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A Review on the Role of Machine Learning in Enabling IoT Based Healthcare Applications

HEMANTHA KRISHNA BHARADWAJ[1], AAYUSH AGARWAL[1], VINAY CHAMOLA[1,2], (Senior Member, IEEE), NAGA RAJIV LAKKANIGA[3,7], VIKAS HASSIJA[4], MOHSEN GUIZANI[5], (Fellow, IEEE), AND BIPLAB SIKDAR[6], (Senior Member, IEEE)

[1]Department of Electrical and Electronics Engineering, Birla Institute of Technology and Science (BITS), Pilani 333031, India
[2]APPCAIR, Birla Institute of Technology and Science (BITS), Pilani 333031, India
[3]Department of Integrative Structural and Computational Biology, The Scripps Research Institute, La Jolla, CA 92037, USA
[4]Department of CSE and IT, Jaypee Institute of Information Technology, Noida 201309, India
[5]Department of Computer Science and Engineering, Qatar University, Doha 2713, Qatar
[6]Department of Electrical and Computer Engineering, National University of Singapore, Singapore 117583
[7]SmartBio Labs, Chennai 600078, India

Corresponding author: Biplab Sikdar (bsikdar@nus.edu.sg)

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ABSTRACT The Internet of Things (IoT) is playing a vital role in the rapid automation of the healthcare sector. The branch of IoT dedicated towards medical science is at times termed as Healthcare Internet of Things (H-IoT). The key elements of all H-IoT applications are data gathering and processing. Due to the large amount of data involved in healthcare, and the enormous value that accurate predictions hold, the integration of machine learning (ML) algorithms into H-IoT is imperative. This paper aims to serve both as a compilation as well as a review of the various state of the art applications of ML algorithms currently being integrated with H-IoT. Some of the most widely used ML algorithms have been briefly introduced and their use in various H-IoT applications has been analyzed in terms of their advantages, scope, and possible improvements. Applications have been divided into the domains of diagnosis, prognosis and spread control, assistive systems, monitoring, and logistics. In healthcare, practical use of a model requires it to be highly accurate and to have ample measures against security attacks. The applications of ML algorithms in H-IoT discussed in this paper have shown experimental evidence of accuracy and practical usability. The constraints and drawbacks of each of these applications have also been described.

INDEX TERMS Healthcare, Internet of Things, machine learning, diagnosis, monitoring, cardiovascular, neurological.

I. INTRODUCTION

The Internet of Things (IoT) has been the subject of great enthusiasm in the healthcare technology community over the last few years. The healthcare domain is of great practical importance and IoT opens up a wide spectrum of opportunities to make it better. Numerous contemporary medical devices and sensors can connect over various networks, which provides access to important information about patients' conditions. This information can then be used for multiple purposes such as monitoring patients remotely, predicting illness and recovery through the greater insight into symptoms, and generally improving the diagnosis and treatment process via increased automation and portability.

Due to the vast multitude of data generated in real-time by these devices and their complex nature, analysis using ML algorithms has proven to be of vital importance to H-IoT. These algorithms allow us to extract valuable information from the acquired data and draw useful inferences. Though ML models can provide great levels of accuracy when trained in the right environment, this is generally easier said than done. Various contemporary research efforts are aimed at finding out new areas of applications of ML algorithms to H-IoT systems, evaluating their suitability for these systems, and increasing the accuracy achieved by prediction and analysis models.

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Using ML based systems has numerous advantages. They can be trained using large volumes of data, termed as training data, and then, through inductive inference, they can assist clinical practice in assessing risk and designing treatment. These systems can reduce error by eliminating human elements from the system, and can perform repetitive jobs, thus improving efficiency compared to manual efforts. Physicians can be assisted by artificial intelligence (AI) that can learn information related to medical science from textbooks, journals, and clinical practices to consult and provide adequate patient care, which, for humans, is tedious. However, the inferences that a human mind can make are still missing in existing AI techniques. Monitoring, managing, and analysing medical reports become easier with integration of ML with IoT devices. Moreover, ML algorithms can process large sets of biological data and detect specific patterns and mutations involved in various diseases, which can accelerate the discovery of novel therapeutics. Health monitoring services and consulting can also be provided digitally by AI to a certain limit — being entitled as "health bots".

There are a few other studies surveying the role of ML in healthcare-IoT. A very important premise for modern systems is the use of fog and edge computing to reduce server load and low latency responses [1]. Greco *et al.* [2] discussed the gradual shift in the implementation of ML models from cloud towards the fog and edge for healthcare IoT. They discussed this change in architecture across applications such as analysis of physiological parameters and rehabilitation systems. Mutlag *et al.* [3] also discussed the scenario of growth in fog computing in the healthcare IoT domain. Deploying models closer to the end devices allows low latency and independence from network failures. Fog based applications have been thoroughly scrutinized and a spectrum of security implementations have been proposed for it [4]. Farahani *et al.* [5] surveyed various systems for applications such as population monitoring and assisted living. Rong *et al.* [6] reviewed some of the applications of AI in healthcare systems with case studies of epileptic seizures and filling of a dysfunctional urinary bladder. ML has also been used to predict the insurance medical costs as well [7], [8]. Lastly, the recent adoption of ML and blockchain in healthcare, its applications, followed by challenges and privacy concerns have also been surveyed [9], [10].

Although there are works in this direction, they are either too specifically focused on the architecture without consideration of the diversity in algorithms or focus on the model without discussing how the data is coming from the IoT system. Hence, it is necessary to review the various architectures for both the IoT systems and ML models to have a grasp over the recent developments. Through this paper, we have tried to cover this existing gap. The main contributions of this work are enumerated below:

1) An overview of various prominent ML algorithms with particular focus on their applications and use cases in the healthcare-IoT industry has been provided.
2) Detailed reviews of important applications of these algorithms in diagnosing patients with common ailments like cardiovascular and neurological disorders, diabetes, etc. and in automating the diagnosis process have been presented.
3) The role of ML algorithms with IoT architecture in forecasting future stages of diseases and controlling the spread of epidemics has been surveyed.
4) Assistive systems for the aid of the physically challenged, the mentally disabled and the elderly, that have the potential to greatly improve their quality of life, have been identified and reviewed.
5) Futuristic ML-IoT based technologies that promise vast strides in making health monitoring systems more accessible and efficient, as well as technology that improves the overall process of obtaining healthcare has been studied.

The rest of this paper is organized in the following manner, as shown in Figure 1. Section II provides the definition as well as general architecture of standard Healthcare-IoT frameworks. Section III provides a brief overview of the various AI algorithms currently being researched for use in the healthcare industry. Sections IV through VIII extensively cover reviews of the state of the art applications of these algorithms to H-IoT in the areas of diagnosis, prognosis and spread control, assistive systems, patient monitoring, and healthcare logistics, respectively. Finally, section IX provides the conclusion to the paper.

II. GENERAL ARCHITECTURE OF H-IOT

The implementation of IoT in healthcare originated from efforts to develop remote patient monitoring systems. The research on various applications of H-IoT has since been growing consistently, and contemporary research aims at incorporating IoT into various facets of healthcare, including disease spread control, effective automated diagnosis, and improved treatment. In this section, we define what a H-IoT system is, and briefly describe the various components of its architecture. Figure 2 shows the various classifications for different H-IoT applications described in literature.

A. DEFINITION OF H-IOT

A healthcare IoT system can be defined as a network of all available health resources connected to each other for rapid transfer of data between them over the Internet [11]. This means that all healthcare resources like doctors, hospitals, rehabilitation centres and all medical devices and sensors along with the patients become interconnected with each other for continuous real-time data transfer. The various sensors coupled with applications that interpret their readings can detect anomalies and send patient data to medical practitioners/hospitals for diagnosis and analysis, after which corrective action can be prescribed and undertaken. For such a framework to exist and work smoothly, three primary requirements need to be met [12]:

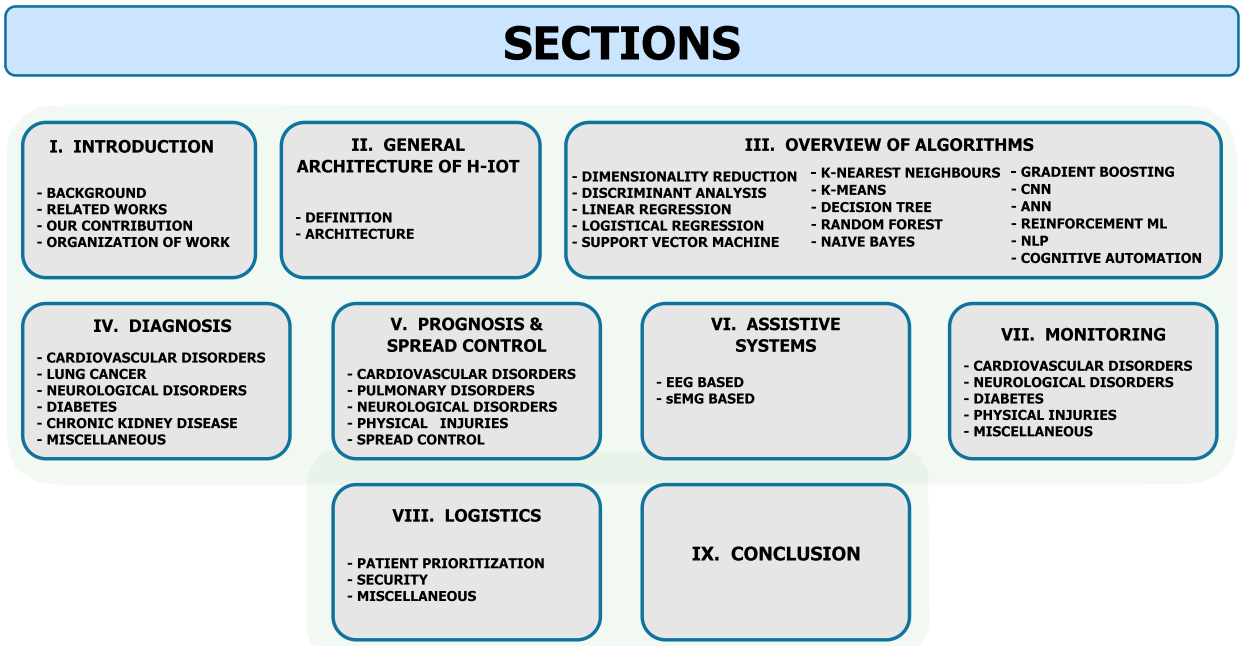

FIGURE 1. Organization of this work.

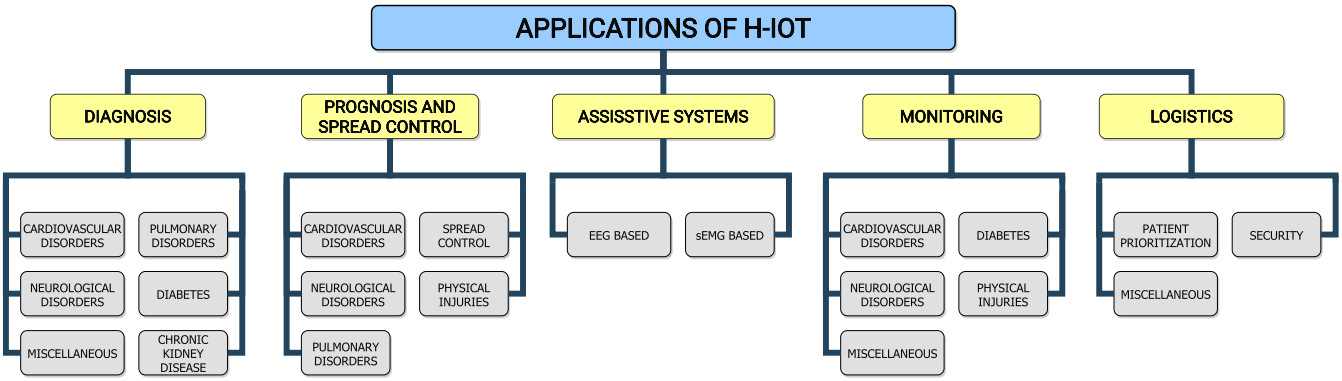

FIGURE 2. Applications of H-IoT.

- **Interoperability**: The wide range of devices being used in the framework should be able to cooperate among each other to enable the desired functionality.
- **Bounded latency and reliability**: For effective handling of emergencies and synchronised analysis of the huge amount of data, the transmission between the entities in the network must be fast and accurate.
- **Privacy and security**: Personal data being transmitted in an H-IoT framework is sensitive and should securely reach only the concerned entities, which necessitates having authentication and security measures in place. Various mechanisms for authorization and authentication of IoT devices are available using technologies such as encryption and physical unclonable functions [13]–[15].

B. ARCHITECTURE OF H-IOT

An H-IoT system comprises of an end-to-end network typically consisting of three major layers of operation [16]:

1) *Data collection layer:* This layer is responsible for the collection of medical data from various sensor devices attached to the patient/test subject that needs to be monitored/examined.
2) *Data storage layer:* This layer is responsible for storage of big data collected from various sensors and transmitted through the Internet.
3) *Data processing layer:* This layer analyzes the data stored in servers to generate the required response through application of computing algorithms. Also, the compilation and visualization of the results are done here.

The implementation of these layers is enabled using the following technologies [11] as shown in Figure 3:

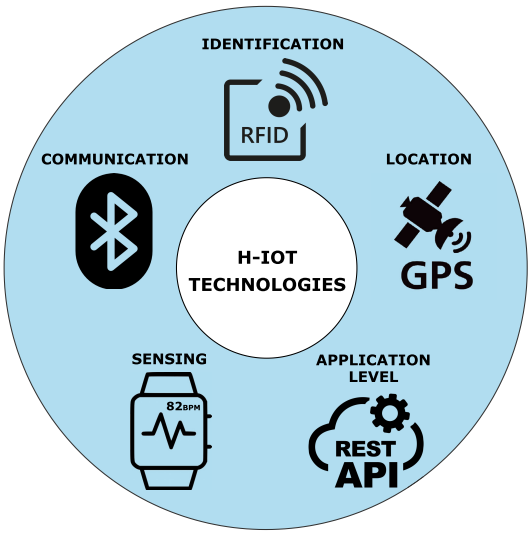

FIGURE 3. H-IoT Technologies.

- **Identification technology**: For the nodes in the network of an H-IoT framework to access information and communicate with each other securely, each node must be identified uniquely through technologies such as a unique identifier (UID) [11].
- **Communication technology**: Both short and long distance communications between the nodes in the H-IoT network require pathways. Long distance communication is undertaken through conventional means such as the Internet, while short distance communication separately requires specific technologies, preferably those that enable fast wireless communication like Bluetooth, Zigbee, RFID etc.
- **Location technology**: Global positioning system (GPS) enables the various nodes to accurately track each other's geographical locations which is extremely important for certain use cases of H-IoT. Various other location tracking systems may also be required to compensate for instances of poor GPS connectivity [11].
- **Sensing technology**: The data analyzed to draw inferences in an H-IoT system is generated by sensors. Therefore, sensing mechanisms that monitor real-time physiological changes in a patient's body are imperative. A large variety of sensors are available for acquisition of such data, for instance, accelerometers for sensing linear acceleration, gyroscopes for measuring angular velocity, and electrocardiogram (ECG) sensors to measure electrical activity in the heart [16]. Evolution in sensor technology is directly related with evolution of H-IoT frameworks leading to more accurate predictions and lower costs.
- **Application level architecture**: Application level architectures such as service oriented architecture (SOA) [17] or representational state transfer (REST) allow the various devices in the system to perform independently of each other. Each device's operations are properly defined and can be altered as and when required without compromising the interoperability of the system.

