IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received June 23, 2021, accepted July 16, 2021, date of publication August 9, 2021, date of current version August 17, 2021.

*Digital Object Identifier 10.1109/ACCESS.2021.3103268*

# Systematic Review on Machine-Learning Algorithms Used in Wearable-Based eHealth Data Analysis

**ADITI SITE, JARI NURMI, (Senior Member, IEEE), AND ELENA SIMONA LOHAN, (Senior Member, IEEE)**
Electrical Engineering Unit, Tampere University, 33720 Tampere, Finland
Corresponding author: Aditi Site (aditi.site@tuni.fi)

**ABSTRACT** In this digitized world, data has become an integral part in any domain, including healthcare. The healthcare industry produces a huge amount of digital data, by utilizing information from all sources of healthcare, including the patients' demographics, medications, vital signs, physician's observations, laboratory data, billing data, data from various wearable sensors, etc. With the rapid growth of the wireless technology applications, there has also been a significant increase in the digital health data. New medical discoveries and new eHealth-related technologies, such as mobile apps, novel sensors, and wearable technology have contributed as important data sources for healthcare data. Nowadays, there is a huge potential to improve the healthcare quality and customer satisfaction with the help of machine learning (ML) algorithms applied on time-domain and frequency-domain healthcare data obtained from wearables and sensors. This systematic literature review examines in depth how health data from sensors can be processed and analyzed using ML techniques. The review focuses on the following diseases for obtaining the eHealth data: diabetes mellitus type 1 and type 2, hypertension and hypotension, atrial fibrillation, bradykinesia, dyskinesia, and fever related diseases. The data for the systematic literature review was collected from four databases, Medline, Proquest, Scopus, and Web of Science. We selected 67 studies for the final in-depth review out of the initial 1530 pre-selected papers. Our study identified that the major part of eHealth data is obtained from the sensors such as accelerometer, gyroscopes, ECG (Electrocardiogram), EEG (Electroencephalogram) monitors, and blood glucose sensors. This study also examines the different feature types, feature extraction methods, and ML algorithms used for eHealth data analysis. Our review also shows that neural network (NN) algorithms and support vector machines (SVM) have shown so far the best performance for analyzing the healthcare data among other ML algorithms studied in the literature.

**INDEX TERMS** Analytical techniques, artificial intelligence, accelerometer, gyroscope, data processing, machine learning (ML), neural networks (NN), remote monitor, sensors, support vector machines (SVM), wearables.

## I. INTRODUCTION

Medical discoveries in the field of sensors and wearables are contributing as an important data source for healthcare data. Different wearable devices and sensors can be used to continuously monitor the conditions of patients and providing health related information, patient's behaviour and multiple physiological parameters. Hence, solutions are needed in order to manage and analyse this continuous, varied, unstructured health data, as well as to acquire meaningful insights from it in a reasonable time, with reasonable complexity and storage capacity.

Continuous remote-monitoring healthcare system is one such solution, which can frequently monitor and analyze patient's status including heart rate, blood pressure level, sleep patterns, and other physiological parameters using new mobile and Internet of Things (IoT) connectivity. This will help doctors in detection, prevention of emergencies, and long-term management of health conditions, especially in case of chronic diseases which need active monitoring of physiological parameters. These IoT systems offer a great platform for achieving faster, cheaper, and more accessible healthcare than traditional systems, which do not make use

The associate editor coordinating the review of this manuscript and approving it for publication was Xueqin Jiang.

of IoT infrastructure. Such systems with more accessible, faster healthcare capabilities can provide required healthcare services for patients at home reducing unessential hospitalization [1]. Moreover, continuous remote monitoring systems will also increase patient's participation in the entire healthcare process and convenience of care and improvised care coordination. Hence, data from multiple sensors can be combined to develop multi-sensing continuous remote health monitoring systems. Such system can be used analyze and provide insights using the continuous data obtained from multiple wearable and sensors, corresponding to various chronic diseases like diabetes, blood disorder, heart diseases, Parkinson's disease, and infectious diseases.

This systematic literature review is focused on one of the most important aspects of multi-sensing continuous remote health monitoring systems, which is data analysis. This paper discusses the findings based on 1530 research studies identified from four databases: Medline, Proquest, Scopus, and Web of Science. Previous studies in this context focused on analyzing the data related to a particular disease, in which the physiological parameters and signals were also obtained from a single source. So, the aim of this systematic literature review is to explore the information about different eHealth signals obtained from multiple sources, their feature types, feature selection and feature extraction techniques, machine learning algorithms and evaluation criteria for analyzing the eHealth data. The information gathered from this systematic literature review will be utilized to design an optimized model/solution for predicting the chronic diseases using continuous and real-time data obtained from multiple sensors. Combining data from different sensors can help, not only to improve the detection performance of chronic disease care, but also to identify patterns and correlations between different physiological signals. The studies which are identified in this review, analyze the data obtained from the various sensors such as accelerometers, gyroscopes, voice signals, EEG (Electroencephalogram) and ECG (Electrocardiogram) signals, respiratory flow signals, and other wearable sensor data. We identified different pre-processing, feature extraction, and feature selection techniques along with machine learning algorithms which are used for the analysis of digital healthcare data especially when raw signals are used. Raw signals [2] are electrical signals or voltage coming out of sensor not represented in tabular form. The eHealth data can be in the form of time-domain signals, frequency domain signals, images etc. So, we have also explored which algorithms can show better performance for such heterogeneous types of data. Hence, this review provides an overall picture on the sensors used, data type distribution of eHealth data, machine learning algorithms and, evaluation criteria used for wearable eHealth data analysis.

The following subsections provide a small overview on the various components of a continuous remote monitoring system. The first subsection gives a description about the remote monitoring system, the next subsection discusses the chronic diseases, corresponding to which signals/data is obtained from sensors/wearable. The third subsection tells about the wearable and sensors being used for monitoring various physiological parameters. The last subsection provides an overview on the machine learning algorithms for analyzing the physiological parameters obtained from sensors corresponding to chronic diseases.

