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Integrating artificial intelligence with the Internet of Things for state-of-the-art medical care systems

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ABSTRACT

The goal of this study is to investigate the AIoT the integration of artificial intelligence (AI) and the Internet of Things (IoT) in healthcare systems and to create a thorough research plan that will look at different machine learning approaches in IoT-based e-health systems. Using a survey-based methodology, this study independently investigates the current uses of machine learning and the Internet of Things in the healthcare industry. It emphasizes how effective these technologies are and how integrating AIoT could lead to benefits. Initial results show that although AI and IoT work well together in a variety of IT applications, their combination in healthcare with AIoT offers more potential. In order to enhance continuous monitoring of data and decision-making procedures in e-health systems, the study identifies important gaps and opportunities for developing machine learning algorithms. With an emphasis on overcoming obstacles and seizing opportunities to maximize e-health systems, the knowledge gathered from this study can direct future advancements in AIoT for healthcare. For IT developers and healthcare experts hoping to successfully deploy AIoT systems, this will have real-world repercussions.

Contribution/Originality: With a focus on the analysis of different data types, this study uniquely investigates the intricate integration of IoT and AI, including machine learning and deep learning, in e-health. It addresses the challenges of integrating IoT and AI in healthcare in a novel way and offers fresh perspectives on how to overcome these obstacles.

1. INTRODUCTION

Undoubtedly, the IoT is a rapidly developing technology, particularly in the healthcare industry, where it is revolutionizing patient care and medical services. Live data collection, processing, and transmission enabled by these instruments greatly augment patient outcomes, diagnostic precision, and healthcare operations [1]. The IoT consists of several networks that use the Internet as their backbone. It connects a number of different actuators, sensors, and computing systems to provide intelligent services to humans [2]. This study developed an IoT remote patient and e-health monitoring system for tracking patients' physiological health signals based on CoAP and MQTT, the two most well-known IoT messaging protocols. These medical signals may consist of elements such as electrocardiogram (ECG), patient temperature, blood pressure, and heart rate signals. This useful comparison of CoAP and MQTT aims to determine which is most appropriate for e-health systems [3]. As the Internet of Intelligent Things (IoIT) continues to grow, applications have become smarter, and connected devices have become more prevalent, allowing them to be used in every facet of modern city life. As the amount of data grows, AI techniques are used to improve the application's intelligence and capabilities. Many researchers have been drawn to the area of healthcare, which has been explored using both IoT techniques and ML [4]. In this investigation, all AI technologies will be linked with the IoT so that individuals can be diagnosed automatically and anticipate conditions, assisting doctors and emergency rooms in discovering and analyzing ailments remotely without having to physically visit clinics or hospitals [5]. AI and IoT have been combined to revolutionize healthcare in recent years, especially in the areas of predictive analytics and real-time patient monitoring. Wearable sensors and other IoT devices continuously collect patient data. AI-driven algorithms are then used to analyze the data. This combination improves patient outcomes by enabling early diagnosis, prompt therapies, and real-time health monitoring [6]. An AI-powered self-sufficient network for e-health IoT is conceived as a promising option, given the recent expansion of AI being employed in a variety of fields [7]. In most industries, many situations have evolved in which ML and IoT can be coupled. In the past few years, there has been an increase in engagement in creating and deploying AI approaches to aid decision-making and knowledge acquisition. Computer engineers and physicians are increasingly forming integrated multidisciplinary research teams, indicating the necessity for collaboration in this emerging area. To illustrate the potential of the Internet of Intelligent Things (IoIT), as displayed in Figure 1.

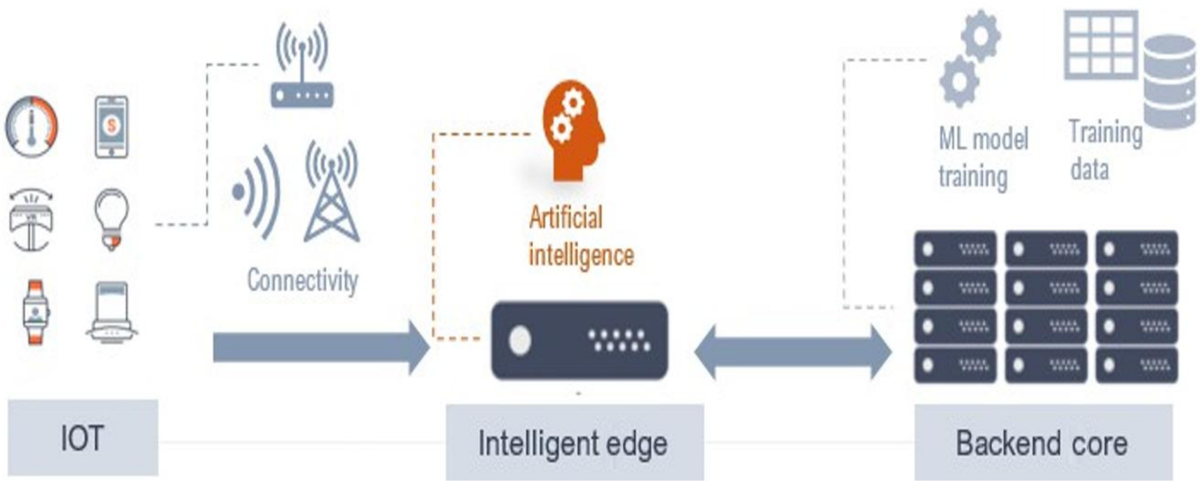

Figure 1. General architecture of e-health system.

Source: Zantalis, et al. [4].

IoIT adds the brain to systems that reduce human interaction. It is a blend of various ML technologies and the IoT. It also has the capability to learn and make decisions, especially in health systems that require quick actions, where human interaction may be delayed. After the emergence of IoT, applications became more intelligent; however, when the volume of information grows, it is necessary to link IoT with AI techniques so that IoIT can be used effectively in a variety of situations. It is challenging to create an AI model through which data is sent via IoT. Given the research issues highlighted, a stand-alone ML method examined with IoT applications in e-health systems is necessary. Many applications demonstrate the link between ML and additionally the IoT, as Figure 2 depicts. Many scholars are interested in improving the trajectory of the Internet of Things throughout the last five years. A survey will be presented of the several methods in which IoT and AI can be suitably linked for different applications. A model is also proposed through which they can be linked through the cloud. An application for IoT is made with AI in comparison to the IoT initiative.

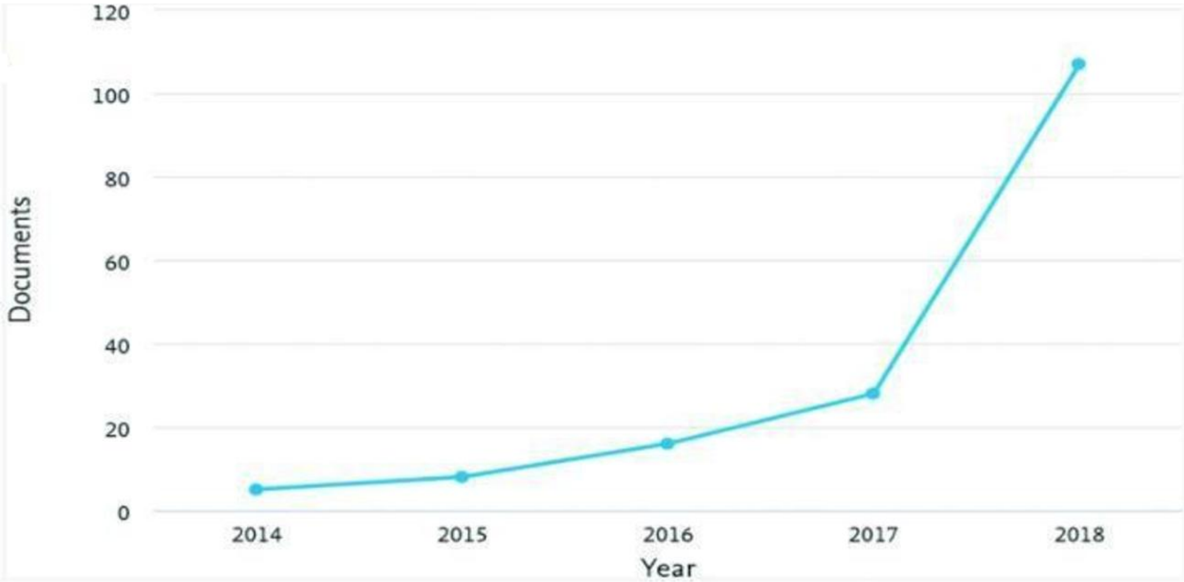

Figure 2. Growth at an exponential speed in using IoT, as well as ML methods for electronic health system.
Source: Butt, et al. [6].