III. OVERVIEW OF ALGORITHMS

This section provides a brief overview of prominent algorithms used in H-IoT, and a few examples of their H-IoT applications. In general, these algorithms can be divided into supervised and unsupervised learning algorithms, depending on whether the desired classification labels are provided in the input dataset (supervised) or not (unsupervised). Machine learning algorithms generally prefer labeled data, while deep learning algorithms are more adept at exploiting unlabeled data.

A. DIMENSIONALITY REDUCTION ALGORITHMS (DRA)

DRA are a set of algorithms such as linear discriminant analysis (LDA) and principal component analysis (PCA) which take in large data sets as input, identify the correlations and patterns in them, and provide a much smaller data set (in terms of the number of dimensions) as output without losing any critical information previously provided. This removes inconsistencies, redundant data, and highly correlated features of the data. Dimensionality reduction is performed through the following steps:

1) Standardization: each data point is scaled as:
New variable = (original variable - mean of all variables of the feature)/(standard deviation of all variables of the feature).
2) Computing the covariance matrix:
$[feature][feature]^T$.
3) Calculating the eigenvectors and eigenvalues.
4) Computing the principal components.

Significant promises have been made for diagnosis of Parkinson's disease and breast cancer by combining IoT and DRA such as LDA [18]. The significance of a combination of IoT and DRA to boost diagnostic capabilities is well discussed in available literatures [19], [20].

B. DISCRIMINANT ANALYSIS

Discriminant analysis, which is an important type of DRA, projects data points to a space of lower dimensions such that the classes get separated appropriately into non-overlapping groups. Such classification is similar to multiple regression when only two groups are involved, but proves to get more complicated as the number of groups increases. In healthcare, discriminant analysis finds applications mainly in measuring disease prognosis and severity in a patient. LDA classifies by finding a linear combination of features, while a more general multiple discriminant analysis extends the same to a non-linear space.

C. LINEAR REGRESSION

Linear regression is a modeling technique which uses linear approach for finding a relationship between a dependent variable and one or more independent variables. It is preferred in cases where only continuous independent variables exist. Many techniques for preparing a linear regression model exist, of which ordinary least squares and gradient descent method are most commonly used. The former tries to directly minimize the sum of squared error values to find out the coefficients, while the latter uses an iterative approach to minimizing the sum of squared residuals.

D. LOGISTIC REGRESSION

Logistic regression is a probability-based algorithm in which its sigmoid function acts as the cost function and assumes a value between zero and one. The sigmoid function is given by:

$$f(x) = \frac{1}{1 + e^{-x}}. \tag{1}$$

Logistic regression can be of two types. When the observations are to be classified into two classes, binary logistic regression is used, while more than two class classifications require the use of multinomial logistic regression. Using logistic regression is especially advantageous when the regression problem has a dichotomous dependent variable.

E. SUPPORT VECTOR MACHINE

This algorithm uses the concept of a classifying hyper-plane. The aim is to identify a plane that divides the dataset into two groups such that the gap between the data points in the two groups is maximized. This hyper-plane is said to have the maximum range. Data points falling on different sides of the hyper-plane are assigned to different groups. The dimension of the hyper-plane depends on the number of features. For features less than or equal to 2 in number, the hyper-plane is simply a line. It turns to a 2-D plane for 3 features, while picturing it for more than 3 features becomes difficult. SVMs are advantageous in that they are extremely resilient to overfitting problems. SVMs can not only work as linear classifiers, they can also use non-linear kernels to classify datasets using non-linear functions. Ginantra *et al.* [21] proposed a model that demonstrated an SVM classifier which outperformed other classifiers for identifying whether a person suffers from influenza-like illnesses (ILI) (i.e., acute respiratory infections). SVM is found to be the most accurate in location verification [22] without the requirement of channel characteristics data to operate. SVMs were also used to develop methods for solving the classification task of medical implant materials [23].

F. K NEAREST NEIGHBORS (KNN)

KNN is a supervised learning method where objects are classified based on their similarity to certain features of other objects whose category is predetermined. Distances, mostly Euclidean, are calculated for the object whose category is determined to its k closest neighbors. That is the difference between the features of the neighbors is taken and summed to find the distance. The Euclidean distance is given by Eq. 2. Then, voting is done to determine the category in which the majority of the k nearest objects belong to. The value of k is determined through the process of parameter tuning. It is usually chosen to be around the square root of the total number of objects, and is generally an odd number to avoid the possibility of multiple categories getting equal votes.

$$\begin{aligned} Distance^2 = {} & (feature_{1,object} - feature_{1,neighbor})^2 \\ & + (feature_{2,object} - feature_{2,neighbor})^2 \ldots \\ & + (feature_{n,object} - feature_{n,neighbor})^2 \end{aligned} \tag{2}$$

KNN is helpful for the classification of labeled data even when the training set is very small and is widely used in various applications. Ahmed [24] used KNN on data collected from IoT devices to predict heart attacks. It was used on data collected from 20 Kinect sensors to measure the positions of different joints in the body [25]. These were then passed through KNN classifiers used with both Euclidian and Minkowski distances to predict the user's current activity. This has great potential for use in fitness measurement once classification is developed for a variety of activities. Azimi *et al.* [26] proposed to use multiple KNN imputations to estimate lost or missing data points collected to monitor pregnant women. This application can be reliably used, both as a medical B2C service or as a tool for research on maternal health. Hossain *et al.* [27] showcased another activity measurement application using long range wide area network (LoRaWAN) sensors and accelerometer for detection using KNN with an accuracy of 80%.

G. K-MEANS

K-means classifies objects based on whether or not they fall within the parameters of a certain class. Hence, the categories of classification are limited to "similar" and "dissimilar". Euclidean distances are used to determine the centroid of the cluster for each category, and a new object is simply classified based on the distance from each cluster. This method finds its applications in numerous web engines and wireless sensor network (WSN) systems. K-means classification is also used in other diverse fields, ranging from using wearable sensor networks to detect injury among soldiers away from their posts during a war [28], to monitoring the ECG of patients using data collected through wearable IoT nodes [29]. Sood and Mahajan [30] proposed using similar technology to provide remote diagnostics for a chikungunya epidemic through fog computing and using fuzzy k-means to track the possibility of disease transmission. This is a tested method that may be expanded for COVID-19 tracking as well. Further, Kim *et al.* [31] demonstrated the use of k-means clustering on MRI images for information deduction to speed up the detection of brain tumors.

H. DECISION TREE

A decision tree consists of three components: internal nodes, branches, and leaf nodes which represent features, decision rules, and outcomes, respectively. Gini index and entropy are two of the most widely used methods to classify data. Cho [32] used decision trees to track the location of persons during a pandemic. Xie *et al.* [33] used decision trees to develop a heartbeat classification algorithm that identifies premature ventricular contraction (PVC) to diagnose arrhythmia using amplitudes and intervals of heartbeat as features.

I. RANDOM FOREST(RF)

Decision trees adapt according to the particular data used for training them. The results obtained using a decision tree vary drastically if the training data is altered. This algorithm is computationally expensive. A local optima is generally calculated because going back is not possible once splitting occurs. Random forest method addresses these limitations. In this model, several decision trees are trained simultaneously to produce a single output. Such decision tree merging is called bagging. As an example, Al Hossain *et al.* [34] demonstrated the application of a random forest model that outperformed other models with 95% accuracy in predicting the number of people infected by influenza in public places. It shows a high accuracy due to its ability to combine the outputs of all decision trees. Gupta *et al.* [35] presented a random forest classifier that outperformed KNN, SVM, and decision tree with 77.8% accuracy in detection of abnormal crowd motion.

J. NAIVE BAYES (NB)

NB classification is conceptually based on the Bayes theorem. 'Naive' refers to the fact that all features are assumed to be independent of each other. The data is split into a feature matrix and a response vector. The rows of the feature matrix provide the whole data collection in terms of vectors, each of which represents the relative variable type. On the other hand, each row of the response vector represents an outcome class. Sadhukhan *et al.* [36] and Assery *et al.* [37] mentioned situations where NB outperformed all other classifiers to classify tweets that can help in managing the social networking issues in disaster or pandemic periods.

K. GRADIENT BOOSTING & ADABOOST

In the general case of weak learners, the accuracy is just about as good as a random outcome generator. Thus, a good way to utilize them is to combine them through more than one ML algorithm to create a strong learner. This methodology of using multiple learners to train a model is also known as ensemble learning. Boosting is an ensemble learning method that creates decision boundaries for each weak learner and assigns each of the weights based on how accurately the boundaries classified or estimated the data. This is repeated till a satisfactory model is created. Adaboost gives each observation (for the first boundary) equal weight in the beginning and then keeps increasing the weights for the incorrectly classified objects and altering the boundaries accordingly until all observations are correctly classified. In gradient boosting, multiple boundaries (learners) are created one after the other such that each consecutive learner accounts for some errors of the previous one. Extreme gradient boosting can be used to predict heart patients' irregular cycles with 92.1% accuracy [38]. Similarly, voice signals collected from wearables can be used to detect early signs of Parkinson's disease [39], whereas predictive analytics can be used to diagnose diabetes in clients [40]. Constrained IoT devices can also be used to efficiently detect seizures [41].

L. CONVOLUTIONAL NEURAL NETWORKS(CNN)

CNN is a feed-forward network used in classification problems [42]. It breaks the input down into constituents and then passes them on to a convolution layer, which puts these parts into different combinations until some patterns emerge from them (convolution). A rectified linear unit (ReLU) layer then maps the input images against these patterns to form a rectified feature layer and passes them on to a pooling layer. The pooling layer reduces the map to give a pooled feature map, which is then flattened to form a linear vector and fed into a fully connected network to categorize the input. CNNs are used extensively in areas that require visual interpretation of images with a grid-like topology. Alhussein *et al.* [43] converted brain wave values received as a 2D time series to predict epileptic seizures and inform health authorities with immediacy. Ke *et al.* [44] proposed the use of raw electroencephalogram (EEG) to evaluate depression using lightweight CNN. Ciocca *et al.* [45] used images to recognize food and in turn, calories, which has applications in nutrition and fitness. Alhussein and Muhammad [46] used mobile healthcare frameworks to detect voice pathologies using deep learning on pitch tones. Bansal *et al.* [47] proposed a resnet based framework for lung cancer classification and 3D segmentation, achieving an accuracy of 92.7% for segmentation and 88.3% for detection using the LUNA16 dataset.

M. ARTIFICIAL NEURAL NETWORKS

An artificial neural network (ANN) is a ML model that mimics the learning process of the human brain: there exists an input layer that receives the data to be processed, several layers that process the data, and an output layer that gives the output. In ANNs, the hidden layers receive intermediate inputs, assign a random weight and bias to each of the inputs and calculate several weighted sums, which are then passed through layers with weights and sums, until they reach the last layer, which uses an activation function to determine the output. When the outputs are incorrect, they are fed back to the previous layers (back propagation) in accordance with a cost-function to alter the weights until answers are received with sufficient accuracy.

ANNs are extremely dynamic and find applications in domains related to pattern recognition. Kim *et al.* [48] used an inconspicuous method of IR sensors placed throughout the house to monitor movement, bathroom time, sleep, and excursions to detect signs of depression among elderly

people through processing information received over telecom data using ANN. Bhatia and Sood [49] proposed using back propagation ANN to predict probabilistic health state vulnerabilities during exercising. Sood and Mahajan [50] and Humayun [51] used a fog-layer framework to identify and control hypertension (BP) attacks, and to manage data pertaining to heart attacks in patients, respectively. Hassija *et al.* [52] worked on a neural network-based smart contract that was used in conjunction with a blockchain network to form a traffic estimation system.

N. REINFORCEMENT MACHINE LEARNING

Reinforcement learning is based on the methodology by which infants learn to interpret the world around them. This comprises an agent, or the learner, who starts from a specific state in the environment, say S0. The agent then takes an action, A0, and the state updates to S1. If the action was in the correct direction, the environment rewards the agent with R1. This is repeated until the reward is maximized. It comprises of a set of algorithms such as Monte Carlo and Q Learning. Park *et al.* [53] discussed automated diagnostics of high volumes of patients through IoT wearables using Q learning. Zhao *et al.* [54] provided a novel method to route crowds in a smart city using reinforcement learning, a technology that may prove pivotal to lifting lockdowns during COVID-19 while keeping up with social distancing norms. Dourado *et al.* [55] used topographic images of the skull to detect strokes using a deep learning IoT model. Liu *et al.* [56] used similar models to detect lung cancer.

O. NATURAL LANGUAGE PROCESSING(NLP)

NLP refers to the application of ML algorithms for computers to understand and interpret natural human language, speech, and text. Its linguistic extraction features make it extremely easy to process and quantify unstructured information. The algorithm uses the following approach:

1) Stemming and tokenization: breaking down words into root words and categorizing them.
2) Semantic analysis and disambiguation: extracting the literal meaning of words used and breaking them down into context and intent.
3) Topic modeling: understanding the domain of which the conversation is a part of.

The most common libraries for NLP available today include Scikit-learn, NLTK, spaCY, and TextBlob. NLP applications go beyond their dependence on textual or image data to extract information and are hence used in widely varied applications, like food intake and nutrition tracking [57] and to evaluate the emotional response of the patient on medicine intake [58]. Amin *et al.* [59] proposed using NLP to evaluate speech, facial expressions, movement etc. in real-time through smart city networks to assess the patients and provide them with required emergency help. This technology also finds varied use in mental health applications [60], where NLP was used on data from both social media and IoT device data.

P. COGNITIVE AUTOMATION

Cognitive automation is a sub-element of AI. It uses advanced technologies like data mining, emotion recognition, NLP and cognitive reasoning with the objective of imitating human intelligence. Cognitive automation tries to imitate human intelligence using technology to solve problems. It acts as a catalyst mechanism behind efficient and improved responses generated by an AI device.

Cognitive automation, by offering a more collective approach to H-IoT, helps in applications where a synchronised use of physiological and psychological systems is required for dealing with medical emergencies. Muhammad *et al.* [61] developed a 5G cognitive healthcare monitoring system that can revolutionise healthcare systems, especially in smart cities by running a data and a resource cognitive engine simultaneously. Alhussein *et al.* [43] studied cognitive IoT frameworks developed for the monitoring and diagnosis of epilepsy.

IV. DIAGNOSIS

In this section, we present an overview of various use cases for diagnosis where AI and IoT based systems have been used or proposed. Diagnosis is generally carried out by the identification of the nature of an illness which the patient is currently facing by examination of the symptoms which are measured by sensors. Table 2 at the end of this section gives a brief summary of the reviewed publications that pertain to use cases of ML algorithms for diagnosis.

A. CARDIOVASCULAR DISORDERS

Heart diseases are one of the major causes of mortality around the world. Predicting a heart disease is a complex task. However, the integration of IoT into healthcare systems has shown a remarkable way to monitor patients' health and diagnose anomalies. The most commonly used sensors are for ECG, blood pressure, heart pulse and body temperature. ECG signals represent the electrical activity of the heart at rest. It can be used to draw inferences about the heart rate and rhythm, and can be useful for diagnosing the enlargement of the heart due to high blood pressure, elevated heart rate, and dysrhythmia or heart attacks. Figure 4 shows some of the most commonly used sensors related to cardiovascular diagnosis.