### A. REMOTE MONITORING

Remote monitoring systems are one of the important solutions which can reduce unnecessary hospitalizations and can help in the continuous progress tracking of the patient's health. It can also ensure long term management of the health conditions. Continuous monitoring healthcare systems are especially important for elderly people as regular hospital visits become difficult at times [1]. Remote monitoring is an effective solution for monitoring chronic diseases that require active monitoring of the vital signs and the physiological parameters. A continuous remote monitoring system generally consist of three main components. The first component is the body area network or wearables, responsible for the collection of the various physiological parameters. The second is the data transmission or communication module, which is responsible for providing connectivity between the devices and the storage servers. Third module is the data analytics and visualization module which is responsible for the analyzing this continuous healthcare data. Continuous remote monitoring system can be either mono-sensing or multi-sensing based on the physiological parameters being obtained from single sensor or multiple sensor [1].

With remote monitoring systems in place and delivering continuous stream of data or real-time data, physiological parameters can be analyzed regularly which can help in detecting life-critical events and early predictions of diseases/symptoms. Such systems will also ensure remote reporting and alert generation, where a person can get daily health status on his/her personal devices such as laptop or mobile phone, and alerts can be generated in case of emergencies.

### B. CHRONIC DISEASES

This study focuses on the eHealth data from the patients having chronic diseases because these diseases require active monitoring and – if not monitored – can even develop into adverse symptoms/diseases. Chronic diseases are conditions that last one year or more and require ongoing medical attention or limit the activities of daily living, so it is essential to monitor such diseases on continuous basis to detect and prevent the emergencies.

Chronic diseases include diabetes, blood disorders, heart diseases, infections which can eventually lead to certain lung diseases, Parkinson's disease, neurological disorders such as schizophrenia, and strokes. All these diseases have various types and symptoms. For example, diabetes can be classified as Type 1 diabetes mellitus, Type 2 diabetes mellitus, or gestational diabetes [3]. In case of Type 2 diabetes mellitus, it is important to monitor the daily activities of the person such as the physical activity, sedentary behaviour, food intake, etc., whereas Type 1 diabetes is determined by considering the insulin level in the blood and it is also known as the insulin-dependent diabetes. Blood disorders can lead to hypertension [4] and need continuous monitoring of systolic and diastolic blood pressure. Atrial fibrillation (AF) [5], [6] or arrhythmia is also a condition which can be determined by varying electrocardiogram (ECG) levels, that can help in detection of various heart diseases. In case of infectious disease [7] which can lead to lung disease, most of them have symptoms such as cough, fever, shortness of breath, dry cough, nausea, weakness etc. and have high mortality rate [8]. In terms of neuro-degenerative diseases, Parkinson's disease [9] is one such long-term neuro-degenerative disorder of the central nervous system that causes motor–tremor at rest, rigidity, bradykinesia, and postural instability– and non-motor manifestations. Such a disease progresses over time and the symptoms usually grow in severity and quantity, increasing the chance of severe complications and worsening of the patient's quality of life.

### C. WEARABLES AND SENSORS

Wearable devices could be used to address some of the challenges related to the detecting and managing adverse health conditions in populations. Wearable sensor data help to track the important statistics or symptoms of diseases, and especially of chronic diseases. Various sensors that can be used to monitor the vital signs of disease include:

- Retinograph for diabetic retinopathy [10].
- Blood Glucose meter for measuring the blood glucose level in the body [11].
- Accelerometers, gyroscopes, and magnetometers for the gait monitoring [9], [12].
- Inertial measurement unit which generally consists of triaxial accelerometer, gyroscope, magnetometer for monitoring various signs in Parkinson's patients [12].
- Various other sensors and smartwatches also provide the Electrocardiogram (ECG) data and pulse oximeter recordings [13]–[15].
- There are biomedical sensors which provide the data of Electroencephalogram (EEG) signals for monitoring parameters in case of neuro-degenerative disorders [16].
- Photoplethysmogram (PPG) sensors can be used for blood disorders [17].

In addition, there are various other sensors that are used for monitoring environmental parameters like temperature sensors, humidity sensors [18].

### D. MACHINE LEARNING ALGORITHMS

Machine learning algorithms consist of various types of classification, clustering, and prediction algorithms and neural network algorithms used for the analysis of different types of data. They also include various feature selection algorithms such as wrapper based methods and filter based methods. Data obtained from sensors and wearable devices can be extracted for important health related parameters and this data can be used to create various classification, clustering, and predictive models for identifying diseases, symptom onset, etc. This digital health data can either be in structured or semi-structured format. Structured data are generally organized in tabular format such as demographic information and semi-structured data needs to be processed in some way to bring it in tabular format, e.g., XML files or JSON files are semi-structured formats. Different structures of healthcare data need different types of pre-processing and analysis methods to extract the important insights from raw data.

Depending on the data and the information to be extracted from the data, various machine learning algorithms for analysis and preprocessing are used. Support vector machines are used for analysing the ECG and EEG data for diabetes classification [19], Random Forest algorithms are used for prediction tasks like diabetes or hypertension prediction [20], [21]. Neural network algorithms have been used for the prediction task for disease diagnosis using data from wearable medical sensors [22], multilayer perceptrons are used for classification of different types of diabetes and for behavioural analysis for Parkinson's disease [3], [23]. Similarly, artificial neural networks (ANN) are used for the analysis of EEG, Electromyogram (EMG), voice signals [24], [25]. Along with this there are many pre-processing methods and feature selection methods being used for obtaining better accuracy of models. Methods such as Density-Based Spatial Clustering of Applications with Noise(DBSCAN) are used for outlier detection, Synthetic Minority Oversampling Technique (SMOTE) for dataset balancing to balance between the different type of classes or labels [21]. Also, for selecting the relevant parameters, filter based and wrapper based selection methods are used [26].

## II. LITERATURE STUDY

This section briefly describes the approach being followed for identifying the suitable literature/studies related to the research work. The first subsection describes the aim of this systematic literature review and the questions being focused while doing the literature review. The next subsection tells about the step-wise process carried out for literature review including database selection, search query formation, specifying inclusion/exclusion criteria etc., and the last subsection describes the study selection process.

### A. STUDY DESCRIPTION

The objective of this systematic literature review is to study the literature and identify the previous work and previous studies which have been carried out in the area of healthcare technology, for analyzing the healthcare data obtained from varied sources using various machine learning algorithms. This literature review aims to compile the information obtained from the previous research and to present a generalized view of all the information being gathered from the studies, regarding data and algorithms used for the digital healthcare data analysis. This systematic literature review addresses the following questions:

1) How can the heterogeneous types of digital healthcare data and the continuous stream of data be efficiently combined, processed, analyzed using various machine-learning algorithms?
2) What are the kinds of sensors/wearable devices that are mainly used for gathering the healthcare data especially for certain chronic disease?
3) How does the feature-type distribution go in case of digital healthcare data when its sources are different?
4) How is the healthcare data analyzed by using different machine-learning algorithms and, in particular, what is the proportion in ML algorithms employing neural networks?