IoT is a major milestone in the era of advanced technological growth, specifically for millennials, who have solely experienced the human chronology response time. Manual examination in the midst of doctors or other certified medical assistance was an unquestionable necessity in the healthcare monitoring sector for the purpose of keeping track of a patient's rehabilitation. The findings of medical testing had to be awaited for days before being interpreted depending on the diagnosis. As IoT devices became more prevalent, the introduction of AI-based gadgets that employ continuous monitoring to improve disease identification and inform caretakers or physicians through a notification system followed. Aside from that, these gadgets can also help in the decision-making process via a system for supporting decisions. The change of duties from a manual, frantic, and lengthy process to a smarter, computerized, and time-saving methodology was a major benefit of this transformation. There have already been incidents where medical practitioners have been unable to attend to patients due to the absence of information about emergency situations, resulting in disastrous decisions or even death. Those machines are programmed using unique established AI algorithms such as ML as well as DL, which, once inputted into the machines, adjust them and prepare them for use. The application of these algorithms has resulted in the creation of a number of novel architectures. Algorithms are the core of successful estimation techniques with extreme precision and accuracy. This essay focuses on these core algorithms, which are the foundation of any current powerful and effective IoT solution utilized in healthcare. Because of the high data-generating pace, this article focuses mainly on connected systems in the healthcare arena. In addition, when equipment is linked to cloud computing, its availability and scalability are improved [8]. For example, numerous virtual machines (VMs) optimizing models in addition to ML techniques have been designed to boost the productivity of HCS. These virtual machine models are primarily concerned with maximizing the use of cloud services [9]. There are also unstructured models, which are used in a few circumstances, and we possess much information but no prior knowledge to proceed [10]. Fog computing, which spatially defines the cooperation of multiple healthcare equipment with high reaction times, actual data transmissions, and other architectures, further contributes to the significance of IoT equipment and healthcare [11]. DL has opened the approach for extensive advancements in the health care domain by identifying pioneering structures like HiCH, which, when combined with concepts such as Convolutional Neural Networks (CNN), allow IoT instruments to overcome the constraints of a lack of accuracy in Wireless Body Area Networks [12]. Methods of ML such as C5.0, C4.5, EM, and KNN, which focus on finding missing values, generating decision trees, and other AI improvements, ensure the operation architecture is considerably more optimized in its AI upgrades [10, 13-15]. There are also varieties of meta-algorithms that increase the efficiency of ML algorithms [16].

The subsequent details explain how this review article is arranged. IoT and its architecture are presented in Section 2. AI, a survey study on DL and ML algorithms, is approached in an assortment of ways, and the research needs that this review article intends to fill are described in Section 3. Healthcare based on AI surveys are presented in Section 4. Integration between AI and IoT to implement healthcare is discussed in Section 5. Opportunities and challenges of AIoT in the healthcare field will be discussed in Section 6.

2. INTERNET OF THINGS

Promising applications in a variety of disciplines, many research contributions in the field of IoT have recently been recorded. With diverse technologies, IoT provides a viable solution to make life easier and deliver a better quality of life for consumers. Furthermore, with the popularity of remote cloud applications and big data, IoT technologies have gained traction. New IoT applications have emerged as a result of easy access to resources. Smart homes, wearable technology such as fitness trackers, cars, smart cities, online environments, IoT in farming, IoT in healthcare, intelligent retail, and power engagement are some of the most significant new IoT applications [17]. Furthermore, the utilization of data received from IoT devices raises questions about how and where this information might be used. One of these instances is when we understand that a comprehensive picture of DL additionally ML has yet to be investigated, which is the survey's key contribution. IoT is a group of advanced instruments that have been embedded in physical networks. These gadgets are linked, and the exchange of significant quantities of data is possible. without the requirement for human interaction. IoT networks make it simple and comfortable to use everything from household gadgets to mechanical devices [18]. When used with WSNs, IoT generates a massive volume of information that the infrastructure must handle. The remedy to these issues is to adapt conventional wired designs to the most recent network intelligence standards, which assure maximum security [19].

Medical institutions, healthcare facilities, and outpatient centers require a single, economical network architecture that conforms to data security laws while also being simple to use and operate [20]. These devices share and transmit data across disparate platforms using standardized communication protocols [21]. Consequently, the IoT improves the interactivity as well as the efficiency of vital infrastructures like security, transportation, agriculture, education, and healthcare.

2.1. Architecture Internet of Things (IoT)

Hardware, connection, communication infrastructure, large data collection and data evaluation, and IoT applications are the four tiers of IoT architecture. The stages of this architecture are briefly detailed in the subsequent sections, as in Figure 3.

- Hardware level contains a variety of intelligent devices; for example, actuators and sensors that can generate and handle signals. Data is collected by sensors and environmental data, whereas actuators are in charge of transforming electrical signals into responses. Sensors gather data instantly, allowing digital networks and physical devices to communicate with one another. This depends on the goals of IoT applications. A variety of sensors serve different roles. Wearable sensors, for example, are used to offer accurate information on human activities, whereas other sensors are developed to evaluate various elements, including humidity, temperature, pressure, length, air quality, time, speed, and movement [23].
- Middleware for communication and connectivity. The information gathered by sensors is often saved in the cloud. The transfer of the information collected is handled by connectivity and middleware for communication. These forms of middleware serve as a channel for data to flow from the hardware to analytics and storage tools. Wi-Fi, Ethernet, and RFID are examples of middleware [24].
- Analytics and storage of enormous quantities of data. IoT information must be saved and processed to extract relevant insights that can aid decision-making [25]. The process of transforming information from raw quantities into insights and actions is known as data analysis.

- IoT applications are the final level of IoT architecture. Transportation, monitoring, agronomy, smart buildings, healthcare, and energy management are just a few of the applications that can benefit from IoT. These applications allow the environment to perform intelligent, immediate actions and behaviors.

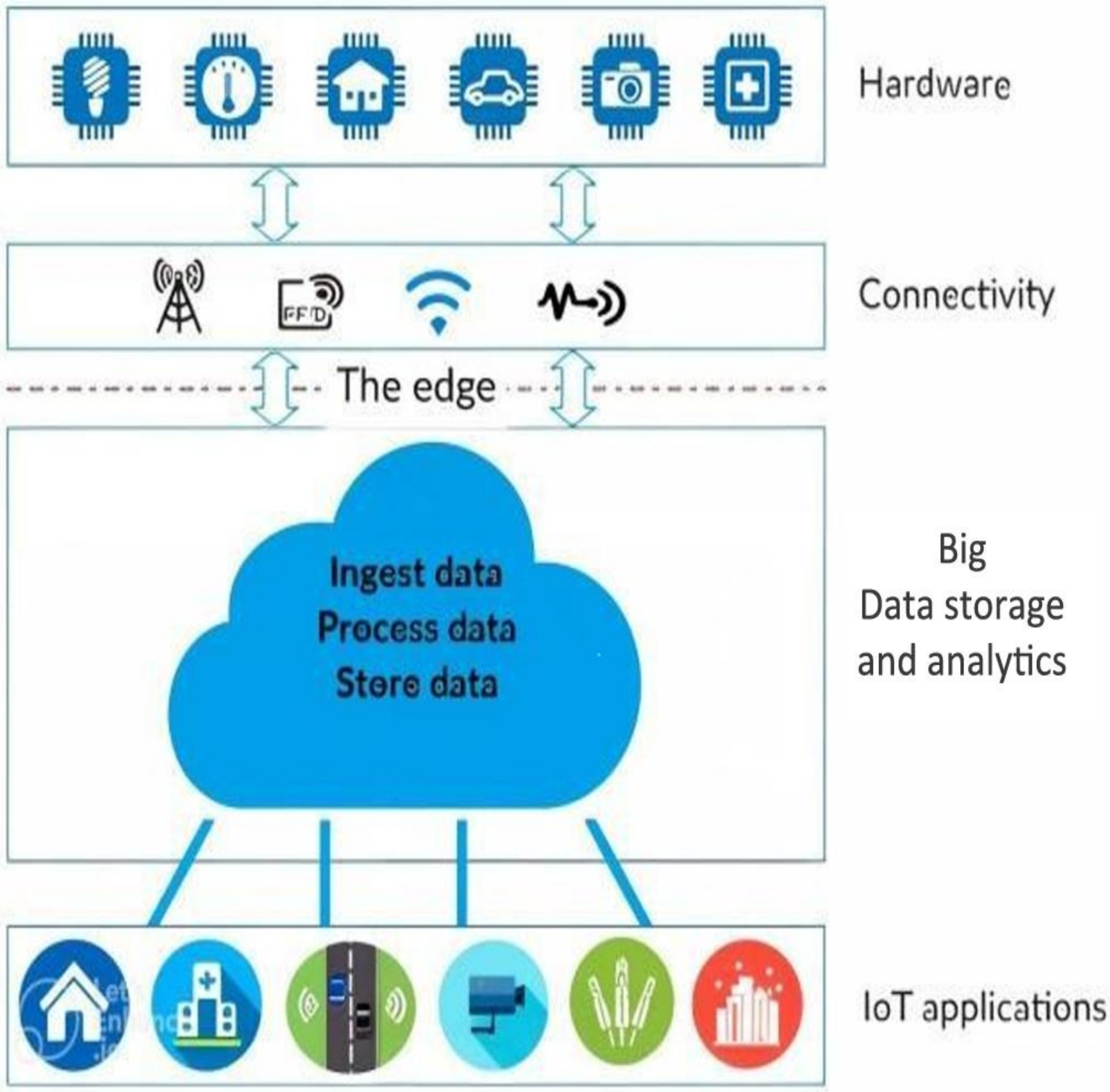

Figure 3. General IoT architecture.

Source: Atitallah, et al. [22].

3. ARTIFICIAL INTELLIGENCE

The process of making robots intelligent in a manner similar to the human brain is known as AI. The study of AI is included in computer science as "intelligent agents," which are devices that sense their surroundings and take actions to increase their likelihood of achieving their goals. When a machine can perform functions that humans associate with human thought, including "learning" and "solving problems," it is referred to as "AI." Learning is an important feature of machines. As a result, ML is considered a branch of AI. Figure 4 displays the early studies that led to the development of DL. DL involves the examination of deep artificial neural networks. A neural network (NN) with multiple layers is referred to as "deep." There are multiple hidden layers in a deep network, whereas there is only one in a shallow network.