Gupta *et al.* [62] proposed using a ML based model to diagnose heart diseases by monitoring several parameters in real time, using wearable IoT technology. The aim of the study was to use real-time ECG, pulse and temperature monitoring as inputs to a trained prediction model to predict if the user is at risk for any heart disease or arrhythmia. The project was carried out in three phases: data pre-processing, model training phase, and prototyping for live prediction. In the first phase the electronic health records (EHR) dataset was consolidated, and the parameters considered relevant to the predictor were isolated. The values that were missing in the dataset were replaced with the most frequently occurring value (i.e., the mode) for each feature. A correlation

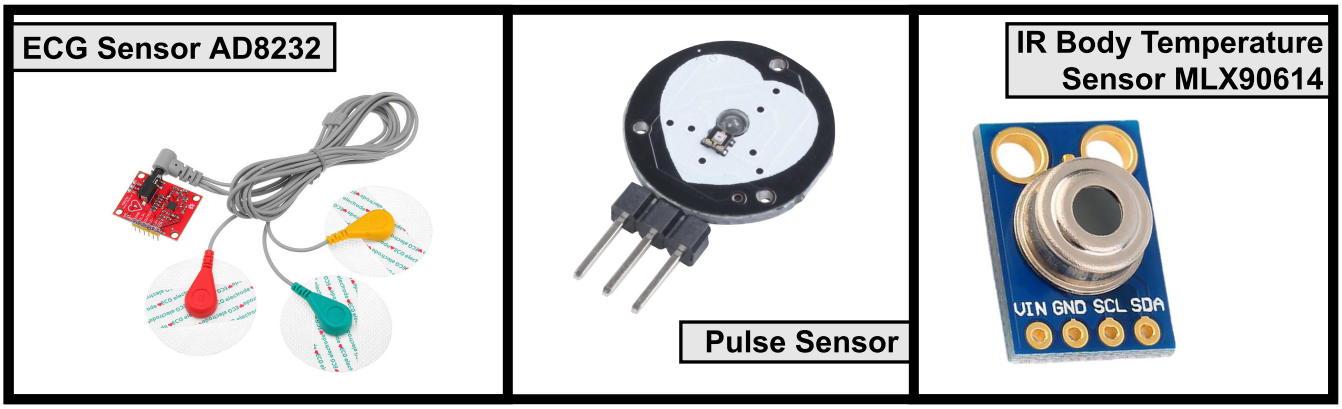

FIGURE 4. Common sensors for cardiovascular diagnosis.

assessment was done to determine the different parameters following very similar trends. Such trends which did not contribute in the learning of the model, and would simply add to the program complexity were removed (dimensionality reduction). In the second phase, the pre-processed dataset was split into training and testing sets followed by model training on the training dataset. Different classification algorithms namely KNN, SVM, NB, decision tree and random forest were evaluated for accuracy, hit rate, etc. The third phase included the hardware prototype development for collection of data and cloud connectivity, and most importantly, real time prediction. Using the ESP8266 WiFi supported development board, the AD8232 ECG sensor, HW01 pulse sensor and the MAX30205 temperature sensor, the node was connected to a laptop feeding continuous data into the trained model, along with other static data such as age, sex and sugar levels. After this, a laptop ran the model giving an 88.9% accurate judgement using KNN to identify if the patient was at risk for heart problems. Although this was a fairly simple method, more research needs to be done for improving the accuracy. Hence, this technology needs to be further developed with better training over time and better instrumentation for a broader real-time dataset. Taştan [63] reported similar studies by using only a real-time monitoring approach while Davis *et al.* [64] also accounted for the past health record of the patient.

Khan [65] proposed an IoT healthcare system for evaluating heart diseases using the modified deep CNN (MDCNN). The data used for training and testing was collected from Framingham, the UCI ML Repository and public health dataset. A smartwatch and heart monitoring device were used to collect information about the blood pressure and ECG which were then transmitted to the server using LoRa. Based on this transmitted information, the MDCNN model classified the patient as having a normal or an abnormal heart condition, and alerted the doctor in case of an abnormality. This was also carried out in three stages: pre-processing, feature selection and classification. The first stage comprised of adding the missing attributes based on the patient's age, blood pressure and cholesterol, removing redundancies, and separation of patients based on the type of chest pain they had: typical angina, atypical angina, non-anginal pain, and asymptomatic. The most important features for evaluating heart diseases were selected by using the mapping-based cuttlefish optimization algorithm (MCFA) [66]. Finally, for the classification stage, the weight values to be used in the model were optimized using the adaptive elephant herd optimization algorithm. For the actual prototype, an Omron HeartGuid-bp8000m was used to measure the resting blood pressure. However due to unavailability of wearable devices for the serum cholesterol and glucose levels, pseudo numbers were generated in a fixed range. Lastly, an AD8232 sensor was used for measuring the ECG data. A Raspberry Pi was used for interfacing which sent the data to the cloud using a SX1272 900MHz LoRa transmitter. The results from this study are given below in Table 1.

TABLE 1. Results for MDCNN [65].

Dataset	# Records	Total Features	Features selected	Accuracy
UCI	303	16	7	93.3%
Framing-ham	4000	16	7	98.2%
Public health	1025	14	8	97.6%
Sensor data	900	16	6	96.3%

Azariadi *et al.* [67] proposed heart diagnosis using ECG analysis and classification on an embedded IoT system. The model developed could be used with wearable sensors for ECG diagnosis, which allowed continuous monitoring around the clock. The proposed system had 4 steps: detection of the heartbeat, segmentation, feature extraction and classification. The MIT-BIH arrhythmia database was used for developing the classifier. Discrete wavelet transform was used for

feature extraction while classification was done using SVM. The algorithm was later coded and implemented for Intel's Galileo IoT board. The ECG signal was read and digitized at a sampling rate of 360 samples per second while analysis was done for every 3000 samples. The average accuracy was 97%.

Wang *et al.* [68] proposed a model combining logistic regression and ANN for prediction of chronic diseases or risks by covering a case study of hypertension based on health risk assessment (HRA). The integrated model utilized data available to all from behavioral risk factor surveillance system (BRFSS) of centers of disease control and prevention (CDC). First the binary logistic regression was used to select risk elements having consequential p-values. While selecting the important risk elements, multi-factor logistic regression model integrated with partial maximum likelihood (PML) estimation and forward-step regression analysis was used on the experimentation data. As a result, eleven factors such as age, exercise, marriage, diabetes, income, body mass index, gender, smoking and drinking habits were chosen as the significant risk-factors. Then, multi layer perceptron (MLP) neural network was constructed and trained with back propagation (BP) algorithm for the specific factors to diagnose if an individual was enduring hypertension or not. Increasing the number of hidden layers in this MLP-NN model can escalate the precision of predictions. However, the number of hidden layers must be more than two-thirds of input factors [69]. The dataset was divided into training and testing sets with a ratio of 7:3. The accuracy varied from 71.91% to 72.12% when the number of hidden layers was increased from 8 to 11. Initially, the default threshold was assumed to be 0.5, which was changed with every training iteration. Experimental results have shown that the integrated model of ANN and logistic regression is better than any of the two acting individually. The future goals of this study are to involve more risk factors and training the data over more iterations for better prediction results.

Acute coronary syndrome (ACS) is a serious medical condition due to the imbalance created among the metabolic needs in the body. This condition is characterized by chest pain that radiates to the neck and left arm. Medical professionals prescribe different laboratory tests and ECG based on patient conditions. Berikol *et al.* [70] studied building models for diagnosing ACS using the ML method for SVM with several patient attributes such as age, risk factors, sex, and cardiac enzymes' presence.

Berikol *et al.* [70] used the data of 228 patients with their medical history, clinical, laboratory, and imaging information to build a ML model. In this study, four methods were tested starting with SVM, NB, ANN, and logistic regression. The result showed that SVM had the highest precision in the patient group ranging from 19 years to 91 years. It was found that out of 228 patients, 99 were listed as with ACS and 129 as without ACS. SVM model gave 99.13% accurate predictions in diagnosing ACS. Diagnostics is a wide field and modern scientific methods are always evolving. This study showed the system can be integrated with medical departments for decision making in the future. However, the study was conducted on the patient history and ECG findings. Risk factors of patients were not included in the study which is a major limitation. Measuring pain may need a more practical approach than theoretical analysis. Finally, more real-time data is required for model training and real-time decision making.

IoT systems are still developing and are bound to bring more technological changes. More data, research methods and advanced techniques will help improve the estimates for better accuracy in the future. In addition to ECG analysis which is being actively researched in, another challenge is development of wearable devices which can be used constantly and are financially viable. Modern wearable solutions can help to further enhance the process and bring a more sophisticated healthcare IoT system for improved decision making.

B. LUNG CANCER

Lung cancer is the most common cancer with 1.76 million deaths in the year 2018 [71]. Valluru and Jeya [72] presented a model based on optimal SVM for classifying computerized tomography (CT) lung images with optimized SVM parameters to diagnose lung cancer. To improve the results of SVM, feature selection and parameter optimisation were done effectively. In this SVM, feature selection was done by modifying grey wolf optimization (GWO) algorithm integrated with genetic algorithm (GA). This experiment took place in 3 phases: testing for parameter optimization, feature selection, and optimal SVM. A set of experiments were carried out to explore the results in terms of feature selection and performance of classifier. The simulation follow-up distinctly defined the enhanced performance of the optimal SVM among the collated methods. GWO algorithm is classified into 4 types: alpha, beta, delta, and omega. GWO algorithm has 2 phases: exploration and exploitation. The exploration stage selects optimal solutions in the local database. Upon finding the optimal results, the search agents change their location based on the best solution procured. GWO-GA algorithm makes use of binary encoding which makes cooperation between attributes simpler. The solution of GA is taken in as the initial population of GWO algorithm. When a particular individual's fitness level computes to be superior to that of GA, the GA gets replaced by said individual and then reinitializes. Therefore, GWO-GA algorithm gets executed until the terminating criteria is satisfied. Originally, the attributes are calculated using the optimal SVM, followed by categorization of images using an SVM classifier. To look for a hyperplane, classifier training is availed which distinguishes the negative samples from the positive samples. This complete process is a straightforward linearly separable problem in high dimensions, and the transformation is based on SVM's kernel function. The presented procedure shows its better outcomes on every applied test image following multiple aspects. Above all, it achieves an average accuracy

for classification of 93.54% which is clearly more than the compared methods, those being GA, BPSO and BDE. The detailed analysis experiments on the test images proved that the proposed procedure can be successfully applied in real time data analysis in hospitals and other healthcare institutions. This proposed algorithm can be further improved by the incorporation of deep learning models.

C. NEUROLOGICAL DISORDERS

For neurological disorders such as epilepsy and Alzheimer's, EEG based monitoring is one of the most important ways in which smart healthcare systems can contribute to monitoring patients. EEG is a diagnostic method used to detect electrical signals in the brain using electrodes attached to the scalp. Another type of brain signal diagram that has not been extensively used for neurological diagnosis is magnetoencephalography (MEG). MEG signals are less attenuated as compared to EEG signals and is therefore a promising diagnostic tool.

A cognitive IoT framework for EEG-based pathology detection was proposed by Amin *et al.* [59]. In this framework, the multimodal data from EEG electrodes was processed and sent to a cognitive system in the cloud which analyzed the patient's state and transmitted this data to a deep learning system for detection of disease. The deep learning system used CNN and sent the results of classification back to the cognitive system which finally decided on the emergency response and sent it back to the medical professionals for further analysis. The model proposed by Amin *et al.* [59] used two popular CNN models separately to conduct two sets of experiments- the VGG-16 and the AlexNet models. The system with the VGG-16 model achieved an accuracy of 86.59% while the one with AlexNet achieved 87.32%, which are higher than those obtained by the state-of-the-art models. This shows future prospects of implementing smart IoT-cloud integrated deep learning frameworks in smart cities with the use of cognitive engines to overlook the decision making.

Another study by Khalid *et al.* [73] aimed to provide a method for automating spike detection in MEG signal data. To differentiate between spike and non-spike signals, features are extracted using the common spatial patterns algorithm. These features were found to follow normal distribution. Thus, LDA was chosen as classification method. Since the LDA is being performed for two classes, namely spike and non-spike signals, the Fisher criterion [74] was maximized to provide predictors that separate the said classes. This method of classification was evaluated using leave-one-out cross-validation (LOOCV). The evaluation metrics used were sensitivity and specificity, which averaged for seven trials at 91.03% and 94.21% respectively. These results indicated that identification of MEG spikes using LDA is a promising approach to diagnose epilepsy.

Apart from using classifier algorithm models for the classification of EEG data, computer aided diagnostics (CAD) can also rely on convoluted neural network (CNN) based models to classify EEG signals and classify them as normal, preictal, and seizure classes. As the EEG signals are non stationary and highly complex in nature, visual interpretation is rather difficult. Application of convoluted neural network models in the EEG data results in an automated detection of various classes of epilepsy. Acharya *et al.* [75] employed CNN to automatically classify EEG datasets into 3 classes. Acharya *et al.* [75] discussed models that used traditional CNN architecture consisting of convolutional layer, pooling layer and fully connected layer. The model also used two types of activation functions: rectified linear activation unit and Softmax. The model was evaluated on metrics including accuracy, specificity, and sensitivity. The CNN based model reported an accuracy of 88.67%, specificity of 90%, and sensitivity of 95%.

Use of CNN models for EEG based classification shows promise; however, application of CNN to physiological signals is still a relatively unexplored area with scope for more research.

D. DIABETES AND PANCREATIC CANCER

Type 2 diabetes, which results in high amounts of blood sugar is one of the most widely affecting chronic diseases that can prove fatal if not kept in check. The incidence of diabetes is constantly increasing, with most individuals suffering from Type 2 diabetes mellitus often going undiagnosed. Efficient identification of undiagnosed diabetic individuals will lead to better and informed treatment of the disease and an overall reduced mortality rate.

Han *et al.* [76] provided an identification model for undiagnosed patients of type 2 diabetes mellitus using SVMs. Due to the less comprehensible nature of SVMs, instead of directly using an SVM model, the tuned SVM model is used to extract support vectors that are in turn used to generate artificial data. Using this artificial data in a random forest model, rules were finally extracted to diagnose diabetes. This proposed model was tested based on three different scores: precision, F score and recall. The model was found to have a precision of 89.6%, outperforming the four other models that comparisons were drawn with, namely random forest, C4.5, NB tree, and back propagation neural network. The rule extraction ensemble approach using SVM with random forest improves the accuracy of the original SVM model. Han *et al.* [76] also used this ensemble approach since a black box model provided by an SVM will have less transparency in terms of the rules used to arrive at the prediction, which is especially unfavourable in medical diagnosis.

CAD systems use computed tomography scans for automatic segmentation of various abdominal organs. Automatic segmentation of the pancreas is particularly challenging due to the organ location in the body and large variations in its shape and size. Statistical shape models that are used for other organs do not lead to accurate results for pancreas segmentation. A high accuracy pancreas segmentation method will lead to great improvements in analysing CT scans of diabetes and pancreatic cancer patients.

Farag *et al.* [77] employed random forest classification for labeling of image-patches generated using over-segmentation. CT scan images are decomposed into meaningful regions called superpixels, which are then used to extract 46 patch-level image features for training a random forest classifier. The classification was conducted with 50 trees, such that minimum leaf size is 150. In an extension of the method, a cascade of two random forest classification frameworks were also formed. This method was evaluated using six-fold cross-validation. The evaluation metrics used were Dice similarity coefficient, Jaccard index, volumetric precision and volumetric recall. It was found that the response maps plotted corresponding to the classification and dense labelling show success in pancreas segmentation, with a 70.7% Dice coefficient and 57.9% Jaccard index. The major contribution of the proposed method is a computation time of 6-8 minutes per testing case compared to >10 hours for other methods. However, the superpixel generation process can lead to loss of boundaries that are of lower contrast and cause segmentation leakage.