### B. SEARCH PROCESS OVERVIEW

The literature identified for the systematic literature review were based on the step-wise process starting from defining the protocol, followed by database selection, concept terms/search terms identification, search query formation, and then scrutinizing the studies based on title, abstract and full text. The step-wise process followed is described below:

#### 1) PROTOCOL DEFINITION

This includes specifying the research question, aim of the research project, objective of systematic literature review and the inclusion and exclusion criteria. Table 1 defines each of the parameters required for protocol definition.

**TABLE 1. Protocol definition.**

| Parameter | Description |
|---|---|
| Main Question | How digital health data (data from wearables and health monitors/sensors), IoT, artificial intelligence can be used for developing connected healthcare system for identifying life critical events and remote monitoring/reporting of patient's health in case of chronic diseases. |
| Aim | The main aim of this research is to develop a connected healthcare system for active monitoring of the patients having chronic diseases using wearable technology, IoT and artificial intelligence. It will also focus on detection and prevention of any life-critical events. |
| Objective of Systematic Literature Review | The objective of this systematic literature review is to identify the previous work which has been carried out in the area of healthcare technology using wearables, sensors, IoT, and ML, and compile the information obtained regarding the analysis of healthcare data. |
| Inclusion Criteria | The criteria for inclusion were:<br>1. Studies that provide knowledge about how wearable or sensors can be used in healthcare data analytics.<br>2. Studies that include the parameters for extracting/preprocessing data from various health sensors.<br>3. Studies that suggest the use of specific wearable devices for monitoring a particular aspect of patient's health.<br>4. Studies that provide information about the analytical techniques used for analyzing the wearable data.<br>5. Studies that involve information about the processing/analysis of continuous stream of real data. |
| Exclusion Criteria | The criteria for exclusion were:<br>1. Study was not in English<br>2. Study is not between 2015-2020. |
| Extended Inclusion Criteria/Rule Sheet | Extended inclusion criteria are:<br>1. Is any prediction/classification/analysis/diagnosis method presented in the paper? If it presents any review, it is relevant to the research concepts?<br>2. Are specific features/disease characteristics/biomarkers mentioned in the paper?<br>3. Does the paper present supportive/relevant information in the form of diagram/tables/pseudocode/framework/design flow/interface? |

#### 2) DATABASE SELECTION

The systematic literature review was conducted with four electronic databases during September-October 2020 with four databases: Medline, Proquest, Scopus and Web of Science.

#### 3) CONCEPT TERMS AND SEARCH TERMS IDENTIFICATION

Four concept terms were identified for the systematic literature review namely disease, wearables and sensors, connected healthcare system, and analytical techniques. All other search terms which are used for the formulation of the search query are categorized under one of the concept terms.

#### 4) SEARCH QUERY

The search phrase "**("chronic disease*" OR "heart disorder*" OR diabetes OR parkinson OR schizophrenia OR "blood disorder*" OR infect* OR stroke OR hypertension) AND (wearable* OR "ambient techn*" OR "wearable techn*" OR device* OR "internet of things" OR "medical sensor*" OR accelerometer OR gyroscope OR glucometer OR ECG OR EEG OR "heart rate sensor" OR "respiratory rate" OR bluetooth OR ble OR "thermal sensor*") AND (surveil* OR diagnos* OR "remote control*" OR "remote report*" OR "remote monitor*" OR "patient monitor*") AND ("data processing" OR "data analysis" OR "Artificial Intelligence" OR "Machine Learning" OR "health* data analy*")**" was used for all the four databases. For all the databases, the search was focused on the title, abstract and keywords and collectively 1530 records were identified at the initial stage from the four databases.

### C. STUDY SELECTION RESULTS

Figure 1 shows the flowchart of the process followed for the selection of the studies. This process is similar to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) including identification and screening of the studies. However, for this review based on the initial results obtained from the databases, the screening process is modified and the changed process is summarized in the flowchart. The study selection process starts with defining the protocol sheet, identifying the concept terms and formulating the search query, once the search query is formulated results are fetched from the database. Search query is modified according to the results obtained from database, search was performed by searching each search term in the four database under title, abstract and key words and these search terms are combined with AND and OR operations. Initially 1530 results were obtained from the search query.

The next step followed was duplicate removal where 870 results were obtained out of 1530. After duplicate removal the papers were selected based on title and abstract, and the results obtained from them are 380 and 256 respectively. Since the number of papers to be evaluated for full text was still very high, an additional step of diagonal evaluation was also done on the papers after abstract evaluation. At this step, the papers were evaluated based on the figures, tables and the rule sheet (mentioned in Table 1) which consisted of more specific questions other than inclusion criteria such as information about the disease bio-markers or features, methodology or algorithm, any supportive or relevant information in the form of diagrams, frameworks or design flow. The papers which satisfied more than 50% of the criteria from the rule sheet were selected. 155 results were obtained after diagonal evaluation and this was followed by full text evaluation which brings the paper count to 67. So, after the selection process 67 papers were selected for the Systematic Literature Review, of which results are presented in the next section.