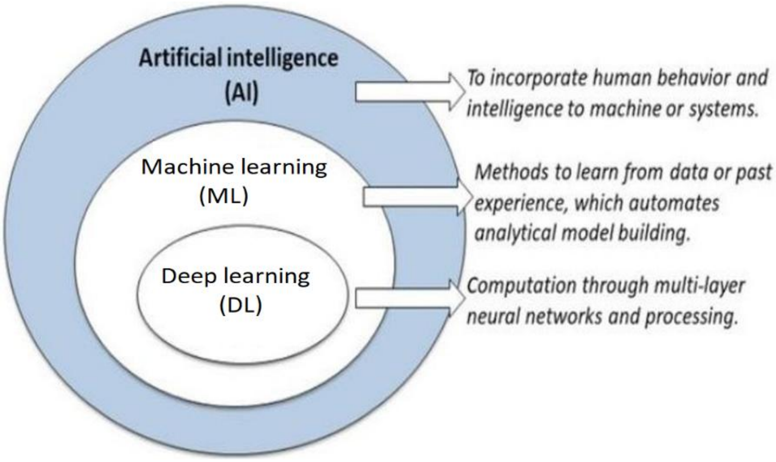

Figure 4. Artificial intelligence.
Source: Sarker [26].

3.1. Machine Learning

The practice of enabling machines to acquire knowledge without the necessity for explicit computer programming is known as ML. ML is primarily concerned with developing computer software that can access data and be used for educational purposes. It is the capacity of machines to engage statistical strategies and intricate algorithms to create more robust predictions and to replace rule-based systems with data-driven systems. Data, which is the foundation of any model, is the most important component of ML. The more relevant the data, the more specific the projections. Following the data, we must choose an algorithm based on the problems to make more accurate forecasts. There is potential for ML to be applied in numerous industries, including finance, retail, and healthcare.

ML algorithms come in a spectrum of shapes and sizes. They can be utilized for a variety of tasks. ML technologies are divided into three categories based on their objectives, which differ from one another. They consist of three types of learning: reinforcement learning, supervised learning, and unsupervised learning. As illustrated in Figure 5.

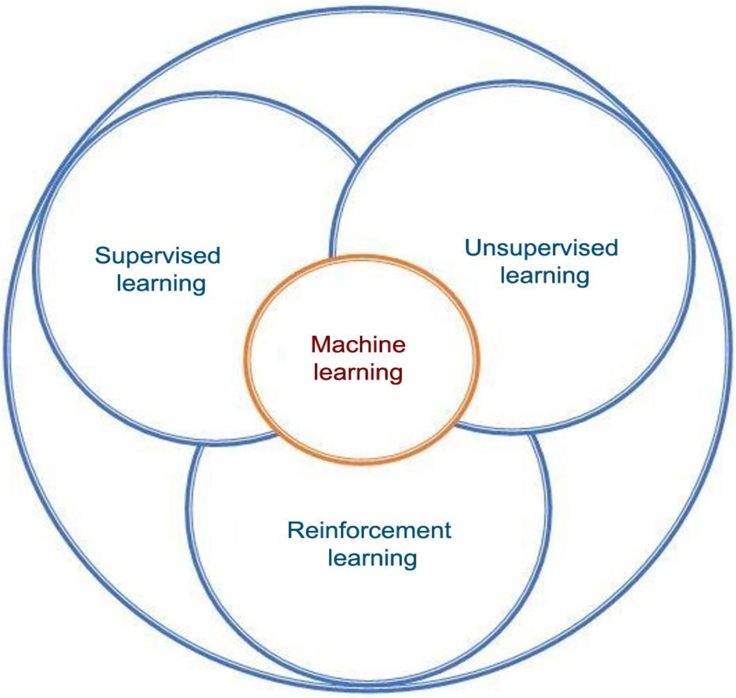

Figure 5. Algorithm of ML.
Source: Musa, et al. [27].

Supervised learning requires the training of a model on labeled data and then applying the trained model to develop forecasts; fresh data is required. It entails dividing data into two groups: a training set and a testing set. The model is first trained only within the training dataset, and then its efficiency is assessed only within the test dataset. Performance indicators can be used to assess the model's functionality. The issue of supervised learning can be classified as such. In supervised classification, the labeled value is discrete. Formulas in this section are utilized to categorize the problem into the appropriate class and category.

On the other hand, supervised regression uses models to predict outcomes based on continuous (numeric) data. For classification of raw data, the information must first be selected, and all NA values are required to be deleted during preprocessing.

The data is then standardized using a z-score or other methods. After normalization, an attribute selection technique is used to choose the best attributes. After you've decided on the features, the raw information is classified using supervised ML with algorithms like decision trees (DT), neural networks (NN), support vector machines (SVM), and ensemble approaches (EA).

Unsupervised learning is comparable to supervised learning in that it entails data training, but the entitled value or specific worth is unknown. In this case, the machine attempts to cluster alike types of information by uncovering a concealed trend.

The primary purpose of unsupervised learning is to determine patterns rather than make predictions. Because the labeled value is missing, the model's performance in unsupervised learning cannot be assessed. Association Rule Mining, K-means clustering, Topic Modeling, and one of the methods used in unsupervised learning are dimensionality reduction techniques.

Semi-supervised learning: Because supervised learning utilizes labeled data as well as unsupervised learning uses unlabeled data, labeled data loses a lot of information that can be acquired from unlabeled data. It's a mix of supervised learning and unsupervised learning that takes both unlabeled and labeled data into account. When compared to unclassified data, classified data must be shorter.

The premise underlying semi-supervised learning is that combining classified and unclassified data results in a significant improvement in performance. The training data set is of brief duration. It's typically employed to detect outliers.

Reinforcement learning is completed by creating a system that boosts overall effectiveness by receiving responses from participants and taking measures to enhance it.

It is the action of interacting with and learning from the surroundings because it lacks the support of humans. It's a methodical procedure.

3.2. Models of Machine Learning

The utilization of useful information in labeled data underpins supervised learning. In supervised learning, classification is the most common activity; nevertheless, manually labeling data is costly and time-consuming. As a result, the primary obstacle to supervised learning is the lack of sufficient annotated data.

Unsupervised learning, on the other hand, recovers valuable characteristic information from unannotated data. Creating training materials is much easier with unsupervised learning strategies; however, they typically underperform in terms of identification compared to supervised learning methods. Figure 6 portrays the most common ML techniques employed in healthcare.

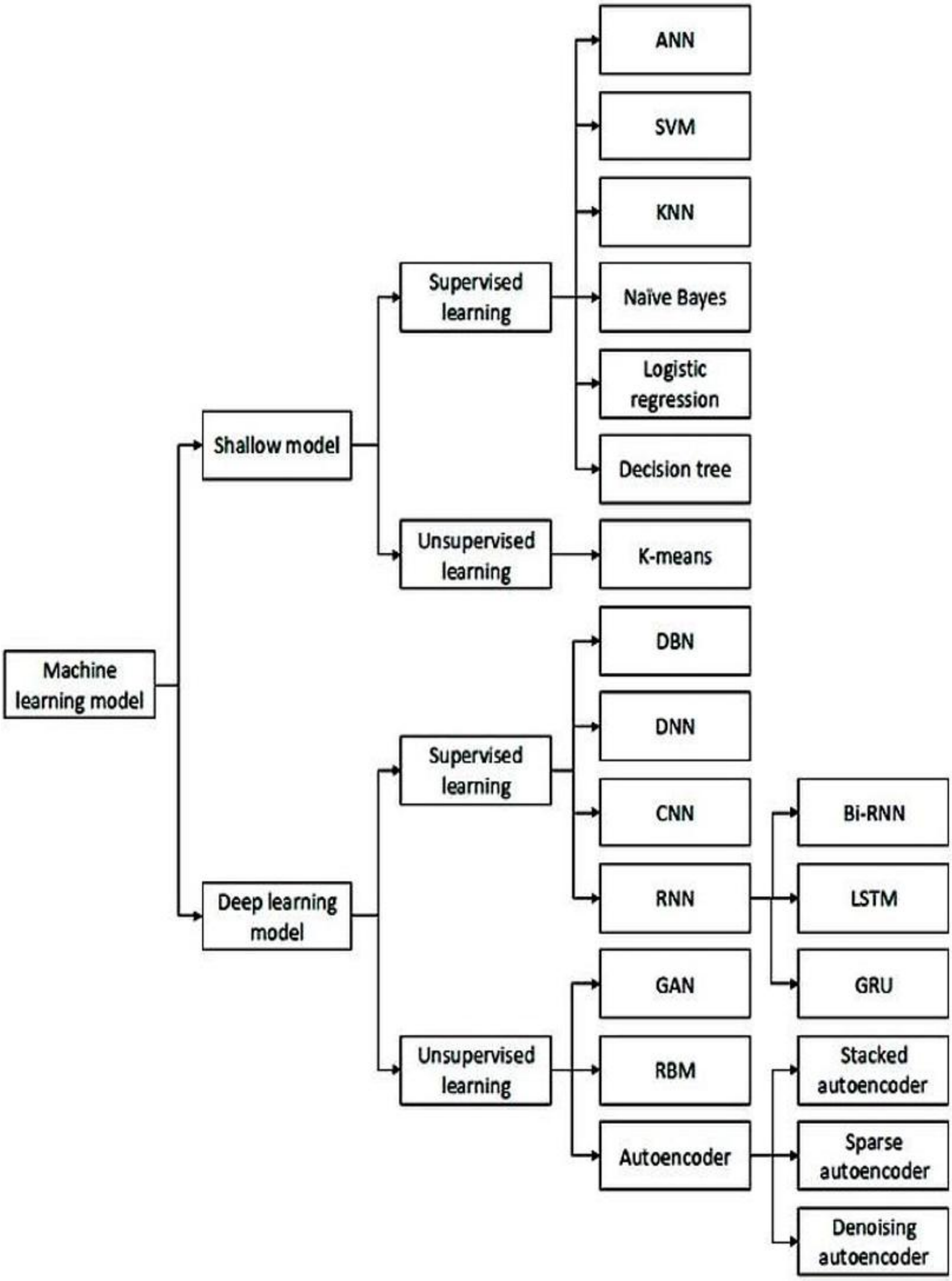

Figure 6. ML techniques of several kinds.