E. CHRONIC KIDNEY DISEASE

Chronic kidney disease (CKD) is a global public health problem, affecting approximately 9.1% of the population worldwide resulting in 1.2 million deaths and was the 12th leading cause of death worldwide in 2017 [78].

Subasi *et al.* [79] did a comparative study of the diagnosis of CKDs using ML algorithms such as ANN, SVM, KNN, decision tree and random forest. Their models were trained using real datasets from the UCI ML Repository. Their dataset had 400 samples collected over a period of 2 months, with 250 positive and 150 negative for CKD. They used the 10-fold cross validation method, in which the dataset is divided into 10 mutually exclusive sets and used 9 of them for training and the last one for testing. This experiment was repeated 10 times. Random forest achieved 100% accuracy followed by decision tree with 99%. The F scores and precision of all the algorithms were compared, with random forest showing the best results. This report suggests that ML algorithms can indeed achieve accuracy levels sufficient for autonomous deployment without the need of human intervention. The paper did lack in considering aspects such as security and implementation in real world along with data collection methods.

F. MISCELLANEOUS

1) CHATBOT

Automated medical chatbots can be used to reduce healthcare charges as well as improve accessibility to medical knowledge and services. Srivastava and Singh [80] proposed a chatbot for providing diagnosis to patients based on their past diagnosis and information obtained over the conversation. While this may be considered immoral and susceptible to inaccuracy as the patient might incorrectly report symptoms, the chatbot is designed to ask the patient for clarification in case of ambiguity. Through the conversational cues about the symptoms, the correct symptoms were identified with a 71% precision and 65% recall.

The conversational cues served as a preliminary step to collect information about the symptoms. Then the bot asked subsequent questions and led the conversation in a simple language without the use of medical jargon. It tried to diagnose the possible diseases by converting the provided information to queries and collect the possible solutions for the patient's condition. Once the disease was identified, the bot estimated the seriousness of the disease and took action accordingly. It either suggested remedies and over-the-counter medication, or connected the patient to a doctor if the measure reached a pre-determined threshold. The bot could not be authorised to give prescriptions at that stage. The algorithm used pattern detection to guide itself through the conversation. For instance, if the patient entered "I am not feeling well" the bot recognised that the user had little or no idea what's wrong, hence it started with standard responses asking if they were experiencing any pain etc. In the other scenario, if the patient was pregnant, for instance, then they already knew certain facts about their condition, and this is now added to the fact that they may be experiencing pains in their abdomen, which could mean different things, such as a complication, labour, or maybe just an upset stomach. Hence, the algorithm could give a more accurate response in shorter time. Using a permanent user profile, this technology was especially useful in geriatric care. If the elderly were living alone and they were not comfortable with modern technology, a Google Home or Amazon Alexa module acting like a simple conversational partner could remind them the schedule of their medications. It could even help them understand their body while simultaneously updating their medical profile and even alerting their healthcare provider in case of emergencies. This could be a more affordable solution to many households, than a registered live-in nurse.

Owing to the critical nature of this application, for the initial testing stages, it is better for the technology to be trained by hospitalised patients, teaching it how to interpret conversational cues and correlate with their hospital records to assess the bot's prediction accuracy. Out of all algorithms tests for classification, SVM is suitable for complex classification tasks [81], while KNN is faster but unable to handle highly complex tasks.

2) AUTOMATION SOFTWARE

Bohra *et al.* [82] proposed a system for automating health monitoring and prescription to a high extent. Here, software applications were generated for a user to interact with. In the backend, NB classifier was used to analyse the data given by the patient and respond with the respective medical diagnosis and prescription. It includes a Java Swing application which provides graphical user interface for the application to execute and interact with the user. For a healthy patient, the application provided the answer to the queries based on the keywords fed by the user. In case of an unhealthy

TABLE 2. Use cases of ML algorithms for diagnosis.

Ref	Year	Use Case	Algorithm	Advantages	Drawbacks
[62]	2019	Diagnosis of heart disease	KNN	Real-time diagnosis using wearable IoT technology	Further improvement in accuracy required for practical use
[72]	2019	Diagnosis of lung cancer	Optimal SVM	The effective feature selection and parameter optimization lead to a highly accurate and practically viable method	Use of deep learning algorithms can lead to further multi-fold improvements
[59]	2019	EEG based pathology detection	CNN	Demonstrates the potential that IoT-cloud integrated smart frameworks hold for use in smart cities in the future	Requires sophisticated architecture like deep learning servers and a cognitive engine in the cloud
[73]	2016	Automated spike detection in MEG signals	LDA	High sensitivity and specificity show that method can be used to effectively automate epilepsy diagnosis	MEG signals are not currently as widely used as EEG signals for neurological diagnosis
[76]	2015	Diagnosis of type-2 diabetes	SVM + random forest	The ensemble approach used makes the model much more transparent than a generic black box model thus improving reliability	The rule sets obtained are extremely small
[79]	2017	Diagnosis of CKD	ANN, SVM, KNN, decision tree, random forest	Extremely high accuracies demonstrate possibility of application without the need for human intervention	Does not take into account security and other real-world issues.
[80]	2020	Diagnosis chatbot	SVM, KNN	Easy and cheap diagnosis from home without the requirement of medical professionals	Requires extremely long training periods for becoming usable

patient, the patient inputs the symptoms, and the algorithm was implemented to figure out what diseases have the maximum probability of occurring (event A) based on the existing symptoms (event B). The most suitable algorithm for such analysis is Naive Bayes. In case the fitting probabilities were less than average, the case is presented to physicians, who then discussed and consulted the patient and that case was again stored in the database as reference. The application introduced through this facilitates consultation without physically being attended by the doctors. Some biometric techniques could also be integrated with the system in future, like heart beat and blood pressure measurement. Also, the system could be included with video calling feature for interaction between doctors and patients. This system would help patients in getting minor health issues resolved easily. Hence, a software which was initially used for classifying the effect of a medication on an individual, can be used to create a database of its effectiveness. This data could help in future to red flag any such product which may have a negative effect on majority of users. This methodology can be implemented on future recuperative devices that can be used as an channel that consumers can use, to express their feedback. Organizations profit by this regular criticism as this helps them to analyse and address the issue effective immediately.

3) 28 DAY MORTALITY

As the medical technology further develops, the number of parameters that provide information about the human physiological condition keep increasing, forming datasets of higher dimensions. This data is then used to develop ML models that diagnose abnormalities by classification. The high dimensional clinical datasets increase the complexity of classification and thereby lead to poor efficiency and performance. Keeping up with technology trends and the advent of edge and fog computing, it is worthwhile to invest in reducing computing load for basic broad classification and decision making. GAs have been used frequently for feature selection and reducing parameters to only the most significant ones. However, over time GAs have been falling short when there is a need to find and maintain multiple local optima. This led to the development of niche GAs (NGA). This algorithm can easily locate local peaks and hence present multiple optimisation solutions, or in this case multiple parameter reduction scenarios. However this method lacks adaptability to unknown datasets, which led to the improved NGAs (INGA) [83].

There are broadly two steps to take when extremely wide datasets need to be interpreted- feature extraction and feature selection. Feature extraction is used to reduce the

dimension of data by transforming the original feature space into a new one of lower dimension. DRA such as independent component analysis (ICA), PCA and multidimensional scaling (MDS) are some commonly used algorithms. They work by methods functionally similar to finding a "best fit dimension" that is a 1-D line for a 2-dimensional dataset, and a plane for a 3-dimensional dataset. However, after dimension reduction, ICA, PCA and MDS generate new parameters whose significance is not always interpretive. The second step is feature selection, in which the optimal features are shortlisted such that they retain sufficient information for deriving useful decision models and conclusions. The principle behind NGA is application of the biological concept of a niche to the GA's evolutionary computation. A distance parameter L is specified before the survival environment is shown. The L of NGA is set in advance, allowing only a single excellent individual solution in this distance from centre which is known as the niche radius. Setting the value of L requires some knowledge of the expected results. In many cases, it would be useful to pursue every trend/probable solution that can solve the problem differently, as medical expertise may not agree with the algorithm's optimal solution. Hence an adaptive niching method was developed in conjunction to dynamically adjust an NGA algorithm's radius to fit better with the dataset.

The twin-space crowding genetic algorithm (TCGA) and game-theoretic genetic algorithm (GTGA) are often used for feature selection but they are incapable of obtaining the niche distance following evolution. Hence, there is a chance of eliminating the potentially excellent individuals [84], [85]. The INGA algorithm was benchmarked for accuracy on a dataset of sepsis patients to predict the "28-day mortality" where it outperformed any known DRA by yielding an accuracy of 92%. Such a system can yield a weighted solution for associating varying importance to the wide range of medical parameters that can greatly reduce diagnosis time and reduce the compute load on the cloud.

V. PROGNOSIS AND SPREAD CONTROL

IoT has been a topic of great interest in the healthcare community over the last few years. Healthcare is an important domain and IoT opens up a wide spectrum of opportunities to make it better. In this section, we discuss how IoT has been used by researchers over the world to develop systems for monitoring, detecting, preventing and controlling the spread of various diseases.

IoT is essentially a technology where various sensors are used to gather relevant information which are then analyzed over the Internet. This can be done using a single node or a network of nodes. This concept of gathering real time information makes IoT very relevant to today's healthcare. Human body is one marvelous system and so are the ailments that arise in it. However as it may seem in any natural system, our body sends out information through innumerable signals which can provide us a host of information regarding it's status. Thus, this information is of importance to any healthcare provider, as it decides the course of action to be taken to help a patient.

IoT helps gather this information. Technologies such as ML helps us extract valuable information from it. The most common way to read health data of a person is through wearable devices and sensors. This could range from a smartwatch to read pulses to implants in specific regions of the body. These devices have access to first-hand information which can then be relayed to the endpoints or databases through the Internet. Indirect methods include the user inputting data using a smartphone [86].

In this section, we look at certain applications of IoT and ML techniques to control the spread of certain diseases, both infectious and non-infectious. Table 3 at the end of this section gives a brief summary of the reviewed publications that pertain to use cases of ML algorithms for prognosis and spread control.

A. CARDIOVASCULAR DISORDERS

Heart disease mortality rate is still increasing even though the technologies in the area have vastly improved in the last few decades. Therefore it is one of the most prevalent causes of death, especially in the elderly. Major factors that have been identified that lead to heart disease include high blood pressure, high cholesterol, smoking, diabetes, etc. An early and accurate prediction of the likelihood of a person developing heart disease can help not only decrease the mortality rate, but also prevents a vast majority of such cases by targeting the right subgroups of the population to bring in lifestyle changes in order to decrease their already higher chances of risk.

Yadav *et al.* [87] developed a system to predict the onset of heart disease in patients in their early stages using the NB algorithm. The system's easy to use graphical user interface and the requirement of a low number of records for the training of the NB classifier made this system especially useful. The data was obtained from the Cleveland hospital and consisted of 303 patients with their particulars of age, sex, ECG reports, blood pressure, etc. Input data was used in two forms, first to train the model and then test the remaining data to find the system efficacy. Results were obtained in binary form with 1 predicting the presence of heart disease and 2 predicting the absence of heart disease. Though the models showed high efficiency of 85%, further training on larger datasets is required before adopting in real life scenarios.

Choi *et al.* [88] used NLP to obtain patient sentences (ordered sequences of various medical codes) as distributed vectors by using skip-gram method and classification methods such as logistic regression, neural network, SVM and KNN. Using skip-gram embedding, concept and encounter representations are generated from which patient vectors are then derived. These represented the patient's medical history and are used to predict heart failure. Significant improvement in heart failure prediction was observed by the authors. Not only was the model using ML methods more accurate, but also the time taken to train this model was less as compared to other models. Out of SVM, logistic regression, MLP and

TABLE 3. Use cases of ML algorithms for prognosis and spread control.

Ref	Year	Use Case	Algorithm	Advantages	Drawbacks
[87]	2018	Predicting heart disease onset in early stages	NB	Easy to use GUI, less training required	Real-world deployment requires inclusion of various secondary factors not included in the model
[90]	2015	Detection of Influenza virus	NLP	Lesser training time, does not require preprocessing for missing values	The data used has come from a single health system
[91]	2016	Classifying epilepsy risk levels	KNN	Dimensionally reduced power spectral densities were used for better output values	High number of false alarms
[100]	2019	Predicting hemorrhagic shock recovery	Logistic regression	Outperforms baseline classifier in multiple testing protocols	Test dataset used was small
[103]	2020	Identification of COVID-19	CNN	Distinguishes SARS-Cov-2 strains from other viruses extremely accurately	Has been tested using a small number of genome sequences
[104]	2018	IoT based cloud framework for Ebola spread control	Decision tree	Easy large scale implementation using RFID and wearable sensors	Missing data estimation model has not been developed

KNN, KNN was found to benefit the most from the use of these medical concept vectors.

B. PULMONARY DISORDERS

The prevention of a pandemic outbreak requires early diagnosis. Pulmonary infections like the influenza virus have a long history of quickly turning into pandemics, with the most recent worldwide pandemic also being one that affects the respiratory system- the COVID-19 pandemic. Therefore, it is required that there is a system in place to identify and predict the occurrence of such diseases that might cause outbreaks before they actually take effect, since it is easier to control these diseases at an early stage than when they start spreading rapidly.

Yin *et al.* [89] established a stacking model to make predictions on antigenic variants of the H1N1 influenza virus. They approached this by first classifying past cases as pandemic-based and epidemic-based. Entropy was calculated to find out the variation in strain mutation in different periods. Three different feature engineering methods, viz. residue-based method, ten regional band-based method, and five epitope region-based method were used to validate if the model was universally adhering. The stacking model used is conceptually similar to k-fold cross-validation and provides out-of-sample predictions for small and medium data-sets. Using neural networks, level 2 models were designed to get better results than a single level model. Rapid antigenic shifts can cause variants to occur, which make it tough to understand the effects of specific mutations on antigenicity. This model could be improved upon by taking into account more of crucial factors like climate and the human immune system.

Prediction of cases of Acute Upper Respiratory Tract Infections (URTI) during its early stages is crucial to minimizing its adverse effects on infants and preventing fatality. In order to predict URTI cases, Ginantra *et al.* [21] collected URTI data from community health clinics in Indonesia and used KNN classifiers for prediction. The features used to classify comprise of various symptoms of the disease such as fever, headache and flu. Results obtained using a confusion matrix showed 97.4% sensitivity, 90% specificity, and 94.7% accuracy for the KNN classifier.

López Pineda *et al.* [90] showed a promising application of NLP for the detection of influenza. Collection of data was done through free-text emergency department (ED) medical reports from 4 hospitals. The data comprised of:

1) 468 reports on polymerise chain reaction (PCR) positive influenza patients in the period from January, 2010 to August, 2010; and
2) 29,004 reports of patients NOT associated with a positive PCR test in the period July 1, 2010, to August 31, 2010.

Topaz was used as the NLP parser to classify the data between non-acute, acute, and missing. The authors drew a comparison between the prediction capabilities of 7 different ML classifiers and an expert-built Bayesian classifier. Performance was evaluated using three different configurations with the aim to correctly deal with missing data. The performance of the NLP-finding-extraction system was measured using accuracy, recall, and precision scores. NB, logistic regression, SVM, and ANN algorithms all showed almost equally competent performance. The NB classifier was superior (BSS: 0.35, Area Under Curve (AUC): 0.93) due to having a lesser training time and not requiring pre-processing to

treat missing values. It was concluded by the authors that ML classifiers showed performance superior to expert Bayesian classifiers for the given use case.