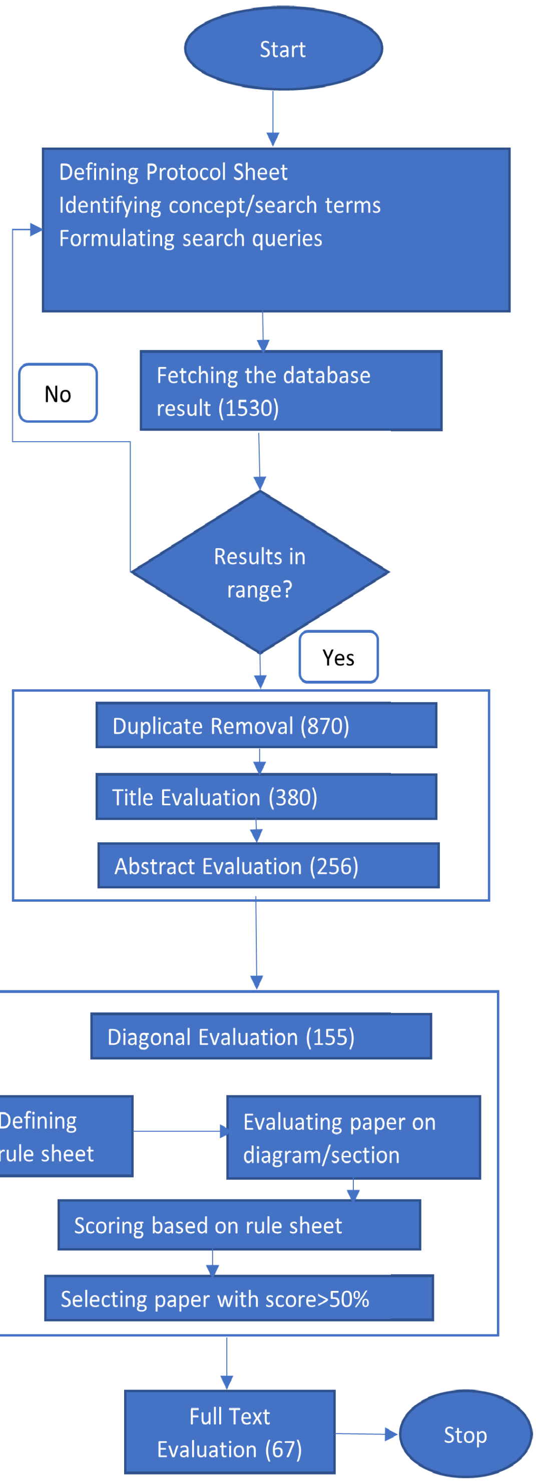


**FIGURE 1. Flow chart of selection process.**

## III. RESULTS

This systematic literature review was done using 67 studies selected from a systematic process (as mentioned in Figure 1). The information obtained from the evaluation of these studies is compiled in the form of bar plots and pie-charts for good readability of the results. This section gives a detailed description of the plots and the findings from those plots which can be utilized for the follow-up research work.

This section is divided into five subsections: the first subsection presents the information about the sensors; the second subsection focuses on the distribution of feature types; the third subsection presents the algorithms being used for the analysis of the different parameters, mentions the neural-network algorithms typically in use and presents the algorithms reported in the literature with best performance among studied ones; the fourth subsection gives an overview of the evaluation criteria used for the performance evaluation; the fifth subsection shows a cumulative overview of the process of healthcare data analytics.

### A. DESCRIPTION OF SENSORS USED IN THE STUDIES

This section presents the information obtained from the literature concerning the different types of sensors used for obtaining data about vital signs, symptoms or other health data for various chronic diseases. Figure 2 shows the relative percentage of the sensors that have been used in the studies. This data is obtained from 56 studies, as the rest of 11 studies have obtained the data from repositories such as UCI repository [27] and the sensors used in the dataset is not mentioned. Other studies have used sensors to obtain the data. These sensors include accelerometers, gyroscopes, EEG sensors, ECG sensors, PPG sensors, pulse oximeters, smart watches, smart phones, gait sensors, heart rate sensors, humidity and temperature sensors.

As per the information obtained from the analyzed papers, sensors such as accelerometers, gyroscopes, and magnetometers are used for the measurement of orientation, acceleration, or angular velocity especially in the case of Parkinson's disease. Accelerometers are also used for counting the steps in case of diabetes or heart diseases, so it can be seen from Figure 2 that accelerometer sensors have been used in more than 23% of studies. Sensors such as gyroscopes have also been used in more than 10% of studies. ECG sensors, EEG sensors, PPG sensors are mainly used for monitoring parameters of diabetes, heart diseases, and blood disorders. However, EEG sensors are also used for the diagnostics of Parkinson's disease and schizophrenia. These sensors have been used for more than 23% of studies. Even smartwatches/wearables or smartphone built-in sensors can be used to monitor sleep patterns or activity data, they have been used for 14% of studies. Other sensors such as heart rate sensors, pulse oximeter, temperature sensor, humidity sensors, free-style libre sensor, blood glucose sensors, or retinograph are used for less than 5% of studies because they are used to obtain a particular characteristic of the body.

This shows that most of the eHealth applications use the data obtained from the sensors such as accelerometer, gyroscopes, smart watch/smart phone/wearables, EEG/ECG/PPG etc. Accelerometer or tri-axial accelerometers, gyroscopes are used in more number of cases for the detection of the freezing of gait [28], bradykinesia [29], tremors [30] stroke [31] using machine learning algorithms, compared to other inertial sensors or gait sensors. Moreover, accelerometers can also be used for activity monitoring [32] when detecting the conditions of heart disease/diabetes. In some cases, EEG and EMG [16] signals are also used for the gait analysis and early detection of the Parkinson's disease. Similarly algorithms on ECG data can help for the early detection and prevention of atrial fibrilation or arrythmia, and they can also help in obtaining certain parameter such as heart rate, heart rate variability so pacemakers/heart rate sensors are used only in very few applications since the similar parameters can be obtained using ECG signals. Built-in smart phone sensors [33] are also used to capture the images for diabetic retinopathy screening rather than retinograph, so most of the studies have identified the diabetic retinopathy using the images from smart phone sensors. Hence, most of the physiological information related to the various chronic diseases can be obtained from a set of sensors namely accelerometer, gyroscopes, EEG/ECG/PPG, smart watches/smart phones/wearables etc. This multi-sensor data from the above mentioned set of sensors can be combined, processed using various algorithms to obtained the specific features to detect/classify/predict the diseases.