Source: Liu and Lang [28].

3.2.1. Shallow Models

Artificial neural networks (ANN), decision trees, K-nearest neighbors (KNN), support vector machines (SVM), logistic regression (LR), naive Bayes, clustering, and mixed or hybrid approaches are among the conventional (shallow models) ML models for healthcare. Some of these solutions have indeed been studied for decades and have well-developed methodologies. Their concerns extend beyond the detection impact but also include practical issues such as data management and detection efficiency.

Neural Network Artificial (ANN): is engineered to work similarly to how human brains function. An ANN is made up of several concealed layers, an input stage, and an output stage. The elements in adjacent strata are totally interrelated. An ANN consists of a vast quantity of units and may potentially estimate any function; as a result, it has a good fitting ability. Training ANNs takes a long time because of the complicated model arrangement. The backpropagation algorithm, which cannot be utilized to train (DN), is used to instruct ANN models. As a result, an ANN is a shallow model that differs from DL models.

Support Vector Machine (SVM): In SVMs, the objective is to identify a maximum-margin isolation hyper-plane in the n-dimensional attribute space. Thus, because the segregation hyper plane is controlled by a finite number of SV, SVMs are also able to generate satisfying outcomes using limited training data. SVMs, on the contrary, are prone to the surrounding noise in the hyper plane. SVMs are quite good at resolving linear issues. It is common practice to use kernel functions with nonlinear data. A kernel function that moves the old space into the new space can be used to partition the original nonlinear data. Kernel trickery is common in SVMs and several other ML algorithms.

K-Nearest Neighbor (KNN): The varied assumption is the cornerstone of KNN. If the majority of a sample's neighbors all belong to the identical group, because the classification result is restricted to the top k nearest neighbors, the sample is probably from that class as well. The efficiency of KNN models is highly dependent on the parameter k. The likelihood of overfitting increases with model complexity, which decreases with k. Conversely, the larger the k value, the more compact the model and the worse its capacity to fit.

Naïve Bayes: conditional probability as well as the notion of trait self-sufficiency are the cornerstones of the Nave Bayes process. The conditional probabilities across distinct classes are calculated by the Nave Bayes classifier for every instance. The sample has been assigned to the maximum probability class. As indicated in Formula, the conditional probability calculation is done (1).

$$P(X = x \mid Y = c_k) = \prod_{i=1}^{n} p\left(X^{(i)} = x^{(i)} \mid Y = c_k\right) \tag{1}$$

The Naive Bayes method achieves the best results when the trait independence hypothesis is satisfied. Unfortunately, in reality, the assumption is hard to fulfill; as a consequence, the Naive Bayes algorithm performs poorly concerning attribute-based data.

Logistic Regression (LR): The logarithm linear model LR is a type of generalized linear logarithm. As shown in Formula (2), the LR algorithm computes the probabilities of separate classes using a parametric logistic distribution.

$$P(Y = k \mid x) = \frac{e^{v_k N_x}}{1+\sum_{k}^{N_1} e^{v_k + x}} \tag{2}$$

Where k is equal to 1, 2, K1. A maximum likelihood class is assigned to sample x. The construction of an LR model is simple; therefore, model training is quick. However, LR struggles to handle nonlinear information, which restricts its usefulness.

Decision tree: The model uses a set of rules to classify data. It resembles a tree, making it simple to comprehend. The decision tree method can automatically filter out features that are irrelevant or redundant. Tree generation, feature selection, and tree pruning are all part of the learning process. When training a decision tree model, an algorithm chooses the best attributes one by one and creates sub-nodes stemming from the root node. Several decision trees are utilized in some complex algorithms, including XGBoost and the random forest.

Clustering: Is founded on the theory of similarity, which group extremely comparable data within the same bunches while categorizing data that is more dissimilar into distinct bundles. Clustering is unsupervised learning that differs from classification. Clustering techniques don't necessitate any prior knowledge; hence, the data set process is very simple. When using clustering methods to identify attacks, however, external information is required.

One popular method for clustering is K-means, with K denoting the same quantity of clusters and averages denoting the attribute means. The K-means algorithm uses distance as a criterion for semantic similarity. The two data objects that are closer to one another are more likely to be grouped within the same cluster. Although the K-means algorithm adjusts suitably for linear data, the results on non-convex data are less than optimal. Furthermore, the K-means algorithm is impacted by the parameter K and the initialization circumstances. As a result, several repeated tests are necessary to ascertain the correct parameter value.

3.2.2. Deep Learning Models

The DL methods are composed of a variety of deep networks. (RBMs), (GANs), and autoencoders are supervised learning methods, while (DBNs), (CNNs), (DNNs), and (RNNs) are unsupervised learning methods. From 2016 to the present, the number of studies on DL-based healthcare has increased dramatically. DL models learn feature representations directly from the source data, including text and images, eliminating the need for manual feature engineering. As a result, DL approaches can be utilized from start to finish. DL methods have a significant advantage over shallow models when dealing with large datasets. Network architecture, hyperparameter selection, and optimization techniques are the main areas of research for DL.

Autoencoder: As shown in Figure 7, an autoencoder is made up of two symmetrical components: an encoder and a decoder. The encoder collects attributes from the data, while the decoder reassembles the information based on the features extracted. The divergence between both during training, the input of the encoder and the output of the decoder, is successively reduced. With the help of the features that were extracted, the decoder can recreate the data; this signifies that the encoder's features represent the essence of the data. It's important to note that using supervised data is not required for this entire process. Sparse autoencoders [29-31] and denoising autoencoders are two well-known types of autoencoders.

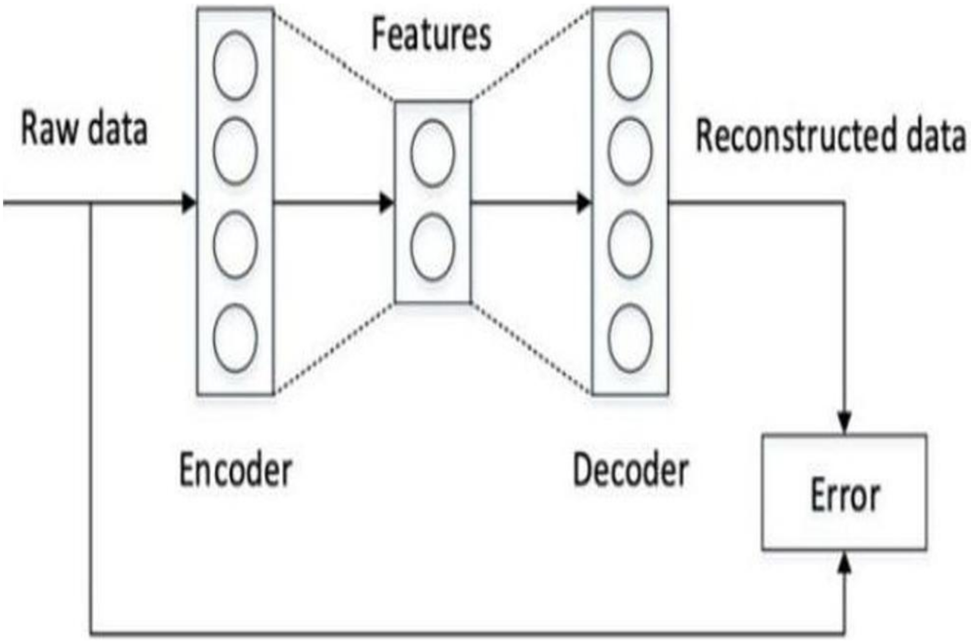

Figure 7. The auto-encoder structure.

Source: Liu and Lang [28].

Restricted Boltzmann Machine (RBM): An unranked neural network with Boltzmann distribution segments is known as an RBM. There are two layers to an RBM: one visible and one hidden. As seen in Figure 8, segments in the same layer are not connected, but segments in different layers are. A visible layer is denoted as VI, and a hidden layer is denoted as HI. RBMs do not differentiate between forward and reverse directions; hence, the weights are the same in both directions. RBMs are unsupervised learning models that are commonly used for feature extraction or denoising and are trained using the divergence algorithm [32].

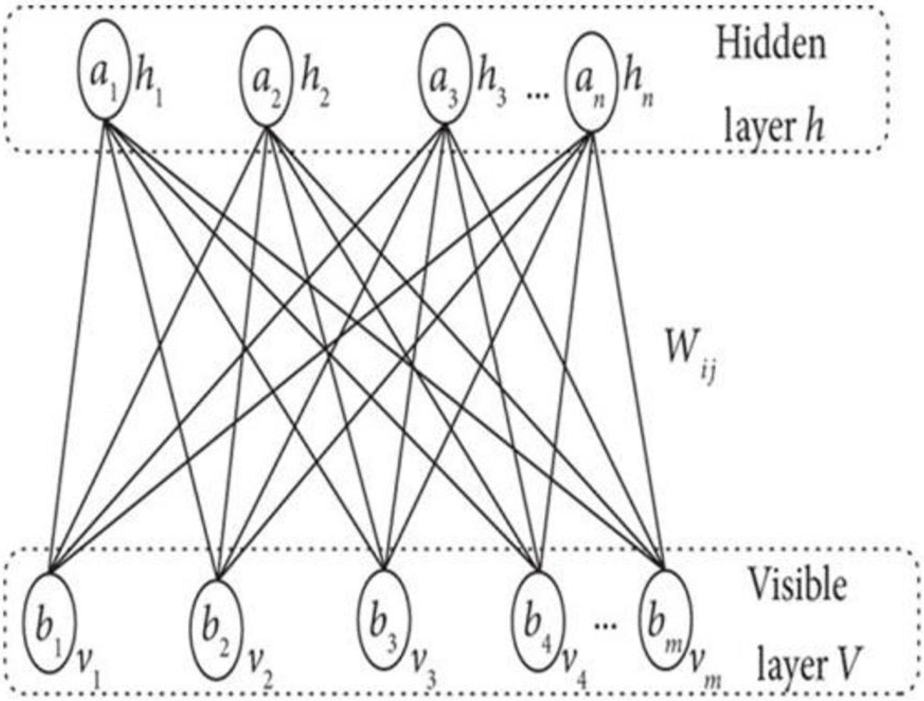

Figure 8. The RBM structure.