C. NEUROLOGICAL DISORDERS

Epilepsy is a fairly common neurological disorder that affects people of all ages across the globe. EEG is one of the most simplistic tools used to diagnose the disorder. EEG helps the doctors analyze the electrical activity of the brain, and any disruptions in this activity could be due to epilepsy. EEG reports are visually inspected by a diagnostician. However, visual inspection has certain limitations and can have a huge error margin, subjective to the competence of the doctor. Deployment of ML algorithms for classifying the risk levels of epilepsy from EEG data is a promising way out from the limitations of visual inspection.

Performance of KNN classifiers in classifying the epilepsy risk levels were analyzed in detail by Manjusha and Harikumar [91]. Here, KNN stores all the sample datasets and new cases can be classified by measuring their similarity with the old cases. Authors of this work applied this algorithm to the power spectral density values with reduced dimensions for better outputs. Manjusha and Harikumar [91] used different parameters to calculate the efficiency of the KNN algorithm. KNN was evaluated on parameters such as classification perfection (83%), performance index (78%), sensitivity (90%), and specificity (93%). As researched by Birjandtalab *et al.* [92], KNN is very helpful in studying the nonlinear data, giving it an advantage over several other classification algorithms. However, KNN fails to solve the false alarm situation, KNN reports false alarms approximately 10% of the times. Thus, this statistics will have to be taken into account while deploying this algorithm.

The high number of false alarm cases encountered in the use of KNN classifiers are undesirable, which is why an alternative to KNN for this application is necessary. Manjusha and Harikumar [91] discussed the use of k-means clustering algorithm as a classifier. k-means is a commonly used partitional clustering technique. Using this algorithm, different clusters of datasets can be created based on certain parameters, such that a given cluster has datasets with maximum similarity and different clusters will have minimum similarity. Authors analyzed the performance of k-means clustering algorithm on the same parameters as KNN [91]. k-means performed really well on the false alarm parameter, generating 0% false alarms, and 100% sensitivity. It's correct classification percentage was close to 94. This shows k-means is a better algorithm than KNN for epilepsy risk level classification from EEG data. However, k-means fails to provide similar outputs when dimensions of input increase. It must be applied on dimensionally reduced data, which can be achieved by different dimension reducing methods.

Another AI based framework used for classification based on EEG data is given by Amin et al. [59]. They proposed a cognitive healthcare framework that classifies a patient's EEG signals as pathologic or normal and outlines the next steps to be taken. In the proposed model, various sensors are embedded in a patient's vicinity to read body temperature, heartbeat, blood pressure, voice, facial expressions, body movement, and EEG. This data is sent to the cloud system through a WAN. Now, in the cloud, a cognitive engine is said to be working. It is to be noted that this engine was not implemented by the authors, nor its specifications given. It is said to have a backbone of AI and deep learning algorithms. Looking at the data, the engine decides whether to send the data for more analysis. If so, the data is sent to a classifier model (in the cloud system). CNN models VGG 16 and AlexNet are used for detection and classification. The results are sent back to the cognitive engine which then takes further steps if the patient's signals are pathological. The patient as well as concerned healthcare professionals get an alert and also suggestions. As is seen in the work by Devi *et al.* [93], the use case of a cognitive system or engine was proposed, but it has not been implemented. This is because much has to be done to bring such a fool-proof system into existence. This remains one of the greatest challenges for implementing cognitive healthcare frameworks.

The use of pre-ictal EEG data for the prediction and suppression of seizures in patients was demonstrated in [95]. A brain computer interface (BCI) developed in a cloud computing framework predicts seizure onset using CNN and then the required neurostimulatory signal is given to suppress the seizure. The combined use of cloud computing, proper preprocessing of data, and CNN results in the model outperforming other EEG prediction systems, displaying an accuracy of 96% and precision and sensitivity of 97% each. This system, although very accurate, is constrained by the requirement of large data storage and high computing capabilities.

Another important and upcoming area of neurological application of AI is for Parkinson's disease which is a progressive and chronic movement disorder. It can result in poor movement, balance, stiffness in arms and legs, trembling and speech disorder. Sixty thousand Parkinson's cases are diagnosed in the US every year, while the number touches a million in India. No known cure is available, but early identification can help in patient management. Parkinson's is a topic of active research with firms and researchers involved in drug development as well as monitoring systems [96]. Recently IBM along with Pfizer Inc. developed a new way to measure intensity of Parkinson's by IoT based remote patient monitoring solutions [97].

Panda and Panda [98] addressed the issue of better classification of Parkinson's using nodes. The data used is voice recordings from digital home virtual assistant devices. It is accumulated in a dataset called Lee Silverman Voice Therapy (LSVT) voice data. Feature extraction of the raw data was done using PCA. Post that, recorded features were fed to the three classifiers: NB, random forest and decision tree. In terms of speed of execution, NB was the fastest while in terms of performance, random forest gave best results.

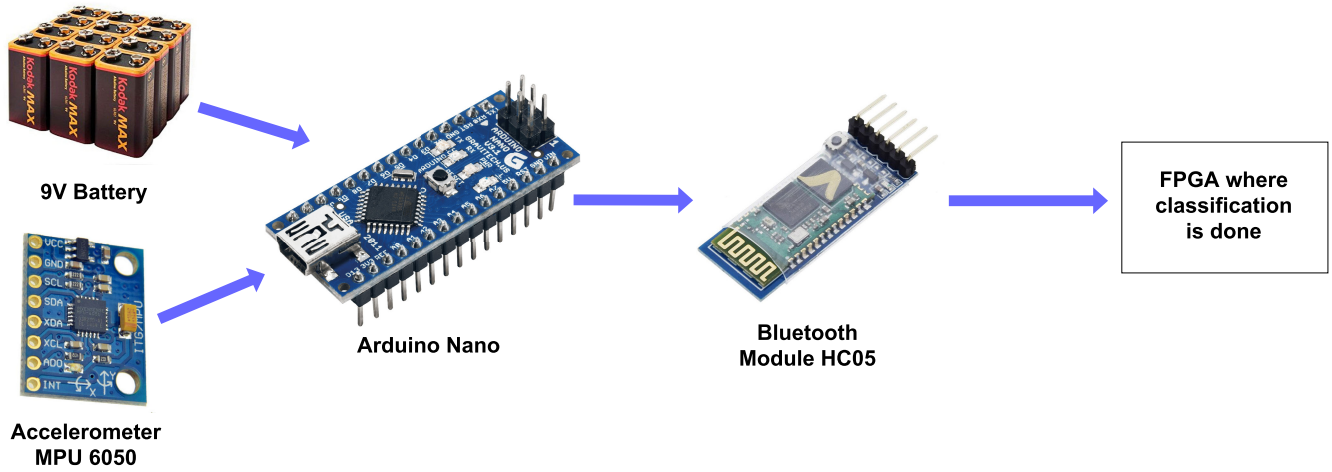

FIGURE 5. Fall Detection System [94].

D. PHYSICAL INJURIES

Over 10% of the world's deaths result from trauma caused by physical injuries [99]. When a physical injury causes too much blood loss, the oxygen supply to the body's organs is not able to satisfy its demand. The body is said to be in hemorrhagic shock (HS) in such a situation. The severity of a hemorrhagic shock determines how urgently its treatment needs to be performed. In such a scenario, accurate prediction of hemorrhagic shock severity and the patient's recovery from it is imperative to prioritize severe cases, so as to minimize the mortality rate.

Lucas *et al.* [100] used logistic regression to model a prediction system that can predict whether a patient will recover from hemorrhagic shock after resuscitation, using rats as test subjects. The rats were classified into two groups based on whether they recovered from the HS or not. After extracting all features and discarding the irrelevant ones, a total of 69 features were used to form a feature vector using which three different classifiers were trained and tested. The scikit-learn python library was used for applying logistic regression. The performance of this logistic regression model was measured in [100] using three different metrics: mean cross-validation accuracy (using 10-fold validation), Younden's J statistic, and Cohen's kappa coefficient. The classifier with the reduced feature set, namely the final classifier, showed an accuracy of $0.833+-0.114$, with a Cohen's kappa value of 0.617. The J value for the final classifier was 0.76. This classifier's results outperformed a baseline classifier that represented currently used methodologies of using heart rate and mean arterial pressure, even when multiple experimental protocols were used. Although the proposed method in [100] shows promise, the size of the test dataset was small due to which it is difficult to say that it will show good results for all scenarios and cases.

Among the various physical injuries people are vulnerable to, a deadly but preventable class that particularly stands out is injury caused by falls. Falls are much more frequent in the elderly and are especially dangerous to their relatively fragile anatomies. Fall risk is normally assessed through testaments of the subject or physical examinations. These are unreliable and incomplete. Non-linear SVM (NLSVM) along with some other algorithms were used for patient-specific fall prediction [43] and detection system [94]. Continuous observation and documentation, with prompt decision making set up is critical for fall prone patients as similar systems have been introduced for heart patients [101]. Saadeh *et al.* [94] proposed a system that senses the movements through a triaxial accelerometer sampling at 256 samples/s attached to the thigh. The acquired acceleration along three orthogonal axes is then sent via low energy Bluetooth interface to an FPGA. The acceleration is used to extract features. The offline NLSVM learner uses fall information of a patient to give personalized parameters that are uploaded to the processor. Figure 5 shows a visual representation of the architecture of the proposed system. The NLSVM classifier then processes the feature vector during runtime to decide whether it is a pre-fall case or not. To prevent false positives, three consecutive decisions are needed before the alarm is set off. The study was conducted with 20 subjects aged over 65, with over 100 instances of activities of daily living and falls. When validated using the Mobifall dataset, the model achieved a 97.8% sensitivity and 99.1% specificity, outperforming models using linear SVM, decision tree and KNN classifiers.

E. SPREAD CONTROL

The current scenario of the world facing the uncontrollable spread of the coronavirus pandemic and its drastic repercussions has led to people realising the scale of the impact that such contagious diseases can have. Therefore a lot of research attention has been directed toward controlling the spread of such contagious diseases. Such pandemics cause not only a surge in patient numbers worldwide, but also lead to disruption of economies on a huge scale and drastically affect the quality of life due to their isolation requirements.

State-of-the-art ML based models can prove extremely effective in predicting the consequent spread of a contagion and can thereby lead to accurate and early decision-making in response to it [102].

Lopez-Rincon *et al.* [103] proposed identification of SARS-CoV-2 using state of the art deep CNNs by automatic creation of features from genome sequencing. Genome sequence data from the 2019 repository novel coronavirus resource and NCBI repository was divided into two groups of 9:1 for training and testing. A 10-fold cross-validation scheme was used on this sample data. The experiments showed that the above approach successfully classifies SARS-CoV-2 and distinguishes it from other viruses of the coronavirus family. The identification itself proved to be 98% accurate while classification into different coronaviruses shows an accuracy of 98.75%, although the training of the model was conducted on a limited data-set and limited genome sequences were considered.

Ebola is another extremely contagious disease that spreads rapidly. Since 2014, various parts of the world have experienced deadly outbreaks of this infection. Dominican Republic is still battling with the virus. Since it is infectious and can be spread from human to human, early detection and monitoring of infected patients is an important step in controlling the spread. Sareen *et al.* [104] proposed an IoT based cloud framework to control the spread of the virus. A system based on RFID (Radio Frequency Identification Device), wearable sensors, and cloud computing was given. Under the model, each patient is first registered using a mobile phone and thus gets a unique identification for future references. Data from body sensors is collected using the mobile phone through bluetooth. This data is sent to the cloud environment for analysis. It is classified using a decision tree approach, which classifies the user among six categories (determined using the state of the symptoms). Next, the user is classified using RFID and wireless body area network (WBAN). RFID detects close proximity interactions (CPI) between the patient and other people. If an uninfected person comes under CPI, an alert message is sent to him/her through mobile phone. In this identification, a proposed temporal network analysis was done using parameters such as clustering coefficient, centrality, and temporal path length. Based on the experiments conducted, the authors got a classification accuracy of 94% for synthetic data of 2 million patients. Further, other models of classification were tested. Random tree and NB gave accuracy of 50% and 53%, respectively.

In an interesting work, Sato *et al.* [105] built an epidemic spread model using IoT technologies to monitor human mobility and contact data. They introduced the agent-based infections diffusion simulation using real human mobility data as a metapopulation network. Such simulations were found to be very important in controlling the spread of outbreaks such as Ebola.

Adding to these methods, Chen *et al.* [106] sought out to develop a model to track dynamic changes in a network. This network could be an epidemic spread network. They proposed using mobile phone data to build their model. Synthetic data was used for classification. This is because deploying WBANs in areas affected is a big challenge. Also, for this to work, people should have RFID reader enabled mobile phones. Adding to that, patients are often not ready to carry a RFID tag. These are some challenges to be looked at.

Righetto *et al.* [107] used rainfall as a variable to develop a prediction model for the spread of cholera in Haiti. The rainfall pattern acts as a marked Poisson process and the continuous rainfall events are processed as discrete events such that the mark represents the depth of the rainfall. The prediction of the spread of the disease is then done using k-means clustering. This model was limited in its accuracy to predict the evolution of new cases. The real-time improvements in the present situation were also not taken into account.

Malaria is one of the challenging diseases in several parts of China, especially in Henan province. Wang *et al.* [108] conducted a study to evaluate the relationship between the diagnosis and complications emerging in patients with malaria disease. ML model based on decision tree was integrated for defining factors, frequencies, and nodes in the correlation among the healthcare institutions and malaria cases. The decision tree methodology was highly successful in building tree models with accuracy of 82.2% and 74.1% for the purpose of initial diagnosis and complications. This study will help to bridge the gap for decreasing future cases. The study further proposed a more simplified online system in combination with WeChat for evaluating malaria to keep a strict awareness about the different factors. Data were obtained from CDC, Zhengzhou City, the capital of Henan province, for conducting a study on malaria patients, starting from the year 2012 to 2017. All the decision tree methods were evaluated for studying the relation with classification and regression tree (CRT), chi-squared automatic interaction detection (CHAID), and statistical package for social sciences (SPSS) so as to increase model precision. Wang *et al.* [108] found that the malaria patient population studied was predominantly male (366 patients out of 371 total patients were male). The average age of patient came out to be 37 years, ranging from 17 to 67 years. There was no life lost in the study. P. falciaprum, with 319 cases, was the highest while fewer cases for Plasmodium malariae, Plasmodium ovale, and P. Vivax at 5, 13, and 34, respectively, were observed. However, this study was conducted on a very small dataset and requires more repeated trails, improvement, and assessment from the professional experts. Major factors that emerged from complications of imported malaria cases include less number of patients seeking medical advice and insufficient capacity in diagnosing malaria from the health institutions, mainly by the lower medical professionals.

In another work by Kassé *et al.* [109], SVM classification was used for better prediction and control of a parasitic disease called Schistosomiasis or Bilharzia. It is said to affect more than 200 million people spread over 7 countries. A data collection module Wapsmote was used to collect data from various sensors (pH, temperature, radiation), which was

then sent to a cloud database using GSM/3G/GP RS mobile network and an Ethernet network. Based on these inputs, an event detection algorithm using SVM was designed to assess transmission contamination risk. ILI or acute respiratory infections are among the main factors for mortality around the world. Common symptoms include fever above 38 °C, pharyngitis or cough, and these tend to get amplified during winters. As per the World Health Organization (WHO) estimate, there is a 5 to 10% increase in adult influenza-based cases and 20 to 30% increase in influenza-based cases globally in children every year. Studying the pattern of these outbreaks can help governments to minimize the impact of these diseases and implement preventive measures against them.

