs encompass a comprehensive range of information pertaining to patients, including their demographics, medical history, diagnoses, prescriptions, lab tests, vital signs, and outcomes. Machine learning and deep learning techniques have the potential to facilitate the identification of patterns, trends, anomalies, and connections within Electronic Health Records (EHRs). This capability can be leveraged to enhance clinical decision-making processes, anticipate risks, model illness progression, optimise treatment strategies, and improve overall healthcare quality.

- **Wearable devices and sensors:** Machine learning and deep learning techniques can be employed to effectively handle and analyse the data acquired by wearable devices and sensors, including but not limited to smartwatches, fitness trackers, blood pressure monitors, glucose metres, and oximeters. Machine learning and deep learning have the potential to offer users real-time feedback, alerts, recommendations, and interventions by leveraging information about their health state, activity level, behaviour patterns, and preferences. Machine learning and deep learning have the potential to facilitate remote monitoring and telemedicine for patients requiring continuous care or residing in remote regions.

- **Drug Discovery and Development:** The utilisation of machine learning and deep learning techniques has the potential to expedite the drug discovery and development process, hence mitigating the associated financial burdens, time constraints, and intricate nature of this endeavour. The utilisation of machine learning and deep learning methodologies has the potential to contribute significantly to the development of innovative molecules with specific features and functions. Additionally, these techniques can be employed to forecast the effectiveness and potential harmful effects of prospective pharmaceuticals, enhance the process of medication synthesis and formulation, and streamline the progression of clinical trials and regulatory approval for pharmaceutical products.

- **Healthcare Chatbots:** The utilisation of machine learning and deep learning techniques can facilitate the development of conversational agents capable of engaging in natural language interactions with users. Healthcare chatbots have the potential to offer a range of services including the provision of information, guidance, support, diagnosis, treatment ideas, appointment scheduling, prescription reminders, and emotional counselling to individuals seeking health-related information or assistance. Healthcare chatbots can additionally facilitate the collection of user data for research or feedback objectives.

3. **Smart Transportation:** Machine learning and deep learning have emerged as very promising technologies for the prospective advancement of intelligent transportation systems. These technologies have the capability to facilitate a range of applications, including autonomous driving, traffic management, mobility as a service, and vehicle-to-everything connectivity.

   Multimodal data fusion has emerged as a prominent concept in the field of machine learning and deep learning for intelligent transportation systems. This entails the integration of many data sources, including photos, videos, lidar, radar, GPS, and maps, in order to construct a full depiction of the surrounding environment and the prevailing traffic conditions. This has the potential to improve the perception and decision-making abilities of autonomous cars and traffic controllers. An instance of a recent study introduced a multimodal deep learning framework that aims to integrate optical and lidar data for the purpose of detecting and tracking vehicles and pedestrians in intricate urban environments.

   Another emerging phenomenon in the field of smart transportation is the advancement of reinforcement learning and imitation learning techniques. Reinforcement learning is a machine learning paradigm characterised by its ability to acquire knowledge through iterative interactions with an environment, wherein the learning agent receives rewards or penalties based on its actions. Imitation learning is a machine learning paradigm that acquires knowledge by leveraging expert demonstrations or human feedback. These methodologies can be employed to enhance the performance and operational strategies of self-driving vehicles and traffic controllers. A recent study introduced a reinforcement learning algorithm that has the capability to acquire efficient and safe driving skills in mixed traffic situations involving human drivers.

   One emerging trajectory in the field of machine learning and deep learning for intelligent transportation is the convergence of edge computing and cloud computing. Edge computing refers to a form of distributed computing wherein data processing is carried out in close proximity to the data sources, at the periphery of the network. Cloud computing refers to a form of computing that involves the centralization of data processing on distant computers via the internet. These two paradigms have the potential to mutually enhance each other and offer scalable, dependable, and secure solutions for smart transportation. One illustration of the potential benefits of edge computing is its ability to facilitate low-latency and real-time applications, such as autonomous driving and vehicle-to-vehicle communication. On the other hand, cloud computing possesses the capability to support high-performance and large-scale applications, such as traffic analysis and prediction.

VIII. CONCLUSION

Machine learning and deep learning are very influential methodologies that have the capacity to facilitate a wide range of applications inside the realm of the IoT. IoT devices produce substantial volumes of data that can be leveraged for the purpose of training and enhancing machine learning and deep learning models. These models have the capability to offer valuable insights, accurate forecasts, informed suggestions, and efficient automation for

IoT systems. Several emerging tendencies can be observed in this particular field that are explained in the following paragraphs.

Edge computing is a paradigm that involves the localised processing of data at the point of origin, such as sensors, cameras, or smartphones, as opposed to transmitting it to a remote cloud infrastructure. Edge computing has the potential to mitigate latency, bandwidth constraints, and privacy concerns associated with IoT applications. Edge devices have the capability to deploy and execute machine learning and deep learning models. This is made possible by the utilisation of frameworks like TensorFlow Lite or PyTorch Mobile.

Federated learning is an innovative method of distributed learning wherein numerous edge devices can collectively train a common model for machine learning or deep learning purposes, all while avoiding the need to exchange their raw data. Federated learning is a methodology that allows for the preservation of data privacy and security, while simultaneously harnessing the collective intelligence of a network. Federated learning has the potential to facilitate personalised and adaptive learning inside IoT applications, including but not limited to smart home systems and healthcare services.

Transfer learning is a methodology employed in machine learning or deep learning, wherein a model that has been trained on a certain domain or task is modified to suit a different domain or task, while requiring minimal or no new training data. Transfer learning has the potential to mitigate the temporal and financial burdens associated with the development and implementation of IoT applications, since it enables the utilisation of pre-existing models and knowledge. Transfer learning has the potential to facilitate cross-domain and cross-modal learning in the context of IoT applications, including tasks like picture recognition and natural language processing.

Reinforcement learning is a machine learning paradigm wherein an autonomous agent is capable of acquiring knowledge through its own actions and subsequent feedback, without the need for explicit supervision or labelled data. Reinforcement learning has the potential to facilitate autonomous and adaptive IoT applications, including but not limited to smart grid systems and self-driving vehicles. Reinforcement learning has the potential to facilitate multi-agent coordination and collaboration in IoT applications, including swarm robotics and smart city systems.

In summary, the utilisation of machine learning and deep learning techniques is imperative in augmenting the functionalities and efficacy of IoT applications. The forthcoming developments in this domain encompass edge computing, federated learning, transfer learning, and reinforcement learning, which have the potential to effectively tackle the obstacles and capitalise on the opportunities presented by IoT systems.

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