Source: Chu, et al. [33].

Deep Brief Network (DBN): Shown in Figure 9. A DBN consists of a softmax classification layer and many RBM layers. Supervised adjusting and unsupervised pertaining to DBN training [34, 35]. Each RBM is first trained with greedy pre-training layer-wise. Using labeled data, a softmax layer's weight is subsequently calculated. DBNs are employed in identifying attacks both for classification and feature extraction [36-38].

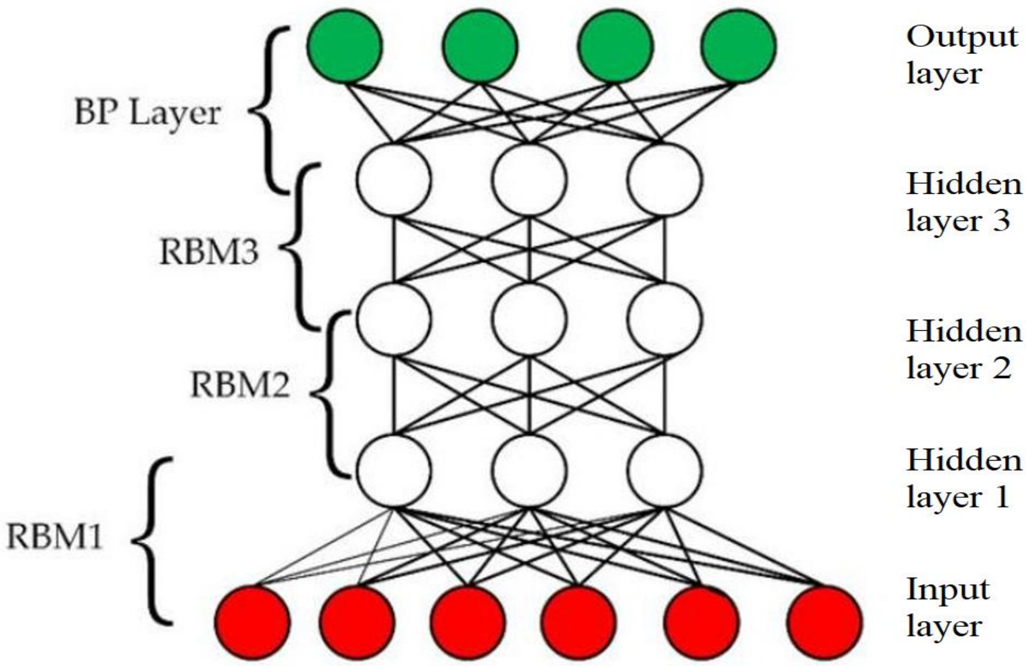

Figure 9. The DBN structure.

Source: Chen, et al. [39].

Deep Neural Network (DNN): DNNs with several layers can be built using fine-tuning and a layer-wise pretraining technique, as shown in Figure 10. A DNN's parameters are learned first and employ unlabeled input for unsupervised learning and labeled data for supervised learning to fine-tune the network. The impressive performance of DNNs is primarily attributable to the unsupervised learning phase.

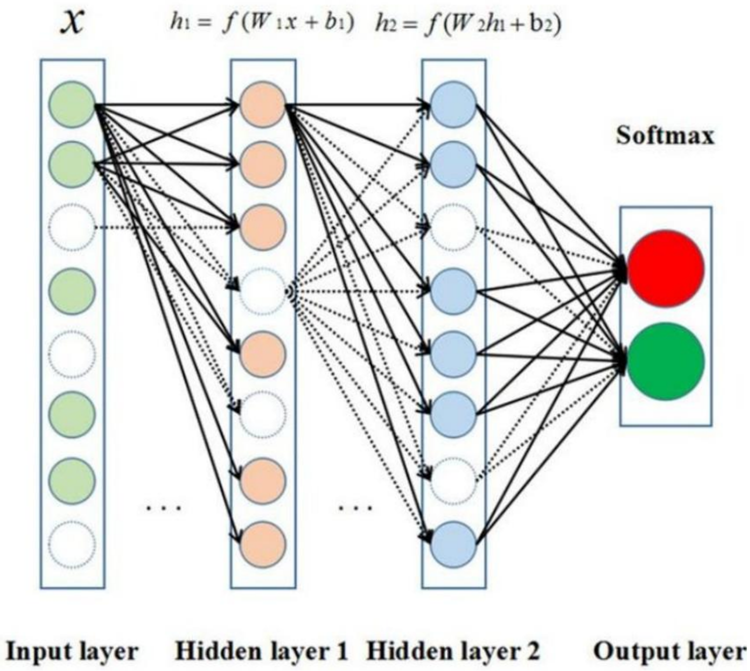

Figure 10. The DNN structure.

Source: Bai et al. [40].

Convolutional Neural Networks (CNNs) are designed to simulate the visual system of humans (HVS). As a result, they have made significant progress in the field of computer vision [41-43]. As demonstrated in Figure 11, layers of pooling and convolutional architecture alternate in CNNs. The pooling layers are used to enhance feature applicability in general, while the convolutional layers are used to extract characteristics. Because CNNs operate with two-dimensional data, the data input needs to be converted into matrices in order to detect attacks.

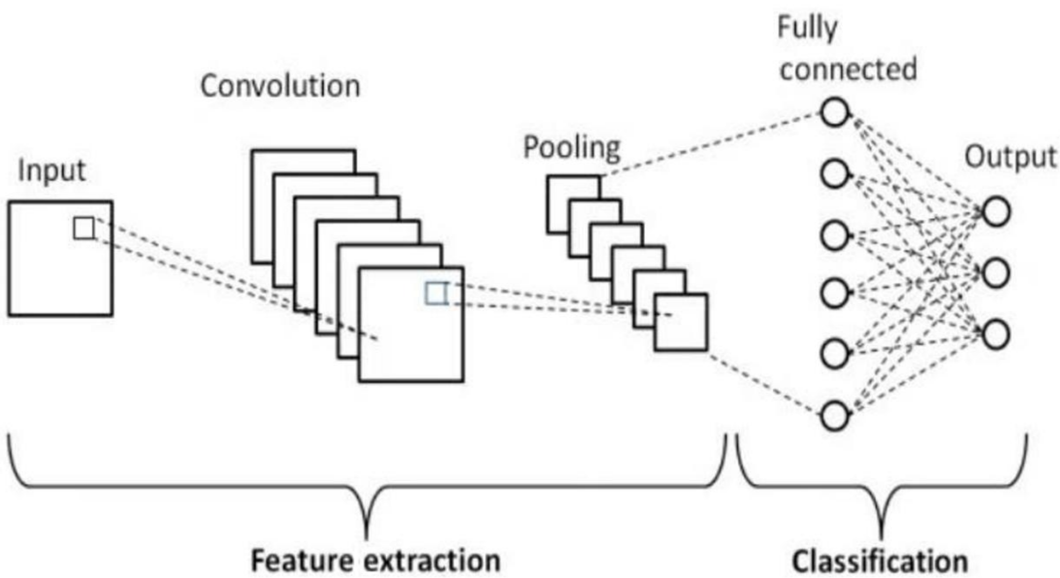

Figure 11. The CNN structure.

Source: Gurucharan [44].

Recurrent Neural Networks (RNN): are networks with data flow that are commonly utilized in NLP, natural language processing [45-47]. Sequential data has contextual properties; examining a sequence's isolated data doesn't make much sense. To acquire contextual information, each component in an RNN obtains not just the present state but also previous states. Figure 8 depicts the architecture of an RNN. In Figure 12, every W item is identical. RNNs suffer disproportionately from vanishing or bursting gradients as a consequence of this property. In actuality, usual RNNs can only deal with brief segments. Numerous RNN iterations have been suggested to address the issue of long-term reliance (GRU) [48], LSTM [49], and bi-RNN [50].

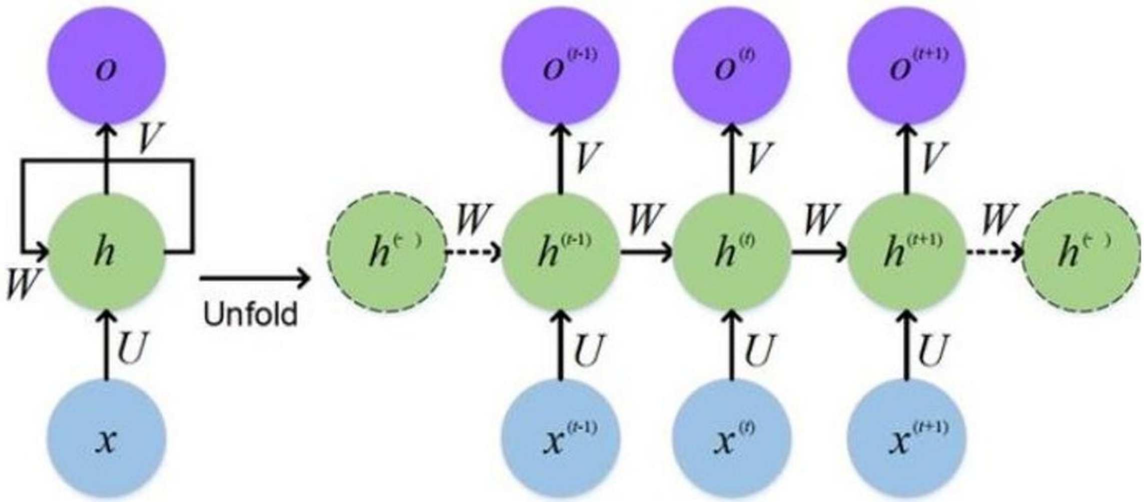

Figure 12. The RNN structure.