Miller *et al.* [110] proposed methods to generate accurate forecast data for influenza outbreaks using smart thermometers. These were connected to a mobile application which can aggregate and store this data onto a cloud based platform for analysis. The data also included location of users using the GPS of their mobile phones. The authors tried to see the correlation between thermometer collected data and readings reported by the CDC. They developed a model for forecasting ILI activity up to three weeks in advance. Also, they analyzed the data to track fever duration and identify biphasic patterns. Further, they researched transmission of febrile illness in family members of users. To get the forecasts, they used a 52 week sliding training period and then evaluated predictions for next week. This was done iteratively to generate 68 such forecasts. The predictions were made using an autoregressive moving average of 52 weeks. This was done for two cases: the CDC data and the CDC data along with thermometer measurements. Then, these were compared to the lagged CDC data to get correlation of forecasted data with real data, forecast error, and forecast correlation using different time periods (1 week, 2 week lags). To analyze forecasting performance, a generalized linear model was used along with autoregressive components. It was found that thermometer readings were highly correlated with national ILI activity. Also, using thermometer readings, forecasts were improved in real time and upto 3 weeks in advance.

Tapak *et al.* [111] investigated different ML methods of ANNs, SVM, and random forest series using root mean square errors (RMSE), intra-class correlation coefficient (ICC), and mean absolute errors (MAE) techniques for building models for influenza based outbreaks. Data for this study was taken from the FluNet tool developed by the World Health Organization for all the cases of influenza-related illness in Iran from the duration of January 2010 onward to February 2018. The study used 73483 influenza cases who had a fever of more than 38°C accompanied by cough. Models were built using multiple ML algorithms of ANN, SVM, and random forest time series to find values, insights, frequencies, and residuals. Tapak *et al.* [111] performed evaluation using RMSE, ICC, and MAE techniques on illness frequencies. Random forest test obtained the best result from all other techniques with RMSE = 22.78, MAE = 14.99 and ICC = 0.88 for the tests set. Positive results show that random forest technique of ML can be used for building models for predicting outbreaks and illness frequencies from influenza. However, the study is limited for not including factors of climatic parameters and weather conditions. Sentinel data from ILI is another limitation of this study. Thus, this information must be carefully evaluated before implementing this algorithm for predicting the outbreaks of ILI.

VI. ASSISTIVE SYSTEMS

Assistive systems are systems that act as rehabilitative frameworks or provide support in daily life for people with disabilities. These form an important class of applications for ML based IoT frameworks since a lot of these systems rely on accurate judgement of whether and to what extent the disabled person is able to perform a task. This could be anything from limb movement [112] (for which assistive systems may provide physical rehabilitation) to being able to hear properly (like cochlear implants). This section aims to discuss a few of the important applications in EEG and surface electromyography (sEMG) signal based assistive systems that require ML for the processing of these signals. Table 4 at the end of this section gives a brief summary of the reviewed publications that pertain to use cases of ML algorithms for assistive systems.

A. EEG BASED

One of the most important applications of BCI devices is to help physically disabled patients transcend the limits of their disabilities and live a normal life [114]. This is achieved by providing them with BCI devices that they can control with their natural impulse so that no physical movement of their body parts is required to perform an action. Such implementation is made possible by using EEG signals from brain neurons as control for the systems. The recent advances being made in BCI technology form the foundation stone for next generation prosthetic implants. Such prosthetic implants and other BCI assistive systems can prove life-changing for persons with disabilities.

Poorna *et al.* [115] looked into an application of analysis of EEG signals where it was used to gather ocular information (eye blinking) and classify it in such a way that it can be used for a control application. Control applications could be anything ranging from home automation to navigation. Such applications help people to overcome the barriers due to physical shortcomings to interact with the environment. In the said work, the emotive EPOC headset was used to obtain EEG signals corresponding to the closure of the eyes. The data gathered from EEG electrodes was in the form of small voltage (micro) signals. Thus, it was embedded with a lot of noise. To remove the same, pre-processing was done using PCA. For feature extraction, the spectral and cepstral features of the blinks were considered, giving a total of six parameters. For classification, three methods were used: quadratic discriminant analysis, ANN, and multi class SVM. Results stated that for combined feature classification,

TABLE 4. Use cases of ML algorithms for assistive systems.

Ref	Year	Use Case	Algorithm	Advantages	Drawbacks
[115]	2018	Classifying ocular information for navigation assistance applications	DA, ANN, SVM	Can aid physically limited people and improve their quality of life through improved communication	Lot of noise in used EEG signals which needs to be removed through preprocessing
[116]	2018	Typing systems and control robots using EEG signals	RL	System is designed to be highly adaptive to the user	The optimal order cannot be guaranteed in the first try requiring multiple tries for a desired result
[117]	2019	Gait phase detection for lower limb movement rehabilitation	LDA	Ensemble of multiple learning models has been used to achieve optimal performance	Slightly slower due to more calculation time as compared to other contemporary models
2018	2018	Hand gesture identification for stroke rehabilitation	DR	Highly accurate hand gesture identification allows for robot hand to mimic gestures and help in rehabilitation of physical trauma patients	Both training and verification data came from same user, therefore the model was not made user-independent

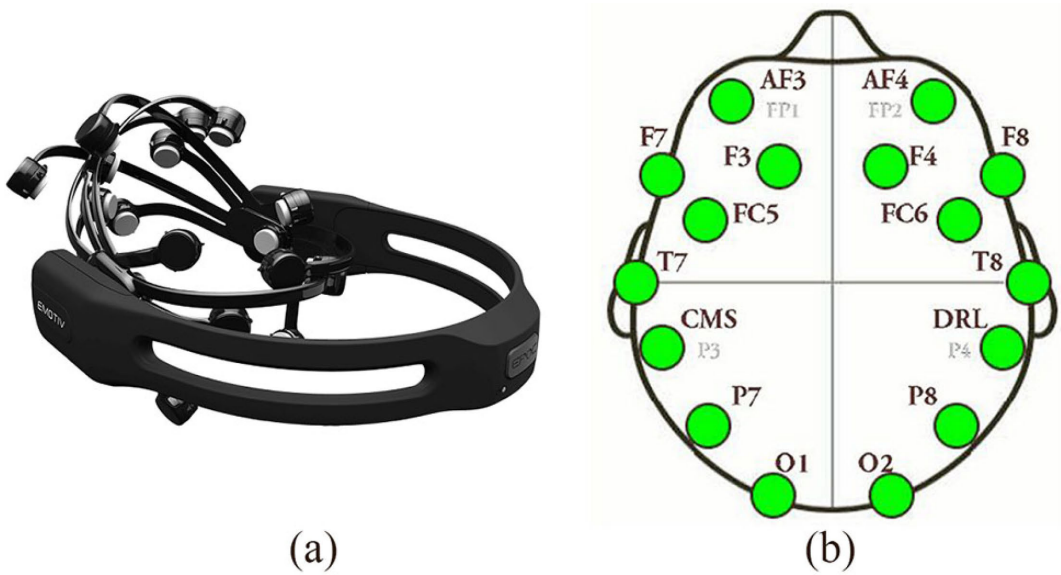

FIGURE 6. (a) Emotiv Epoc headset used by Poorna et al. [113] (b) Electrode positions of Emotiv Epoc.

quadratic discriminant analysis gave the best accuracy of 81%.

Zhang *et al.* [116] proposed the use of BCI integrated with a unified deep learning framework for various applications like making typing systems from EEG signal patterns and controlling robots for domestic assistance. Such systems are of paramount importance to speech and/or visually impaired people. The authors used RML for the classification of various EEG signal patterns. Using selective attention mechanism and long short-term memory, they aimed to make the system adaptive to the person using it. The framework was compared with state-of-the-art BCI frameworks and was seen to outperform them with an accuracy of 93.63%.

ANNs such as multi-layer perception are one of the most popular classes of classifiers used in BCI. Poorna *et al.* [113] presented a comparison of various classifiers used in BCI. It has been concluded that ANN classifiers give superior classification accuracy as compared to other classifiers like KNN. While the KNN classified studies gave 96.06% accuracy [113], ANN gave 98.58% accuracy and also surpassed KNN in terms of sensitivity and specificity (94% and 98.89%, respectively, as compared to 87.42% and 97.61%, respectively, for KNN). Figure 6 shows the headset and electrode positions that were used in the literature. While the results presented [113] show ANN's superiority, it must be noted that the different classifier performances were not studied under

FIGURE 7. sEMG sensor.

the same context. Therefore, the comparisons drawn are not objective and cannot be completely relied upon.

Classifying signals based on various EEG sensors is being actively researched. However using them for aiding patients with physical limitations is an open challenge in the field.

B. SEMG BASED

An alternate to BCI by EEG sensors are surface sEMG signals, which are composed of electromyography and neural electrical signal on the skin surface of a shallow muscle. It can be detected from the sensors and can be linked to actuators to complete the action the patient is intending to carry out.

Peng *et al.* [117] discussed gait phase detection to achieve normal movement of lower limb auxiliary robots using a kernel LDA based nonlinear fusion model. The complex stance and swing motion of lower limbs with realistic variations is a challenging model. After feature extraction and selection is done, LDA is used in gait phase recognition as it is efficient and robust against over-fitting. Similar to Novak *et al.* [119] who used a linear ensemble learning model, Peng *et al.* [117] also used a combination of learning techniques for optimal performance. In recent years, usage of softmax regression in neural networks with nonlinear fusion is preferred for multi-classification problems. Here, simple voting fusion and weighted fusion were compared with the non-linear fusion method of their novel approach which gave the best and final results. An accuracy of 92.5% in walking while performing cognitive tasks was achieved. As a real time application, an important performance metric is computational complexity. Their algorithms takes 90 ms which is fit for the application. Chen *et al.* [120] also discussed development of bionic legs and walking assist boots.

Yang *et al.* [118] designed a smart wearable armband which uses sensors to record sEMG signals for hand gesture identification, and to transmit the information to a robotic arm for it to mimic these movements and help in stroke rehabilitation. The processing and classification of the data collected by these sensors is done using PCA. Six different sEMG features were employed for the classification process. This system achieves an accuracy of 96% in identifying the correct hand gesture made by the user.

VII. MONITORING

Continuous monitoring of a person's health is gaining a lot of recognition since it can not only drastically reduce the mortality resulting from sudden emergencies, but also promote awareness about one's own health and hence lead to a healthier lifestyle. This section aims to cover some major advances that are being researched about in this domain and that use ML as their backbone. Table 5 at the end of this section gives a brief summary of the reviewed publications that pertain to use cases of ML algorithms for monitoring applications.

A. CARDIOVASCULAR DISORDERS

A person's blood pressure (BP) is a direct indicator of how healthy their heart is, and high BP (also known as hypertension) can lead to various heart diseases, as well as stroke, dementia, and a number of other serious complications. Hypertension patients are required to regularly monitor their blood pressure so that these complications can be minimized. Most blood pressure measurement devices today are not portable and use cuffs which can be inconvenient to use. Therefore, an accurate and portable continuous blood pressure monitoring system can prove to be extremely useful.

Tabei *et al.* [121] presented a cuff-less approach to continuous BP measurement by using smartphone cameras to record photoplethysmogram (PPG) signals from a person's fingertips and converting them to BP values using a simplified linear relationship. The parameters in this relationship are specific to the person whose BP is being calculated and are found using linear regression. The linear regression model is trained using LOOCV method. The trained model is tested, and the evaluated BP is compared to BP measured with an oscillometric blood pressure monitor. Tabei *et al.* [121] measured both the diastolic blood pressure (DBP) and the systolic blood pressure (SBP), the scatter plots, and correlations. Regression lines were drawn between the estimated and actual values for both of them which showed that there is a positive linear relationship between them. The MAE and standard deviation (SD) found for DBP were 2.98 and 2.49 mm of Hg, respectively, while those for SBP were 3.28 and 2.46 mm of Hg, respectively. These values lie below the universal standard [122] of MAE of 5 mm of Hg and SD of 8 mm of Hg, making the proposed method a practically usable approach.

Ganesan and Sivakumar [123] proposed to gather real time information about patients using wearable IoT devices. This includes blood pressure, blood sugar, and ECG. To train the model, UCI database was used which includes the past logs of the medical data gathered from medical institutions. Post training, the model is tested for incoming data of patients. Classifiers used were J48, logistic regression, MLP and SVM. J48 gave better accuracy than logistic regression, though logistic regression performed better than MLP. An open issue in the area is building a model to train on various kinds of data. This is because patient status is obtained in various forms such as images, test records, graphs, etc. For the system to

TABLE 5. Use cases of ML algorithms for monitoring.

Ref	Year	Use Case	Algorithm	Advantages	Drawbacks
[121]	2020	Cuff-less blood pressure monitoring system using smartphone camera	Linear regression	Non-invasive and portable BP monitoring	Multiple high-end smartphone cameras required
[125]	2017	Continuous patient monitoring for stroke prediction	NB, random forest	Ensemble of multiple algorithms achieves higher performance	Better IoT based sensor systems required for autonomous data collection
[131]	2010	Prediction of future glucose level through present monitoring data	ANN	Emergency diabetes cases can be predicted using this model	Inaccurate for sudden data changes
[135]	2017	Fall prediction system	NB	Multinomial NB is used which outperforms all other algorithms	Research is focused only on hypertensive senior citizens
[136]	2019	Infant health monitoring system	Gradient boosting	Predicts whether preterm infants have bradycardia, allowing for early intervening measures	Study performed on a limited number of bradycardia patients

work properly, the model needs to identify the type of input, classify it, and normalize it with all available formats of input.

Kakria *et al.* [124] developed a monitoring system, such as the one used in the above case. The data was collected using wearable sensors and smartphones. It was then made available to medical personnel through a dedicated interface.

B. NEUROLOGICAL DISORDERS

A stroke occurs when blood flow to a part of the brain stops. This deprives the brain of oxygen and essential nutrients leading to the death of brain cells. It may lead to paralysis, weakness, trouble in speaking or seeing, and even death. It's no surprise that stroke comes in the top five causes of death worldwide. However, stroke is preventable if the risk factors are noted and acted upon in due time. Also, the monitoring of stroke patients can reduce the chances of it happening again.

In an effort to provide a diagnostic prediction for stroke by patient monitoring, Ani *et al.* [125] used IoT and ML techniques. Wearable devices were used to check blood pressure and pulse rate of the patient. Additionally, a sugar sensor (to be operated by the patient) was used to take input of sugar level. The collected data was sent to a cloud storage to be stored and analyzed. The collected data was made available to caretakers and doctors through a web interface. Classification algorithms were used to generate prediction of risk factor of the patient. NB and random forest classifiers were used which had records of 191 patients with both positives and negatives along with attributes such as gender, age, blood pressure, sugar levels and heart rate. Random forest used multiple decision trees for the prediction. It divided the dataset into multiple subsets and each of them leads to a particular decision tree (classifier). Then, these were combined to give a single outcome. For the used dataset, random forest gave an accuracy of 93% while Bayes gave 90%. The challenges that lie ahead are designing better IoT based systems to gather critical parameters of a patient without the need for the patient to input the data himself/herself.

Combining cognitive technology and IoT can significantly improve the healthcare system for remote monitoring. Al-hussein *et al.* [43] conducted a study for monitoring and diagnosing epileptic seizures using deep learning methods under the cognitive IoT healthcare framework. Cognitive healthcare-IoT (CHIoT) is the latest technology that offers a more collective approach for use in the healthcare industry. CHIoT empowers system for combining physiological and psychological applications for dealing with medical emergencies and quick response. A healthcare framework was proposed which uses wearable sensors to obtain signals, (primarily scalp EEG) and a cognitive engine based on deep CNN for extracting features followed by stacked autoencoder. The system does preliminary monitoring at the edge itself by monitoring the patient's gestures, movements, facial expressions and EEG signals to determine the state and in case of possible seizures, sends the data to the cloud. In the cloud, the data is first converted into a 2D matrix with time as the horizontal parameter and electrode as vertical. Next, this 2D representation is passed to the deep CNN to simplify it, that is, represent it in lower dimensions. Traditional dimension reduction algorithms might not have proved effective as the EEG signals for seizure vary for different people. This model had 7 layers with convolution and max pooling blocks with a softmax output. The activation function was a combination of exponential linear units. This was followed by stacked autoencoder with 2 autoencoder layers and a softmax output. It had 1000 neurons in the input layer, 500 in next autoencoder layer, 200 in the next and finally a fully connected softmax with 2 classes. Training was done on CHB-MIT dataset which was collected at Children's Hospital Boston having 686 multiple channel scalp EEG recordings collected from 23 patients. It had 198 positives with the seizure lasting about 25s in most of them. This model gave 99.5% overall accuracy and 93% average sensitivity which is better than most of the other models based on the same dataset. This inference was

finally passed to professionals to decide what service to provide.