### B. FEATURE TYPE DISTRIBUTIONS

This section provides a detailed description of the feature types which have been used in the literature study. This also provides an overview on the data processing techniques used to obtain those features from the raw signals. Figure 3 shows a pie chart which represents the feature type distribution among the literature studies selected. This graph includes 64/67 studies, 3 studies out of 67 are based on:

1) Remote monitoring of patients using BLE. [1]
2) Use of source-wise missing data. [34]
3) Detecting infections using IoT edge technology. [35]

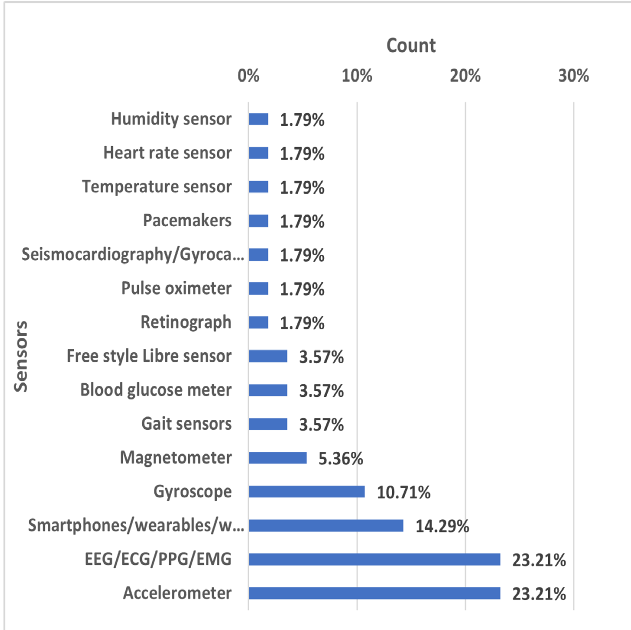


**FIGURE 2.** Sensors used for monitoring symptoms.

To obtain the features from the raw signals, data processing techniques or pre-processing techniques are required. These methods vary according to the type of signals. Certain methods used for processing of signals are data augmentation [13], data normalization [19], [36], data sampling [20], signal segementation [37], wavelet decomposition [38], Fourier transform [39], filters such as Gaussian filters [40], Butterworth bandpass filter [41], other data processing methods also includes DBSCAN [21] for outlier detection, SMOTE [21] for unbalanced data set. All these techniques process the raw data to obtain the features, these features can be time or frequency domain features, time series values, numerical values, spatio-temporal features, images etc.

The pie chart in Figure 3 illustrates the relative distribution of feature types among the studies. Time domain and frequency domain features are used in most of the studies indicated by a maximum proportion of 23% in pie chart. These time and frequency domain features are obtained from the sensors such as accelerometers, gyroscopes, EEG sensors, and ECG sensors. Numerical feature values also hold nearly equal proportion to that of time and frequency domain features and occupy 22% of division in the pie chart. Numerical values are present is in the form of integers, floating point values, etc. There are about 19% of studies which are using raw signals as an input to the machine learning algorithms for data analysis. These raw signals include respiratory signals, gyroscopic signals, acceleration signals, voice signals, sound signals, and ECG/EEG signals, PPG signals [42]. About 14% of studies have also used multi-type feature values, which generally includes values from datasets obtained from repositories such as UCI repositories [27]. These multi-type feature values can be in the form of text, categorical values, integer, and float values, etc. Images from retinograph and portable x-rays are included in 8% of the studies.

Spatio-temporal features and time-series features [43] constitute 6% and 5% proportion respectively. Spatio-temporal data or features describe a phenomenon in a particular location and in a period of time, they are used for gait analysis in case of Parkinson's disease [44]. Time-series data indicates the data points indexed in time order. Studies have used the time-series data for predicting the values of glucose level. However, only 2% studies have used a statistical feature set and 1% of studies have used spectogram for the analysis. Statistical features include features such as mean, median, standard deviation, variance etc. [45], [46]. Spectrogram is visual representation of spectrum of frequencies of a signal as it varies with time, few studies have used spectrogram as an input for ECG signal [5].

As per the distribution of data types represented by the pie chart in Figure 3, time domain features represent the various characteristics of signals over time range, and frequency domain signals represent the characteristics of signals over a frequency range. These components can be used to extract different features from the signals. For ECG signals, features such as HRV (Heart Rate Variability), HR (Heart Rate), QT (time from the start of the Q wave to the end of the T wave), QRS (The period of QRS complex) can be obtained to represents various characteristics of heart [19]. In case of EEG signals, certain frequency bands such as theta, delta, alpha corresponding to different locations of brain helps in extracting the important features from the EEG signals [19]. So time domain and frequency domain features are used in most of the studies. Similarly, the values obtained from the datasets have multi-parameter input data, numerical feature set because they contain the information about the patient's demographics and the vital signs, hence they are also used in most of the studies. Moreover, raw signals also provide many significant features from the signals. These raw signals such as acceleration signals provide the information related to physical activity [28], voice signals for diagnosis of Parkinson's disease [25], sound signal for heart disease [47], respiratory flow signal for identification of breathing patterns [48], etc., so the raw signals also constitute a good proportion in feature type distribution. However, the information obtained from the spatiotemporal, time-series data, images, spectograms and other sources highlights the information related to a specific case, e.g., when representing continuous data or space-time data, time-series features and spatio-temporal data is used. So, they are used in less percentage of studies as compared to the time-domain, frequency domain features, multi-parameter feature set or raw signals. Hence, most of the features obtained from the accelerometer, gyroscopes, EEG/ECG/PPG, smartwatches/smart phones/wearable sensors are in the form of time-domain feature, frequency-domain feature, multi-type feature including numerical feature values and raw signals.

### C. ALGORITHMS USED FOR ANALYSIS

This section mentions the machine learning algorithms used for the analysis of the pre-processed data or signals.

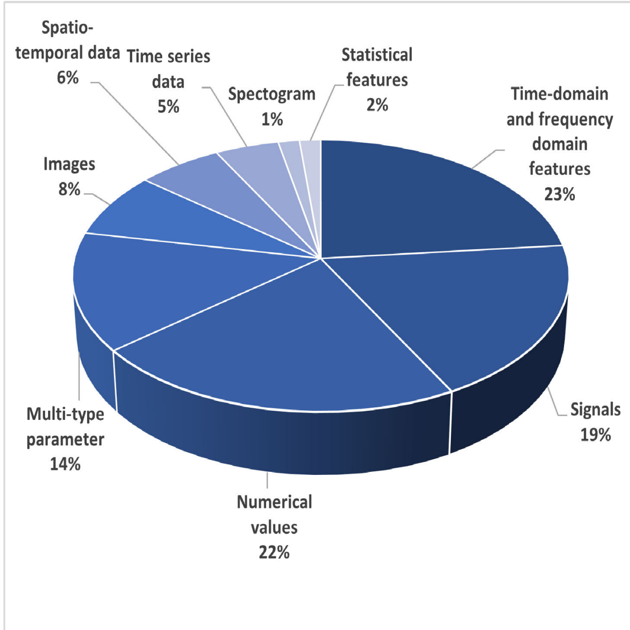


**FIGURE 3.** Feature type distribution.

The section is divided into three subsections, one of which illustrates the number of times particular machine learning algorithm is being used in the studies. The second subsection briefs about the number of times particular neural network algorithms have been used, and the last subsection tells about the relative percentage of the algorithms when it performed the best. This section is based on data from 64/67 studies. similarly as in section B above.