Source: Mao and Sejdić [51].

Generative Adversarial Network (GAN) is a kind of adversarial network. GAN models consist of two sub-networks, a generator and a discriminator. The discriminator's objective is to distinguish between genuine and synthetic data, whereas the generator seeks to create synthetic data that appears to be actual data. Consequently, the two work well together. GANs are a popular field of study right now, and they are employed to supplement data in assault detection; this is beneficial to lessen the problems of healthcare shortages of datasets. Conversely, by incorporating adversarial samples into the training set, GANs, a type of adversarial learning algorithm, can increase the accuracy of model detection.

3.3. Shallow Models Compared to Deep Models

ML is a subfield of DL, and in most cases, the results of DL designs outperform those of classic shallow models (or ML) methods. The following elements mostly reflect the distinctions between shallow and deep models.

- Running time: Both running time includes the time for testing and training. Because deep models are so much more sophisticated than shallow models, they require a lot more time to train and evaluate.
- Number of parameters: Hyperparameters and learnable parameters are the two categories of parameters. The hyperparameters are set by hand before training begins, and the learnable parameters are determined throughout the training phase. Deep models have considerably more hyperparameters and learnable parameters than shallow models; hence, deep model optimization and training take more time.
- Feature representation: Characteristic extraction is input to typical ML models, and characteristic extraction is a necessary step. DL models, on the contrary, can identify visual characteristics from unprocessed data without requiring feature engineering. DL algorithms can run end-to-end, providing them with a substantial advantage over typical ML algorithms.
- Learning capacity: DL methods have complicated architectures and a large number of components (millions or more). As a result, DL models are superior at fitting shallow learning models. DL learning models, on the

contrary, are more prone to overfitting and require a substantially large quantity of data during training. DL models, on the contrary, have a better effect.

- Interpretability: The DL model consists of black boxes with nearly impossible-to-understand results, which is a significant aspect of DL. Conventional DL algorithms like Naive Bayes, on the contrary, possess a high degree of interpretability.

4. ARTIFICIAL INTELLIGENCE-BASED HEALTHCARE

There is a wealth of information regarding patient health, just as there is in the healthcare industry. As a result, humans are unable to digest it. Consequently, ML provides a process for finding patterns in vast amounts of data and applying algorithms to forecast future patient outcomes. In healthcare, ML helps consumers perceive the effectiveness of current programs and recognize the treatment that provides the greatest results according to the state of the patients. When used in conjunction with WSNs, IoT generates a massive volume of data, which the network architecture must handle.

The way to address these problems is to adapt old network architecture to the most recent network analysis standards, which assures maximum safety [19]. Clinics, hospitals, and other care facilities require a single economical network architecture that conforms to data security laws while also being simple to use and operate. The primary disease categories addressed in the AI research are shown in Figure 13.

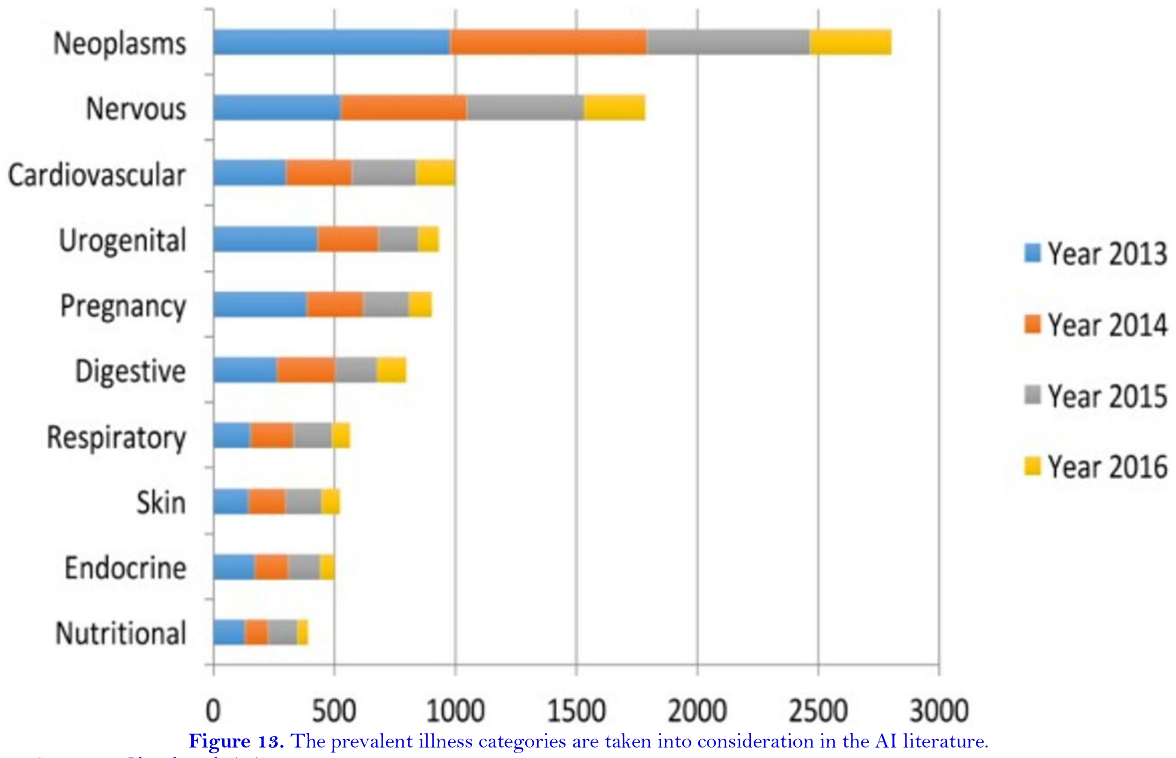

Figure 13. The prevalent illness categories are taken into consideration in the AI literature.
Source: Ghazal, et al. [19].

AI would open the way for a new era in medicine (AI). This is the first word that the researcher discusses in his paper [52]. The proposed artificial neural network (ANN)-based method of pathology detection from diagnostic images is provided. The exploration outcomes for building an NN model to forecast the spread of medical diagnoses are also shown. Our indicator is based on an excellent methodology with a complex design that learns via ANN using model preparation. The training phase has utilized standard image data collection. The suggested method of diagnosis is highly accurate and stable, and it can be utilized for initial diagnosis. It can automatically identify diseases using human physiological characteristics, which lowers labor costs. This review document provides a summary of the state of all systems for the radiology-based diagnosis and detection of COVID-19 as well as its DL-based processing. The results show that DL-based models have a remarkable ability to provide a precise and efficient method for the identification and treatment of COVID-19, the application of which would significantly improve specificity and sensitivity values during the processing of modalities [53]. This review provides a synopsis of the state of all systems for the radiology-based diagnosis and detection of COVID-19 as well as its DL-based processing. The results show that DL-based systems have a remarkable capacity to provide an accurate and efficient method for the identification and treatment of COVID-19, the application of which would significantly improve specificity and sensitivity values during the processing of modalities. (EfficientNet, VGG-19, MobileNetV3, Xception, ResNet50V2, InceptionV3, VGG-16, InceptionResNetV2, NASNetLarge, and DenseNet201) were used to extract features from various data classes. DenseNet201 outperformed the other 10 models in terms of diagnosis and classification. Finally, using this cutting-edge technology, a model was developed and presented. The accuracy, sensitivity, and specificity of this DL-based model were 99.85%, 99.52%, and 99.89%, respectively. The proposed method could help distinguish between benign and ALL occurrences. Hematologists and lab personnel can also benefit from this process by using it to identify ALL subtypes before they choose the best course of action for each subtype [54]. Outpatient care and inpatient care may now be closely monitored thanks to technological advancements in healthcare technology. Without needing to be in the same room as the patient, healthcare providers can monitor and assess physical and vital signs reactions to past treatments using remote patient monitoring (RPM). The device that is used is determined by the patient's health. It could be a heart implant, a networked blood glucose meter, or an airflow monitor, for example. The equipment in question gathers the information required. If the values are incorrect, the data is sent to a database as a recording as well as to the treating clinician at the same time. The doctor may be able to examine the real-time data and respond accordingly.

4.1. Health-Care Data Set Types

Sensor data, omics data, clinical data, and other types of data are all being used in healthcare these days. This type of data necessitates the use of various mining techniques to extract the most relevant elements, followed by the training of different algorithms for positive future predictions.

Sensor data: Consists of data items produced by sensors, such as signals in the time series, which consist of an ordered list of pairs. Computing equipment processes these data elements, which can be categorical values, simple numerical values, or more complicated data.

Clinical data: Refers to information gathered during a patient's ongoing treatment, such as laboratory tests, radiological imaging, allergies, and so forth.

Omics data: A massive collection of complicated and high-dimensional data that includes genomic, transcriptomic, and proteomic information. Various strategies, including ML algorithms, are necessary to handle this type of data.

Genomic Data: It is used in bioinformatics to collect gene expression, copy number variation, sequence number, and DNA data.

Transcriptomic data: A biological sample that contains a collection of numerous mRNA transcript data. These samples are analyzed and extracted to create various datasets.

Proteomic data: A class of proteins expressed within an organism, tissue, or cell. It is a depiction of the actual, active chemicals in the cell.

4.2. Health-Care Dataset used for Deep Learning

This section highlights datasets that have been used to test various DL models in e-health and disease detection. The most commonly utilized cancer or healthcare dataset for DL techniques is shown in Table 1. The CNN method has the most implementations in various databases, as seen in Table 1.