Hadi *et al.* [126] proposed an interdisciplinary approach to achieve remote patient monitoring. In severe cases of seizures and strokes, timely action is crucial. Not all patients are fall-risk patients and need the convenience of travelling. The paper proposed use of both big data analytics for predicting strokes and ML algorithms for making the network robust and optimised. The network also served the dual purpose of locating patients in emergency situations too. The predictive algorithm utilised an ensemble of classifiers that take input from real time readings of vitals from body attached or nearby IoT sensors, as most implementations do, for better performance. It used decision tree, logistic regression, NB classifier in an ensemble system where a soft voting (SV) classifier resides. The ensemble system yielded up to 93% accuracy, a false positive rate of 2.8%, and a false negative rate of 11%.

NB has been commonly used in disease risk prediction [127]. It incurs low computational complexity and does not require large datasets. Ballon [128] proposed a solution for patients with Parkinson's disease. 3D sensors were used to measure movement and analyse reduced flexibility as the disease progressed. Mia *et al.* [129] used a NB classifier to predict coronary problems. The same classifier was utilized by many in Miranda *et al.* [127]. Its accuracy was validated to be more than 80%.

C. DIABETES

Apart from being able to analyze the raw clinical data, IoT can help doctors in monitoring the physical activities of patients using methods such as RML systems. For example, diabetes patients are required to live a lifestyle that promotes engagement in physical activities on a daily basis. With the help of patient monitoring systems, doctors can help patients increase the level of their physical activities. Importance of physical activities is often stressed upon by the doctors to their diabetic patients, but patients often fail to reform their lifestyle. RML systems hand doctors a method to promote healthy lifestyles to their patients.

RML algorithms are able to observe the results of their actions and enhance their learning. Thus, these algorithms yield excellent results where data varies a lot. A mobile app that can run in the background of a patient's phone was designed based on these algorithms [130]. RL algorithms were able to observe the daily physical activity of a patient and send them a SMS that would help increase the physical activity of the patient in the coming day [130]. Results of the RL algorithm based mobile app were studied [130] using a test group of patients and comparing the developments with a control group. Patients reported an increase in their physical activity after installing the mobile application. Moreover, variance analysis between initial performance and later performance of the app was statistically significant (Analysis of variance, $P = 0.04$), indicating that the app was continuously learning. Average HbA1c level of the patients was also improved by 0.28%. However, it should be noted that these methods lacks the level of accuracy that more dedicated systems have.

Real time information of glucose levels in the blood is also of great importance to patients suffering from diabetes. Insulin therapy requires dynamic data of glucose levels. Traditional glucose level monitors require blood samples frequently in a day, which reduces patient comfort and compliance. ANN based models can help achieve the goal of predicting the future glucose levels of a patient. ANNs are particularly useful when working on data that is not linear and does not follow a set pattern. A predictor based on ANNs takes input from a continuous glucose monitor (CGM) and predicts the future glucose levels in the body. Pérez-Gandía *et al.* [131] discussed a predictor that takes the input from a CGM for the preceding 20 min and returns a predicted glucose level at a selected time in future. Pérez-Gandía *et al.* [131] evaluated the accuracy of the ANN model for calculating the RMSE and delay in prediction. Average RMSE was of around 14 min for different prediction horizon time, while the average prediction delay was close to 9 min. Since these models use the past CGM data, inaccuracies were observed whenever there is a sudden data change.

D. PHYSICAL INJURIES

A smart healthcare-IoT architecture involves the development of mechanisms that can identify a user's daily activities for a more personalized treatment. ML algorithms can lead to great advancements in recognizing user activity [133].

Negra *et al.* [134] proposed one such activity recognition system. This system works by calculating the quality of links between different nodes deployed around the user. The channel link quality is estimated by calculating the path loss between nodes to form the dataset, which is operated on by ML classifiers. The transmitting and receiving nodes may be on or off the person. The analysis concludes that the random forest classifier performs best for this application, proving to be the most accurate.

As mentioned before, falls are a major area of concern among senior citizens. It has been found that over a third of people who are aged 65 and above fall, and most of these are recurrent cases [135]. This takes a huge toll on the elderly's quality of life, and increases morbidity and mortality. Castaldo *et al.* [135] aimed to target a specific subgroup of patients, viz. hypertensive old citizens, to develop a fall prediction model based on heart rate variability (HRV) data using five different ML models, among which the NB algorithm is seen to work best. To avoid over-fitting, HRV features used in the models were shortlisted such that only relevant non-redundant features were included. A different dataset than the one used for minimizing features was used to train the models using 3-fold cross validation repeated 10 times and averaging the 10 estimates. A third dataset was used to test the trained models on the parameters of accuracy, specificity, sensitivity, and area under ROC curve (AUC-ROC). The model with the highest AUC-ROC has been selected as the best model. Out of the five models tested,

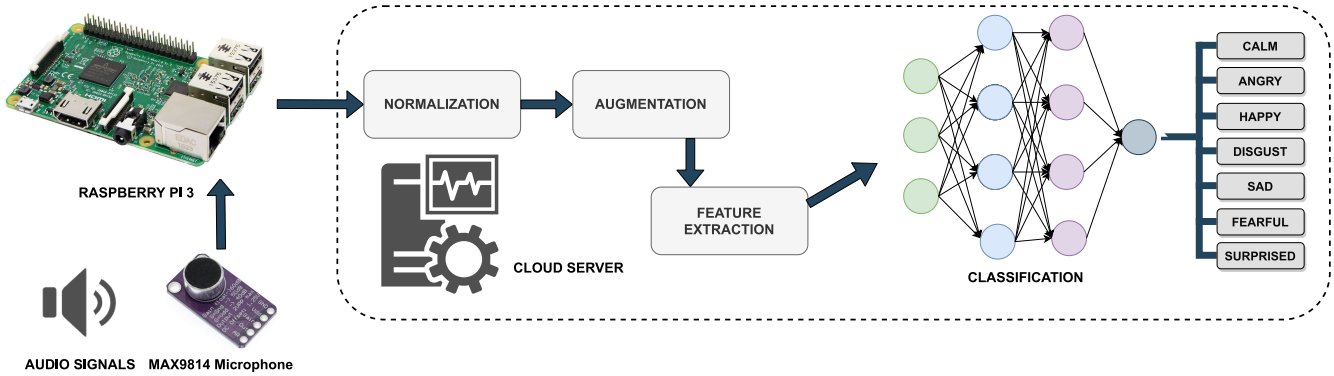

FIGURE 8. Speech emotion detection system [132].

multinomial NB outperformed all the other models with AUC value 70 ± 7.8, while NB stood second with AUC equal to 68 ± 7.5. While the other models showed acceptable specificity and accuracy, their sensitivity was low and therefore multinomial NB was concluded to be the best model for assessing the risk of first-time fallers in elderly hypertensive patients. Although the study resulted in showcasing that NB outperforms other algorithms when it comes to predicting first time fallers, the focus of the said study was only on hypertensive patients which may reduce its applicability in practical scenarios where not all old citizens are hypertensive.

E. MISCELLANEOUS

1) EMOTION RECOGNITION

Emotions are a valid indicator of possible discomforts and state of the body and mind. Sentiment analysis through twitter and reddit posts is a common application of NLP. Some other methods for detection are to monitor facial expressions or speech for stress points. Tariq *et al.* [132] proposed a system for emotion recognition through speech analysis for old people in nursing homes using IoT and deep learning. The chosen emotions were: calm, happy, sad, angry, fearful, surprised and disgust. Figure 8 shows the architecture of the proposed system. The designed system consisted of a Raspberry pi 3 as edge device and MAX9814 electret microphone for audio capture. This specific model of microphone was chosen as it does not need additional components for amplification. The audio is sampled and stored on the Raspberry Pi from where it is transmitted to the server for classification. New audio recording are overwritten over older recordings due to memory constrains and at the server level the clip is trimmed into 3-second clips with data overlapping. Then data processing is done. The audio is first normalised, i.e., the volume is set to an optimal value by multiplying the sampled data points with an amplification factor. For the training set, the data was augmented by adding the same dataset with different amounts of time stretching or pitch shifting, or even dynamic range compression. Artificially creating a bigger training set for the classification model helps in boosting the accuracy of the model. The 80-20% rule was followed for splitting between training and testing data. A 2D CNN model was designed for the final classification that is speech emotion detection (SED). The first layer of the CNN starts off with 24 filters with a 5 × 5 shape, analysing the spectrogram data (in a 128 × 128 shape) output by a librosa library function. The size of the image is slowly waned down to a smaller size using pooling and strides. After a 65 node hidden layer, the final layer yields 10 results, that are the ten different emotions present in the database training and test set. After augmentation, an accuracy of 95% for females and 93% for men was reported.

2) COGNITIVE MONITORING SYSTEMS

The multimodal nature of smart patient-centric healthcare frameworks demands complex decision-making which has led many researchers to introduce cognitive behavior in the development of IoT frameworks [43]. The smart healthcare concept becomes even more relevant with the development of smart cities. The resources of a smart city can never be fully exploited without intelligent, i.e., cognitive machinery [137]. Therefore, notable research efforts are now being made in this direction [61]. Medical resources concentrated in big hospitals and medical institutions in urban areas can be utilized effectively if shared remotely with rural areas. Existing tele-medicine services, even the most efficient ones, fall short on this goal. While physiological diseases can be addressed by them to a good extent, psychological diseases lie way out of their scope. Implementing this distribution of medical resources across space and time to maximize their salvage value, is a challenge. Muhammad *et al.* [61] proposed the model for a 5G cognitive healthcare system which consists of two parts: a resource cognitive engine and a data cognitive engine with the network architecture tailored to enhance transfer speed on different communication modes. This opens new possibilities both in the physiological and psychological domains. The ability to recognize haptic movements (5G tactile internet) makes efficient transfer of a human's actions over 5G wireless networks possible, in turn enabling remote surgery (physiological). Another application is the emotional state evaluation of patients with insomnia,

depression, autism, etc. through data collected and metrics evaluated in real time (psychological). Muhammad *et al.* [61] used a test-bed which was a speech emotion recognition system with behavior feedback from EPIC-robot. Amin *et al.* [59] presented a similar cognitive engine that has been used in conjunction with a CNN to make binary classifications on pathology through processing of EEG signals. The cognitive engine was used to make intelligent decisions on the patient's state before passing the EEG input to more involved processing on the CNN and after that, again to assess the patient's state and notify the appropriate stakeholders.

3) INFANT HEALTH MONITORING

Monitoring systems facilitating sensor fusion through IoT technologies and data processing algorithms are some of the most critical applications for healthcare and new use cases are constantly being proposed. One such case is for monitoring the condition of infants which is otherwise a challenge since their bodies are sensitive and developing. Mahmud *et al.* [136] proposed a framework for monitoring of preterm infants for prediction of bradycardia which refers to an abnormally slow heart rate that may lead to the heart not pumping sufficient oxygen-rich blood to the body. Monitoring and detection of instances of bradycardia in the newborn intensive care unit (NICU) is a good use case for well-being of these infants. Before this system, nurses had to maintain the progress reports themselves which is prone to errors and constrains. The proposed solution uses a multi GPU gradient extreme boosting algorithm on ECG signals. Infants that are born within a duration of 37 weeks are considered premature and they occur at a 10% rate worldwide [138]. For the proposed solution, a positive case of bradycardia was considered when the heart rate was less than 100 bps for more than 1.5 s. The used dataset had 633 bradycardia events which were divided in a 70:30 ratio for training and testing. The ECG signals in infants is characterized by the ventricular activity. Since the R wave usually has the highest amplitude, RR-intervals were used for measuring the inter-beat intervals (IBI). For the HRV, non linear components were also accounted for. To classify the event of an erratic/abnormal interval pattern, a customized extreme gradient boosting, XGBoost was utilized. For feeding the model, only the features which were significant to the label were taken [139], [140]. This produced a faster output as the dimensionality of the data decreased [141]. With an advanced model trained and reliably yielding good results, the model generated can be used to develop solutions for premature infant monitoring with data capture happening locally. Moreover, processing of data may be done at a local hospital level node or on a cloud framework depending on the latency requirements and patient privacy and ethical rules. Results showed the rate of detection of a true positive to be 87%.

VIII. LOGISTICS

This section describes a few of the applications of ML that aim for the overall betterment of H-IoT systems by strengthening them in terms of logistics and security. Such advancements are particularly important since no healthcare system can be implemented without the security concerns accounted for and an upgrade in logistics leads a to better H-IoT system, no matter what the application [142], [143]. Table 6 at the end of this section gives a brief summary of the reviewed publications that pertain to use cases of ML algorithms for logistics.

A. PATIENT PRIORITIZATION

EDs in hospitals often face a situation of overcrowding. Patients have to wait for several hours till a bed becomes available which has a negative impact on the patients' health and overall mortality rate, while also affecting the hospital staff's morale and efficiency. If the number of patients that are to be admitted in the hospital from the ED could be predicted using hospital records, such overcrowding could be foreseen and the hospitals would be able to prevent it and improve patient handling. Also, in situations of crisis which need a strong medical response such as the case of COVID-19, it is important to understand the need to be able to prioritize patients on the basis of their urgency, along with managing the response time, and making the work more efficient.

Bagula *et al.* [144] proposed a solution for prioritizing the patients through a cloud based service as a public health service. It was based on the triage system which is a concept with terms and parameters determined by the World Health Organization. It aimed to ensure that patients at higher risk were treated first while keeping the optimum usage of medical resources as the top priority. The idea proposed was to use wearable tech and "health kiosks" to amass an almost real-time metric of who is more vulnerable and would require immediate medical assistance. As it is a cloud service, the medical data can be stored easily and accessed remotely at all times. This helps in providing a descriptive review of the history of the patient to the healthcare practitioners. This solution also facilitates participatory consultation, improving communication between various specialists for better diagnosis and treatment. For data collection, medical biosensors embedded in e-health kits provide a way of replacing the error-prone manual patient vital signs capture processes by more accurate automated procedures. For example, in the current COVID-19 pandemic [148], a contact-less IR temperature scanner can detect trends of community spread quickly, and possibly prevent fatalities. Such kiosks when paired with the government's COVID tracking applications can track the location of high-risk people, and guide the authorities to provide better treatment and implement quarantine procedures. The system employed k-means clustering to assess the vital signs of the populace and group them in sets based on similarity of vital sign anomalies. For example, people with erratic pulse heartbeats will be in one cluster, people with low blood oxygen levels will be in another, etc. These clusters will have an assigned risk factor, which is effectively a weighted mean of the severity of the recorded vital sign anomalies as determined by the WHO. It was also proposed to

TABLE 6. Use cases of ML algorithms for logistics.