There are certain instances when multiple algorithms are used in a single study, this is because for prediction/classification task, performance of multiple algorithms are compared in those studies.

After obtaining features from the signals, sometimes it is required to select the features of most relevance and reducing the features which are similar or are of least significance based on some coefficients. This stage of processing is called feature selection stage. These methods helps the model to perform better. Some examples of feature selection methods used in the studies included in this review are dimensionality reduction, recursive feature elimination, filter methods, and wrapper methods. Dimensionality reduction transforms the data from a high-dimensional space to a low-dimensional space, retaining the properties of original data [38]. Linear discriminant analysis is one such method used in the studies [48], [49]. Recursive feature elimination fits a model and then removes the weakest feature until specified number of features are obtained. Some studies have used these methods for supervised machine learning approach for Parkinson's disease [45], [50] and also for prediction of fever related disease [7]. Studies have also used filter and wrapper methods for selecting the features. Filter methods measure the relevance of features by their correlation with dependent variable [32] whereas wrapper based methods evaluate all possible combinations of features against some evaluation criteria [26]. After feature selection stage the selected features are used for developing a model based on the machine learning algorithms.

### 1) MACHINE LEARNING ALGORITHMS USED FOR ANALYSIS

For analysis of the heterogeneous types of features several machine learning algorithms have been used in the studies. Machine learning algorithms are classified as supervised, unsupervised and reinforcement learning algorithms. Studies in this review have used supervised and unsupervised algorithms for various classification, regression and clustering tasks. Figure 4 shows the number of times each algorithm has been used for analysis. Support vector machines [51] which is a supervised machine learning algorithm is used in most of the cases. The data shows that its been used 43 times for the analysis of features from signals. Neural network algorithms are also used 41 times for the analysis. Depending on the type of information being extracted, various types of neural network algorithms are being used. More detailed description about the type of neural network algorithms and their count of occurrence is mentioned in the next subsection. Tree-based algorithms like random forest [52] and decision tree are used in 28 and 18 of cases, respectively. K-nearest neighbour is used for diabetes/heart disease based parameters which are multiple type parameters. Data shows that k-nearest neighbour is used in 16 cases. Logistic regression is used for 11 studies and it is used for prediction tasks in diabetes prediction, atrial fibrillation prediction, stroke prediction and prediction of severity for fever related disease. It has also been observed that many studies have used ensemble leaning methods as well. These methods combine several base models for obtaining optimal predictive model. 3 studies have used ensemble classification and regression methods for obtaining better performance in case of time-domain, frequency-domain and numerical feature set [31], [53]. Boosting is also a type of ensemble learning methods which combines similar type of classifiers to convert weak learner models into stronger learner models. 11 studies have used different kinds of boosting methods like adaptive boosting, XGBoost, robust boosting, gradient boosting for analysing the time domain, frequency domain features, or multi-type parameter feature vector [38], [54], [55]. A few studies have used naive Bayes or linear regression for analysing multi-type feature vectors. The bar graph shows that naive Bayes has been used for 7 and linear regression for 5 studies, respectively. Fewer studies have also applied ridge regression (2 studies) which is specialized to analyse multiple regression data having multicollinearity in data. Studies have also used isotonic regression for remote monitoring applications [56]. Other classifiers' count such as Bayesian classifiers and rule-based classifiers are only 2 and 1, respectively. Bayesian classifiers are used for image classifications task. Similarly local binary pattern and gray level co-occurence matrix is used for texture analysis, studies in this review have used these algorithms for classification of diabetic retinopathy [10]. ARIMA models are used in one study for analysing the time series data [20].

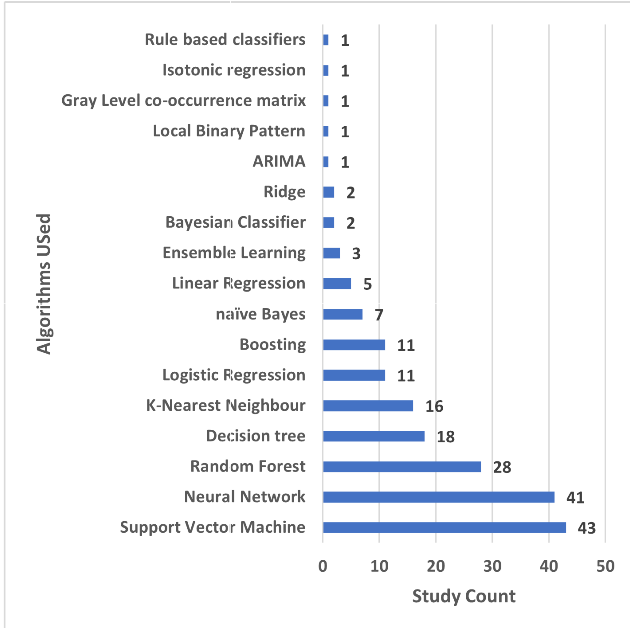


**FIGURE 4. Algorithms used for analysis.**

The data from the bar graph shows that in most of the cases supervised machine learning algorithms are used. Studies have performed classification and regression tasks for analysing the features from health sensors. As compared to regression algorithms, classification algorithms are used predominantly in the studies. Algorithms like support vector machines, neural networks algorithms, tree based algorithms, k nearest neighbour are used in a significant number of studies for classification as compared to algorithms like linear regression, logistic regression, ridge and isotonic regression, ARIMA models. This is because more of the studies have focused on classification or identification of symptoms from the features provided by body sensors rather than predicting the future events. Moreover, support vector machines, neural network algorithms, random forest, and decision tree are used for analysing the multi-parameter feature, time and frequency domain features. Boosting algorithm, Decision tree, linear and logistic regression, naive Bayes are also used for analysis of similar features but the accuracy of naive Bayes and linear regression is less as compared to the support vector machines or neural network algorithms. However, local binary pattern, gray level co-occurence matrix, Bayesian classifier are used for image classification by some studies. ARIMA models are also used for time series analysis. However, predominantly support vector machines, random forest and neural network algorithms have been used for analysing the eHealth data.