Table 1. Shows the most used healthcare for DL.

Paper number	Dataset	CNN	RNN	DNN	DBN	KNN
P1[55]	Bonn University dataset	□				
P2[56]	PPMI, SNUH	□				
P3[57]	Electronic health record dataset		□			
P4[58]	INBreast	□				
P5[59]	DDSM	□				
P6[60]	Dataset related to the popular illness concepts from WebMD, Medline Plus and everyone healthy					□
P7[61]	e-ophtha, MESSIDOR, and DIARETDB1	□				
P8[62]	INCART, SVDB, and MIT-BIH			□		
P9[63]	film-screen mammography and digital mammogram datasets	□				
P10[64]	Gastric cancer dataset	□				
P11[65]	Lung image database consortium and image database resource initiative	□			□	
P12[66]	Dataset III from BCI, Dataset 2b from BCI	□				□
P13[67]	MITOS12, TUPAC16	□				
P14[68]	LUAD, STAD, BRCA			□		
P16[69]	Myelin and T1w	□				
P17[69]	BRATS	□	□			

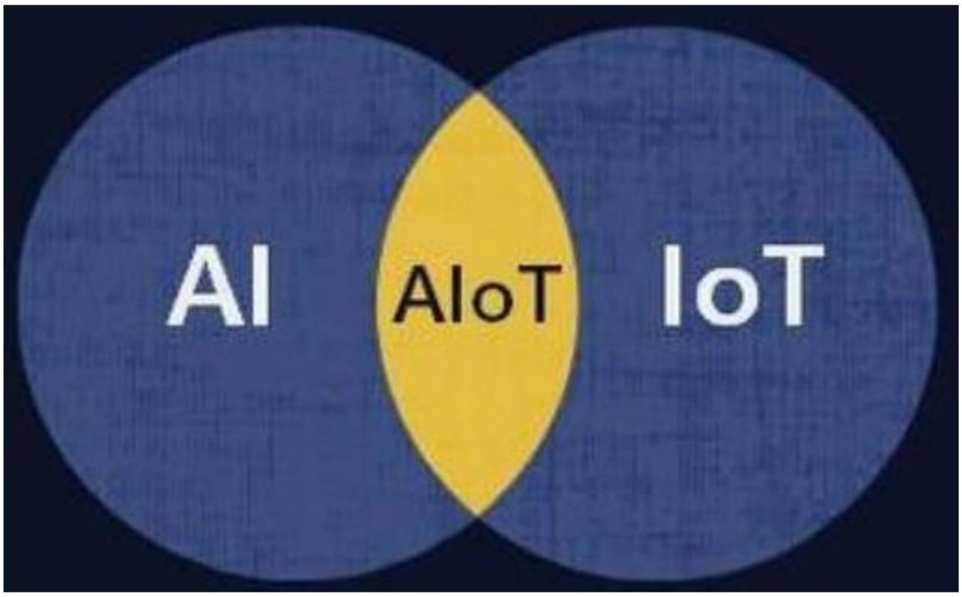

Figure 14. Integration of AI and IoT.

Source: Khachnaoui, et al. [56].

5. INTEGRATION OF AI AND IOT

As Figure 14 shows, in order to facilitate automated diagnosis, improve decision-making for medical practitioners, and enable real-time health monitoring, this study investigates the application of AI-integrated IoT technologies in the healthcare industry. Using cutting-edge technologies like cybersecurity, cloud computing, machine learning, and computer vision, the goal is to create a sustainable healthcare ecosystem. It focuses on creating intelligent healthcare infrastructure that aligns with Industry 4.0 objectives and provides professionals, researchers, and students with information on how to use cutting-edge technology to enhance public health management and medical outcomes [70]. Breathlessness and fever are the main and most common effects of COVID-19, according to research reports. As a result, it is critical to keep track of vital signs like temperature, respiration, heart rate, and blood oxygen saturation. To triage and prioritize the situation of COVID-19 patients within the emergency department, our team conceived and constructed a wrist-worn wearable device that continuously monitors critical vital signs (Figure 15). The team's first goal is to retrain the algorithm using new data from COVID-19 patients who attend the AHEPA emergency room. Then, in addition to training the models to respond effectively when unknown data is captured, an anomaly detection function will be included. Implementing the neural network using the EONTM Compiler could also result in a further on-device speed boost. For unoptimized deployment to shorten the inferential duration, (ROM) & (RAM) utilization while retaining high accuracy, a formal COVID-19 symptom questionnaire with ESI triage protocols will be implemented into the physician's mobile application to be developed. The proposed strategy for evaluating respiration and, by extension, the wearable device is in line with the semiconductor industry's groundbreaking approach to investing in AI and Integrated Circuits (ICs).

Furthermore, market research studies predict that by 2025, the predicted multiplier growth rate (CAGR) with AI ICs will be 5 times larger than that of the traditional IC business. One of the key reasons for this trend is that it is more efficient to continually run AI locally for increased bandwidth sensors, including PPG, than to transmit data across a radio program to expensive, unstable, and energy-hungry cloud systems. Our unique technique incorporates this strategy while intelligently avoiding the aforementioned drawbacks [71].

Figure 15. Enclosure for the device.
Source: Neetha and Narayan [71].

In paper, the visual score is currently used to evaluate anomalies/abnormalities related to COVID-19. Chest Computerized Tomography (CT) imaging is becoming indispensable for staging and controlling coronavirus illness 2019 (COVID-19). Clinicians will benefit greatly from the development of autonomous approaches for quantifying COVID-19 anomalies in CT scans. A characteristic of COVID-19 on lung CT scans is the presence of ground-glass opacification in the lung area, which is difficult to segment manually. Anam-Net, a lightweight CNN based on anamorphic depth embedding, is proposed to segment abnormalities in COVID-19 lung CT images. In comparison to the government UNet (or its variants), the suggested model has 7.8 times fewer variables, making Anam-Net portable and able to draw conclusions on platforms with limited resources (point-of-care). The results of various studies using chest CT scans (test cases) demonstrated that the suggested method could produce a good Dice matching score for diseased and normal lung regions. Attention UNet, Anam-Net has been compared to various cutting-edge architectures such as ENet, LEDNet, SegNet, UNet++, and DeepLabV3+. To show its appropriateness, the intended Anam-Net was deployed on embedded systems like the Raspberry Pi 4 and NVIDIA Jetson Xavier for point-of-care platforms, as well as a smartphone Android app (CovSeg) embedded within Anam-Net. The Model B Raspberry Pi 4 is by far the most recent generation of the Raspberry Pi line of small dual-display computers. In comparison to the Model B Raspberry Pi 3, it is a reduced embedded device with greater connectivity, larger memory, and processing speed. The Model B Raspberry Pi 4 embedded system costs $50 in total.

The learned Anam-Net models are transformed using PyTorch into the TensorFlow Lite version to integrate the Anam-Net on the Raspberry Pi 4. A more compact version of TensorFlow is called TensorFlow Lite, which allows you to execute DL models on mobile IoT and embedded technology (Figure 16). It functions as a speed increaser, reducing the time it takes for models to infer on embedded devices. On the Raspberry Pi, an Anam-Net model in the TensorFlow Lite version took 23.3 seconds to infer, whereas the UNet model in the TensorFlow Lite format took 43.3 seconds to infer. For Android, we currently only provide PyTorch Lite; thus, there is no official support for Raspberry Pi in PyTorch. We can see that the model translation between TensorFlow and PyTorch using external tools is the cause of the long deduction time in the tens of seconds [72].

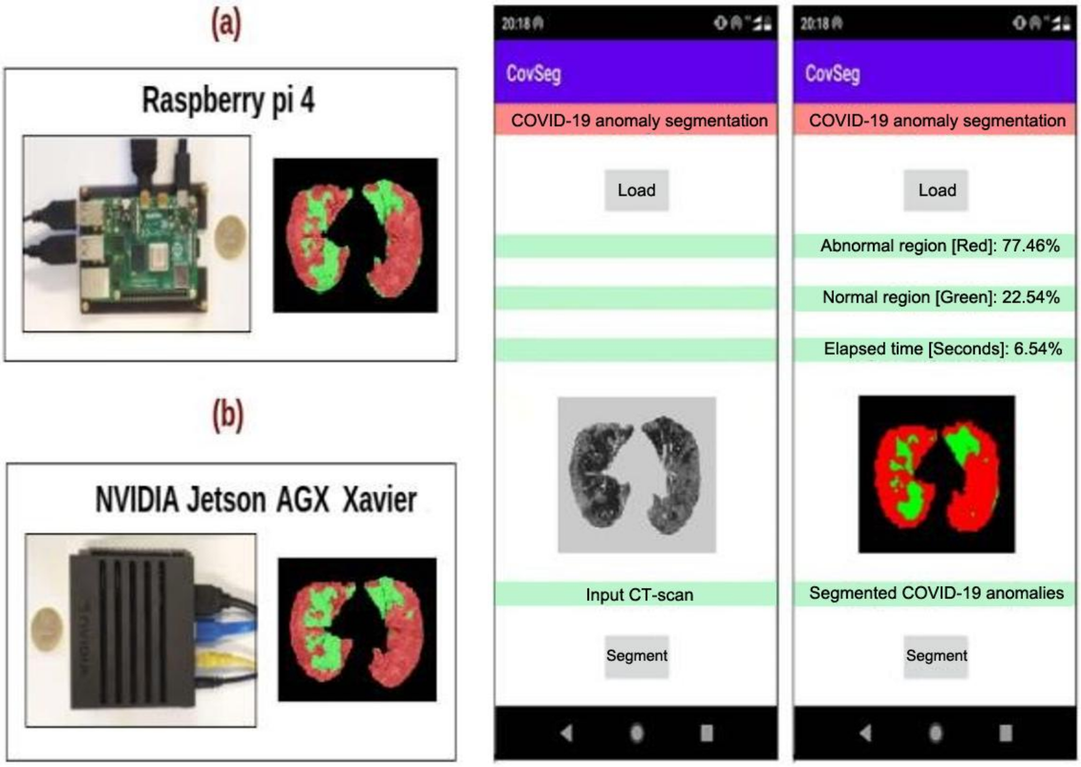

Figure 16. Hardware for implementing the suggested Anam-Net in platforms for point-of-care to detect irregularities related to COVID-19.
Source: Fyntanidou, et al. [73].