Ref	Year	Use Case	Algorithm	Advantages	Drawbacks
[144]	2016	Patient prioritization system	K-means	Helps in optimal allocation of resources and prioritization of emergency cases	Cloud based, better range requires WiFi which increases costs
[145]	2019	Gait detection-based security system	ANN	Provides immunity against hacking methods like dictionary attacks, involves less computation than fingerprints	Proposed system is still vulnerable to brute force attacks, although it is unlikely that the whole system is compromised
[146]	2002	Classifying raw clinical data using ML	NLP	Electronically stored structured data can vastly improve healthcare systems' efficiency	Is not reliable with highly complex data such as that with lexical semantics
[147]	2018	Wireless coexistence likelihood determination	Logistic regression	Overfitting has been mitigated using least absolute shrinkage and selection operator feature selection	Applicable only to few protocols

deploy solar powered motes with a high capacity lithium ion battery UPS system. To make sure that the sensor reading fell withing acceptable ranges, the field readiness of the e-health sensors was tested. The ZigBee protocol was preferred over traditional Wi-Fi in terms of cost, while Wi-Fi does yield better range and spread.

Graham *et al.* [149] provided an ED crowd prediction model using ML techniques, particularly by applying a decision tree model as well as a model that is an ensemble of multiple decision trees, namely gradient boosted machine. Various model parameters were tuned by performing five rounds of ten-fold cross validation over a custom tuning grid. Using the CARET package, which is a library with tuning and training frameworks, both the decision tree and the gradient boosted machine models were trained and tuned using dataset from hospitals in Ireland.

Manikandan *et al.* [150] proposed a scheduling method, called the hash polynomial two-factor decision tree (HP-TDT) to classify patients as normal or critical, and thus increase scheduling efficiency and minimize response time. The HP-TDT model is carried out in three stages: registration phase, data collection phase, and scheduling phase. Compared to previously designed smart health monitors (SHM), the proposed system was more mathematically inclined, and was more efficient, taking more factors into consideration. Open address hashing (OAH) model is used to carry out the registration stage, which reduces the response time of key generation. Using OAH models, unique private and public keys are generated for each user and hospital, and these keys are passed through hash functions to generate unique registration codes. The next part of the design is data collection, from users and hospitals, which is maintained on clouds. To perform this, polynomial data collection (PDC) algorithm is used. Using PDC, two perfect shortest paths are computed along with a maximal disjoint path. An exponential calculation using polynomial distribution is performed over these attributes to identify the critical state. The final step is the two-factor decision tree scheduling. Creation of a decision tree model involves two steps: tree construction (splitting the tree based on attributes) and tree pruning (removing the extra unwanted branches which might lead to outliers). Hence, the corresponding decision tree is created based on the attribute values calculated in the previous method. The schedule is created on three basic conditions and their corresponding threshold values. If any of the threshold values are surpassed, the patient is termed as a critical case, otherwise a normal case.

Manikandan *et al.* [150] presented an implementation using decision trees to reduce their response time while ensuring privacy. The sensor data for a patient is recorded and used to identify state of distress. Data from various sensors for a patient are attributes of the decision tree. Since fewer decisions are needed to classify a critical state, the number of operations is reduced for data collection when using the trained decision tree. Computational overhead is a significant factor for large scale systems. The experiment used a JAVA platform using Cloud Sim on healthcare data set 2019. It gives an improved scheduling efficiency of 14% and 33% as compared to other implementations [151], [152].

B. SECURITY

Due to limited resources, body sensor network devices are often susceptible to security flaws in protecting the sensitive personal health data. This has led to proposals of many methods for implementing security for WBANs that have been developed recently [153], [154]. Out of these, the biometric cryptosystem approach exploits physiological, behavioural and bio-metric traits, such a face recognition, iris scanning, fingerprint scanning, ECG, and PPG patterns.

Sun and Lo [145] proposed a biometric cryptosystem (BCS) based on gait (walking pattern) signal energy variations for implantable and wearable devices using an

ANN framework. The IEEE standard 802.15.6 operating mainly in the industrial, scientific, and medical (ISM) bands defined the WBAN. These channels are available for anyone with matched radio interface configurations, and can be easily intercepted through software defined radio. Thus, attackers can eavesdrop or even participate within the wireless communication networks amongst WBAN sensor nodes and disrupt the regular operations of the network with DDoS attacks or authentication attacks. Many prior attempts have been made to use solutions like voice and facial recognition to unlock smartphones. Gait detection is done by using inertial measurement units (IMU) which are embedded in many wearable devices. The signals from this device are notoriously inconsistent and hence this paper attempted to use ANNs to estimate the signal received at the chest to achieve better correlation between data gathered from other body positions like the wrist, thigh, head, etc. The neural network is trained by placing sensors on the chest and instructing the fitting algorithm to process the signals from the limbs or head to match the signal from the chest. The ANN architecture consists of an input layer, a hidden layer with 10 hidden nodes, and an output layer. To generate the actual key, a moving average (effectively a low pass filter) of the projected chest gait signal from the sensor in the watch is calculated, and by comparing the actual signal value with that moving average, the binary sequence is received. If the actual signal is larger than averaged signal, then the bit associated with that sample is 1 and vice versa for 0. This bit sequence was then resequenced, in the descending order of reliability, i.e. the amount of difference in the actual and averaged signal. This ANN yielded an authentication accuracy of 95% within 4 attempts and the number of the gait cycles required for generating one 128-bit key is sufficiently reduced compared with their previous work [155]. It provides immunity against many modern hacking attempts at extracting the security key such as a dictionary attack [145], [156], providing a highly secure channel as unique as a fingerprint and using very low computational power. Lin *et al.* [157] proposed a differential privacy protection model for body area networks, that ensured data availability whilst reducing the risk of privacy exposure. A case of ECG big data is taken and dynamic thresholds are used. Lastly, the EHR that are stored in cloud databases also needs to be securely stored. It is vital information such as allergies and past surgeries that may be misused by malicious agents. Hence, to safegaurd them, several blockchain based methods in conjunction with ML have also been proposed [154], [158].

C. MISCELLANEOUS

1) WIRELESS COEXISTENCE

Devices equipped with wireless capability are widespread. An increased use of unlicensed wireless spectrum bands like 2.4 GHz ISM band makes medical devices operating on it susceptible to interference and malfunction.

A lack of standardization for determining wireless coexistence prompted ANSI Accredited Standards Committee C63 to publish C63.27 Standard for Evaluation of Wireless Coexistence (2017) and Association for the Advancement of Medical Instrumentation to publish TIR69 (2017): a guidance for risk assessment of wireless coexistence for medical devices. Together, they give the testing methodology and risk assessment of using wireless technology to perform a medical function. Wireless coexistence testing is an iterative process to identify limits of parameters like time, frequency and distance within which medical equipment is safe to use while sharing radio spectrum resources with other systems. No detailed method of aggregation of experimental evaluation exists.

Al Kalaa *et al.* [147] proposed determining likelihood of wireless coexistence by logistic regression. To mitigate overfitting, 'least absolute shrinkage and selection operator' feature selection was employed. The experiment was set up in a noise free environment. The system under test (Zigbee) and interfering system (IEEE 802.11n) maintained a line of sight. Performance of estimated logistic regression model was 92.72%. However, the hypothetical system model is applicable only to some protocols. Other medical applications include sensing ECG signals for tracking status of heart failure [159].

2) DATABASE STRUCTURING

Classifiers and clustering algorithms can be used to increase the efficiency of healthcare systems, but electronic clinical data is a must to help these algorithms operate. NLP addresses this problem. Several clinical practices rely on difficult-to-store-and-process manual data. If this data can be stored electronically, the efficiency can significantly increase. Any healthcare system has a lot of data in narrative form. Unless this database is structured, it cannot be used for any kind of analysis.

NLP is a very effective algorithm for providing a structure to the databases of clinical practices. It converts a machine-readable narrative in structured form. Hripcsak *et al.* [146] had discussed the implementation of these algorithms to raw clinical data. Data from a total of 889,921 chest cardiographic reports were sorted using NLP algorithms and results were compared on the basis of manual coding of 150 reports. Accuracy of the algorithm was satisfactory in the research paper. NLP reported a sensitivity of 0.81 and a specificity of 0.99, making it at par with expert coders.

IX. CONCLUSION

In this review, we have covered the major applications and systems where AI and IoT are proposed for a safer, accurate, and predictive healthcare system. A general trend of shifting the information processing towards the edge has been observed in the discussed architectures. This is perhaps due to the growing availability of resources for edge and fog devices. Although the primary inferencing is still done mainly on the cloud, it is expected that this will also shift towards the edge with upcoming libraries such as TinyML and

specialized hardware like Tensor processing units. Although many novel methods are being proposed, since the healthcare sector cannot afford false negatives and needs high accuracy, some systems cannot be feasibly implemented. Furthermore, security concerns of the patients about their privacy affect their trust and willingness to participate or use such applications. However, with proposals and implementation of applications that assure high data privacy and security, the trust and awareness of patients for these applications is expected to enhance in the near future.

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HEMANTHA KRISHNA BHARADWAJ is currently pursuing the B.E. degree in electrical and electronics engineering with the Birla Institute of Technology and Science, Pilani. He is actively involved in research in the fields of machine learning, signal processing, digital electronics, and control engineering. His research interests include applications of machine learning integrated with signal processing, particularly involving biomedical devices and acoustics.

AAYUSH AGARWAL is currently pursuing the B.E. degree in electronics and instrumentation with the Birla Institute of Technology and Science, Pilani. He has also been as a Teaching Assistant to a course on IoT with the National University of Singapore. He has worked on several projects and actively participates in competitions demonstrating skills spanning in different domains such as web development, IoT, and augmented reality. His research interests include architecture design in IoT and cloud, communication protocols, and penetration security.

VINAY CHAMOLA (Senior Member, IEEE) received the B.E. degree in electrical and electronics engineering and the master's degree in communication engineering from the Birla Institute of Technology and Science, Pilani, India, in 2010 and 2013, respectively, and the Ph.D. degree in electrical and computer engineering from the National University of Singapore, Singapore, in 2016. He was a Visiting Researcher with the Autonomous Networks Research Group (ANRG), University of Southern California, Los Angeles, CA, USA, in 2015. He also worked as a Postdoctoral Research Fellow with the National University of Singapore, where he worked in the area of Internet of Things. He is currently an Assistant Professor with the Department of Electrical and Electronics Engineering, BITS-Pilani, where he heads the IoT Research Group/Lab. He is also the Co-founder and the President of Medsupervision Pvt. Ltd., a healthcare teleconsultation startup based in India. He has over 55 publications in high ranked SCI journals, including more than 38 IEEE Transactions and Journal publications. His works have been published in journals, such as the IEEE Transactions on Communications, the IEEE Transactions on Vehicular Technology, the IEEE Journal on Selected Areas in Communications, the *IEEE Communications Magazine*, and so on. His works have been accepted and presented in reputed conferences, such as IEEE INFOCOM, IEEE GLOBECOM, IEEE ICC, IEEE PerCom to name a few. He has received funding of more than 80K USD as a principal investigator as a part of various national and international projects. His research interests include the IoT security, blockchain, 5G network management, BCI, and addressing research issues in VANETs and UAV networks. He has served as a TPC member in various conferences, such as Sensorsnets 2021, Vienna, Austria, IEEE COMSNETS 2021, ICBC 2021, Sydney, Australia, and so on. He serves as an Area Editor for the *Ad Hoc Networks* (Elsevier). He is an Associate Editor of *IET Networks*, *IET Quantum Communications*, *Internet of Things and Cyber-Physical System* (KaEi), and several other journals. He has been serving as a Guest Editor in various journals, such as the *IEEE Internet of Things Magazine*, *Computer Communications* (Elsevier), *IET Intelligent Transportation Systems*, and so on.

NAGA RAJIV LAKKANIGA received the Ph.D. degree from the University of Arkansas for Medical Sciences, USA. After his Ph.D., he served as a Research Scientist with SmartBio Labs, India, and is currently working as a Postdoctoral Associate with The Scripps Research Institute. His primary expertise is to discover small molecule therapeutics to target proteins involved in various diseases. Some of his inventions are being pursued for clinical applications in oncology. He is also interested in employing computational methods, including molecular dynamics and artificial intelligence-based protocols, to guide drug discovery and provide solutions to address the various challenges in healthcare.

VIKAS HASSIJA received the B.Tech. degree from M.D.U University, Rohtak, India, in 2010, and the M.S. degree in telecommunications and software engineering from the Birla Institute of Technology and Science (BITS), Pilani, India, in 2014. He is currently pursuing the Ph.D. degree in IoT security and blockchain with the Jaypee Institute of Information and technology (JIIT), Noida. He is also an Assistant Professor with JIIT. He has eight years of industry experience and has worked with various telecommunication companies like Tech Mahindra and Accenture. His research interests include the IoT security, network security, blockchain, and distributed computing.

MOHSEN GUIZANI (Fellow, IEEE) received the B.S. (Hons.) and M.S. degrees in electrical engineering, and the M.S. and Ph.D. degrees in computer engineering from Syracuse University, Syracuse, NY, USA, in 1984, 1986, 1987, and 1990, respectively. He served in different academic and administrative positions with the University of Idaho, Western Michigan University, University of West Florida, University of Missouri-Kansas City, University of Colorado-Boulder, and Syracuse University. He is currently a Professor with the Computer Science and Engineering Department, Qatar University, Qatar. He is the author of nine books and more than 500 publications in refereed journals and conferences. His research interests include wireless communications and mobile computing, computer networks, mobile cloud computing, security, and smart grid. He is a Senior Member of ACM. He received the 2017 IEEE Communications Society WTC Recognition Award as well as the 2018 AdHoc Technical Committee Recognition Award for his contribution to outstanding research in wireless communications and Ad-Hoc Sensor networks. He was the Chair of the IEEE Communications Society Wireless Technical Committee and the Chair of the TAOS Technical Committee. He is also the Editor-in-Chief of the *IEEE Network Magazine*, and the Founder and the Editor-in-Chief of *Wireless Communications and Mobile Computing* journal (Wiley). He served as the IEEE Computer Society Distinguished Speaker. He is also the IEEE ComSoc Distinguished Lecturer.

BIPLAB SIKDAR (Senior Member, IEEE) received the B.Tech. degree in electronics and communication engineering from North Eastern Hill University, Shillong, India, in 1996, the M.Tech. degree in electrical engineering from the Indian Institute of Technology Kanpur, Kanpur, India, in 1998, and the Ph.D. degree in electrical engineering from the Rensselaer Polytechnic Institute, Troy, NY, USA, in 2001. He was a Faculty with the Rensselaer Polytechnic Institute, from 2001 to 2013, an Assistant Professor and an Associate Professor. He is currently an Associate Professor with the Department of Electrical and Computer Engineering, National University of Singapore, Singapore. He is also the Vice Dean of Graduate program and as the Area Director of the Communications and Networks Laboratory, NUS. His current research interests include wireless networks, and security for Internet of Things and cyber physical systems. He is a member of Eta Kappa Nu and Tau Beta Pi. He is a Fellow of the Institution of Engineers, Singapore. He has received many reputed fellowships, such as Leiv Eriksson Fellowship, Norway, in 2011, JSPS Fellowship, Japan, in 2010 to name a few. He has served as a TPC in various conferences, such as IEEE LANMAN, GLOBECOM, BROADNETS, and ICC to name a few. From 2007 to 2012, he served as an Associate Editor for the IEEE Transactions on Communications. He also serves as an Associate Editor for the IEEE Transactions on Mobile Computing. He has served as a Guest Editor in various journals, including *Future Generation Computing Systems* (FGCS) (Elsevier), the IEEE Sensors Journal, *Journal on Information Security and Applications* (Elsevier), and so on. He is an ACM Distinguished Speaker.