### 2) NEURAL NETWORK ALGORITHMS USED FOR ANALYSIS

This section illustrates the neural network algorithms used for the health data analytics. Depending on the information being extracted and the application, different types of neural network algorithms are being used. Neural network algorithms have been used in 41 studies for analysing the features obtained from the sensors and wearables. Figure 5 details the

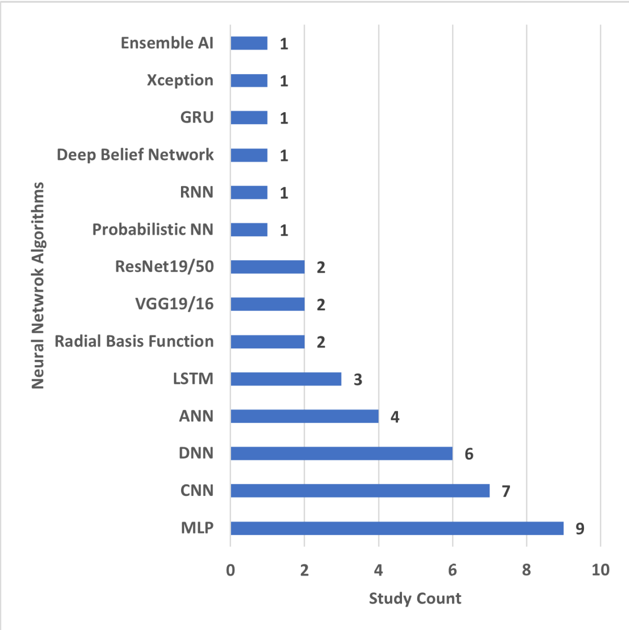


**FIGURE 5.** Neural network algorithms used for analysis.

number of times different neural network algorithms have been used among the 41 studies that have used neural network algorithms.

Different neural network algorithms that are used in the studies are Multilayer perceptron (MLP), Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), Deep Neural Network (DNN), ANN which is basically a simple or shallow neural network, Radial Basis Function Network, Reccurent Neural network (RNN), Deep Belief Network, Gated Recurrent Units (GRU). VGG, which is basically a type of convolutional neural network termed as ''Very Deep Convolutional Networks for Large-Scale Image Recognition''. Depending on the number of layers it is given as VGG16/VGG19. ResNet, also termed as residual neural network is also used for the Image processing applications and works by skipping the connections between the layers. Similarly Xception is also a type of convolutional neural network which is 71 layers deep.

Figure 5 shows that out of 41 studies which have used neural network algorithms, 9 studies have used Multilayer perceptrons. Multilayer perceptron is a feed-forward network and is used in the studies for analysing multiple types of features [57]. CNN or convolutional neural network is used in 7 studies out of 41 studies. CNN is used for image classification applications. Studies have used CNN for ECG image data, ECG signals with spectogram as input [5], and diabetic retinopathy identification [10]. Deep neural network and artificial or shallow neural network is used 6 and 4 studies, respectively. These algorithms are used for the multiple-type parameter and time and frequency domain features [58], [59]. LSTM, RNN and GRU have memory units so the next output depends on the input and the current output, they are used in 3, 1, and 1 studies respectively and these algorithms are used for time series and time domain and frequency domain feature analysis [16], [40], [60], [61]. ResNet19/50 and VGG19/16 [62] are also used for image classification in total 4 studies. Radial basis function network is used 2 times for time and frequency domain features. Radial basis function network is also a type of artificial neural network with a radial basis activation function [63]. All other algorithms like Probabilistic Neural Network, Ensemble AI, Deep Belief Network, Xception are used once for analysis in the studies mainly for analysing time and frequency domain values from signals and multiple type parameters.

### 3) ALGORITHMS WITH BEST PERFORMANCE

This section describes the relative percentage of algorithms when it performed better than other algorithms. The results obtained from the studies are presented as two pie charts. The first pie chart shows the data about machine learning algorithms including the overall percentage of neural network algorithms. The second pie chart shows the data about the distributions of various neural network algorithms that performed the best. This section is based on data from 64/67 studies.

Figure 6 shows the two pie plots. It can be seen from the relative percentages in the graph that Neural networks have performed the best in 28% of studies as compared to other algorithms. This 28% is distributed among different types of neural network algorithms which can be seen in the second pie chart. As per the information from thesecond pie chart, convolutional neural networks have shown better performance than others for relatively 6% of cases followed by artificial neural network algorithms or shallow neural networks. Multilayer perceptrons, deep neural network and long short term memory (LSTM) have shown better performances for 3% of cases each, and remaining algorithms like ResNet, deep belief network, GRU, VGG, and Ensemble AI have shown better performance for 2% of cases. So it can be inferred that CNN have outperformed in most of the cases especially when it is used for image classification applications as compared to ResNet and VGG. Algorithms like multilayer perceptrons, deep neural network and ANN have shown better performance for multi-parameter input and time and frequency domain features. Moreover there are algorithms that have shown better performance when there are specific applications, e.g., LSTM, Ensemble AI (combination of DNN and CNN).

The first pie plot in Figure 6 shows that support vector machines have also shown good performance for 27% of studies followed by the random forest algorithm which have shown good performance for 19% of cases. Since most of the features obtained from the sensors are in the form of time and frequency domain features, multi-type feature vector or numerical feature vectors, the SVM and random forest outperformed in most of the studies. Decision trees and ensemble learning have shown better performance in 6% of studies but it is less than that of random forest because random forest is more robust and limits the overfitting. Boosting methods have also performed well in 5% of studies but the other