In this paper, remote monitoring is a valuable tool for providing at-risk groups with preventative treatment and early intervention. Because of recent improvements in IoT technologies, these surveillance methods are now available, allowing for omnipresent monitoring. Due to the essential conditions of patients in observation, these frameworks demand a level of craftsmanship in features including accessibility and precision. Because a huge amount of information is available, DL approaches are particularly promising in this kind of healthy application to achieve good performance. These strategies are best put in cloud servers within a centralized IoT system powered by the cloud Figure 17. But still, the quality of an internet connection has a significant impact on the reaction time and availability of these services.

Due to their restricted computational capabilities, smart gate devices, nonetheless, are unable to implement deep learning ideas into practice. As a result, we use an ECG classification case study to demonstrate the proposed CNN-enabled framework. In this case, decision-making occurs on the edge, with the user receiving a signal if a disease is detected. First, we compare HiCH's response time and reliability against a standard IoT-based system in which all calculations are performed in the cloud. Because decisions are made locally, the accessibility of an IoT-based application is significantly improved if Internet access is disrupted or connectivity is lost.

The accuracy of HiCH is then assessed, which demonstrates the correctness of making decisions at the start of the observation as well as its development over time. To train and evaluate the classification system, we mimic a node for sensors using the arrhythmia database at MIT. The ESP8266-12E WiFi module, which includes an 80MHz 32-bit RISC microprocessor, 96KB RAM, and 4MB QSPI flash memory, is used as a sensor node simulator. The WiFi module connects to a WiFi network on the local network, and the microprocessor can read MicroSD cards through SPI. The data from the ECG is saved on a micro memory card. Configure the sensor node to read 3600 EKG specimens from files on a Micro SD card for more than a 10-second interval and deliver it to the edge device via a POST uploading request.

The edging machine is a Linux system that runs Apache, PHP, and Python interpreter amenities. This PHP script is given a sample from the sensor node's file and runs Python code to analyze the information and reach conclusions. The result of decision-making is contained in the response to a POST request. We undertake a comparable approach on the cloud computing device, which would be a VPS with the same operating system and services, to compare HiCH and the standard IoT-based framework. The VPS is powered by two 2.50GHz Intel Xeon E5-2680 v3 CPUs, plus 4GB of RAM, as well as a network speed of 40 Gbps [74].

The Internet of Medical Things (IoMT) is examined in this systematic review, focusing on its numerous healthcare applications, including disease prediction, mobile health, remote monitoring, and cutting-edge technologies like smart patches and UWB radar. It tackles issues related to security, privacy, sensor intelligence, and power efficiency. To improve IoMT reliability, the assessment also recommends technological options such as edge computing, blockchain, and cryptography. It classifies applications, assesses the integration of AI and machine learning, and suggests future research avenues to enhance IoMT's contribution to healthcare innovation [75].

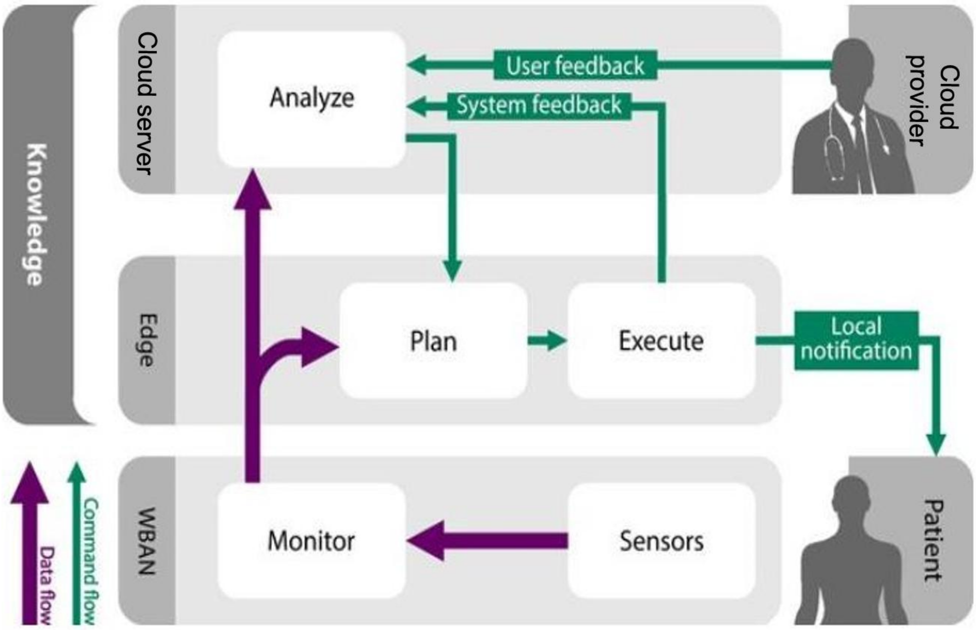

Figure 17. The IoT-based architecture is hierarchical.

Source: Yoo, et al. [69].

6. CHALLENGES AND OPPORTUNITIES

6.1. Challenges

Analysis and data processing utilizing deep learning (DL) produce satisfactory results, as evidenced by current publications. However, before DL is applied to Internet of Things (IoT) applications, several issues must be resolved.

1. Data Collection: DL algorithms rely on data sources to perform well. Regardless of whether the model's structure is well-designed, deep modeling cannot be effective if there isn't enough clean data. Consequently, figuring out how to use the data collection equipment is a crucial inquiry for research. The number of sensors utilized and the way they are deployed have an influence on the quality of the data collected. In fact, the information contained in the data holds the key to solving problems. For the entire IoT application workflow, a data-gathering module must be designed.
2. Model Training: Deep network training necessitates time-consuming tasks. As everyone is aware, the DL model's depth dictates how well it can extract important characteristics. However, when models become more complex, the gradient vanishing issue occurs, causing performance to worsen.
3. Hardware Limitation: DL is indeed a strong technique for handling large amounts of data, which necessitates an abundance of technology. It's still difficult to grow a DL model on an embedded device with limited resources. So far, two categories of studies have been conducted in order to overcome the problem. Final devices (like smartphones) should only be treated as data gatherers. To be evaluated, every piece of data is transferred

to powerful servers. However, we may experience data leakage, network failures, as well as other challenges as a consequence of this process. Another option is to minimize the complexity of the networks while sacrificing some execution so that certain educational tasks can be completed with end gadgets.

4. System Design: A new tendency is to create an edge-learning system that includes both devices as well as the edge cloud. Utilizing the edge, cloud-edge systems will reduce latency, enhance security, and use clever data preservation techniques.

6.2. Opportunities

Despite the difficulties, there are still ways to use DL to resolve IoT issues.

- DL allows us to think more freely. We may have been hesitant to enter some new areas in the past and had difficulties when conducting studies due to a lack of associated professional knowledge. We can now make some educated estimates without having to rely on data analysis software. We can gather and process data information via DL. This means that we can start further research with confidence and help advance science and technology.
- Deep architectures are particularly good at representing learning. In conventional methods, features that characterize the qualities of input data were designed manually. Deep learning enables machines to create features on their own. By employing powerful deep models, we can enhance the end system performance and examine connected IoT research from a fresh angle. (RBMs, autoencoders, CNNs, and RNNs). In addition, we may offer completely new IoT applications and contribute to a "smarter" society.

7. CONCLUSION

A survey about using AIoT in the healthcare field was proposed in this paper. In healthcare, a different form of IoT dataset exists. A variety of ML methods, such as supervised, unsupervised, and reinforcement learning, are employed to examine this diversity of data in order to improve prediction and raise productivity, which may be analyzed using various evaluations of performance like sensitivity, accuracy, and specificity. ML techniques are used to analyze different forms of healthcare data, such as sensor data, omics, and clinical data. According to the results of the survey, numerous ML algorithms developed by various authors can be applied to analyze various types of data in healthcare to enhance e-health. Based on the prospects and challenges of using AI and IoT in healthcare, there are promising opportunities to use AIoT in this field.

7.1. Research Gaps

Data Interoperability and Integration: Smooth data integration, particularly between various healthcare systems, is hindered by the lack of standards for data flow between IoT devices and AI systems.

Limitations on Real-Time Processing: Network latency and hardware limitations frequently make it difficult to process the massive amounts of data generated by the Internet of Medical Things in real time.

Privacy and Security: Ensuring cybersecurity and data privacy in AI-IoMT contexts can be challenging, particularly when dealing with private or sensitive health information.

Resource Efficiency: It's still difficult to optimize IoMT devices' power, storage, and processing capabilities for AI.

Scalability of AI Models: Due to varying device capabilities and network conditions, scaling AI models for IoMT applications is challenging, especially in dynamic contexts.

Research in these fields could improve the privacy, scalability, and dependability of AI-IoMT systems.

7.2. Recommendations

The results showed that inadequate instruction for both doctors and nurses was the major element preventing them from utilizing AI instruments in e-healthcare delivery. Therefore, it is recommended that AI training be provided to both doctors and nurses. Since AI tools generated interest and enthusiasm among healthcare professionals, they recommended these tools to their colleagues as well. It is expected that doctors and nurses will apply these tools in their daily practice when providing care or as professional healthcare practitioners. Therefore, using a range of AI tools in assessment, education, and healthcare is advised.

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Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
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