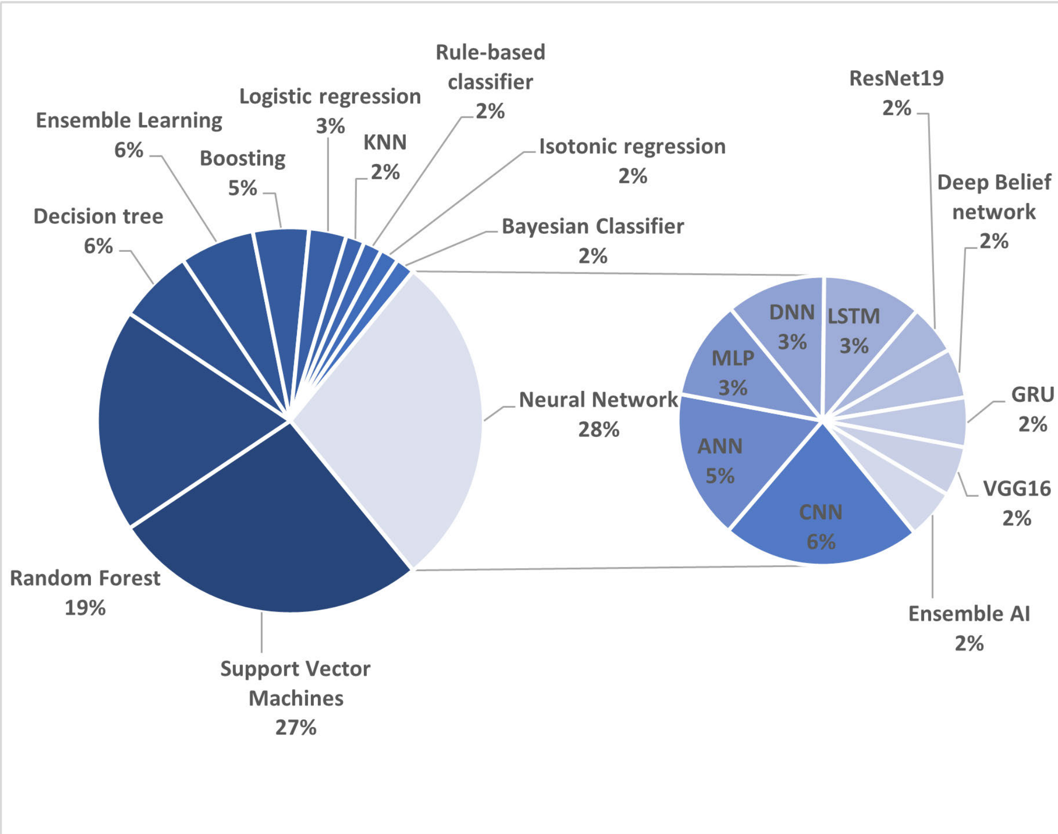


**FIGURE 6.** Algorithms with best performance.

algorithms such as regression, Bayesian classifier, KNN have shown good performance in less than 4% of studies. Hence, from the studies it can be inferred that SVM, random forest algorithm, neural network algorithms such as MLP, CNN, DNN, ANN have performed better for analyzing the features, especially time and frequency domain features, multi-type feature vector, numerical features, and images.

### D. EVALUATION CRITERIA

This section describes the evaluation criteria used for the performance evaluation of machine learning algorithms. From the studies it has been observed that the most common evaluation criteria used for the classification tasks are accuracy, precision, sensitivity, specificity, F1 score, AUC (area under the operating curve), K-fold cross validation. For prediction tasks, evaluation criteria used are root mean square error and mean absolute value. Other criteria use also includes negative predictive rate, false positive rate, false negative rate, goodness index, etc.

Table 2 shows the confusion matrix where Actual Positive and Actual Negative represent the actual results and Predicted Positive and Predicted Negative are the predicted results from algorithms. True Positive are the predicted values which are correctly predicted as true value, True Negative are the predicted values which are correctly predicted as false values. False Positive are negative values which are predicted as positive and False Negative are the positive values which are predicted as negative. Based on the Table 2, various evaluation criteria are defined as follows:

**TABLE 2.** Confusion matrix.

| Values | Predicted Positive | Predicted Negative |
|---|---|---|
| Actual Positive | True Positive (TP) | False Negative (FN) |
| Actual Negative | False Positive (FP) | True Negative (TN) |

#### 1) ACCURACY

Accuracy is defined as the correctly predicted observations by the total number of observations. Accuracy is given by:

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

#### 2) PRECISION

Precision is also known as positive predicted values. It is defined as the correctly predicted positive values to the total predicted positive values. Precision is given by:

$$Precision = \frac{(TP)}{(TP + FP)}$$

Similarly Negative predictive value is given by:

$$NegativePredictiveValue = \frac{(TN)}{(TN + FN)}$$

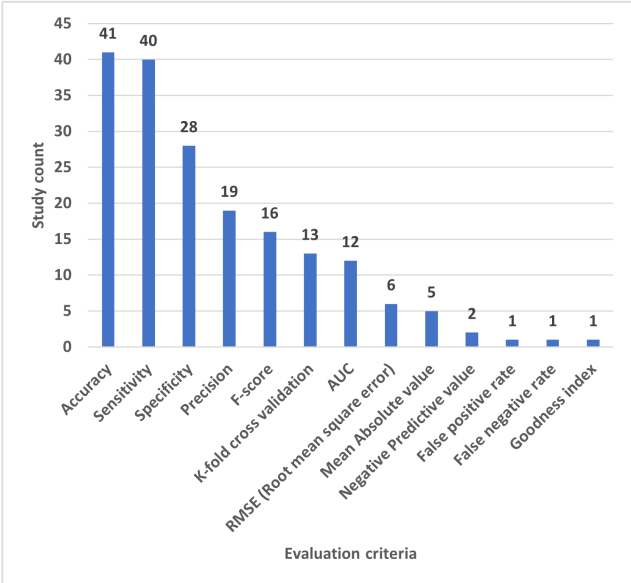


**FIGURE 7.** Evaluation criteria.

### 3) SENSITIVITY

Sensitivity, also known as recall or true positive rate is defined as the proportion of actual positives that were identified correctly. It is given by correctly predicted positive values to the total values that are actually positive. Sensitivity is given by:

$$Sensitivity = \frac{(TP)}{(TP + FN)}$$

Similarly false positive rate is given by:

$$FalsePositiveRate = \frac{(FP)}{(TN + FP)}$$

### 4) SPECIFICITY

Specificity, also known as the true negative rate, is defined as the ratio of correctly predicted negative values to the total values that are actually negative. Specificity is given by:

$$Specificity = \frac{(TN)}{(TN + FP)}$$

### 5) F-SCORE

This is the weighted average of the recall or sensitivity and precision. It is given by:

$$\mathrm{F} - Score = \frac{(2 * precision * Recall)}{(Precision + Recall)}$$

Figure 7 shows the number of studies in which these evaluation criteria have been used. As per the bar chart it can be seen that Accuracy, Sensitivity, Specificity, and Precision have been used in most of the studies with count of 41, 40, 28, and 19 respectively. Classification studies have also used F-score and Area under ROC (receiver operating curve) in 16 and 12 studies, respectively. K-fold cross-validation methods are also used in 13 studies, they are re-sampling methods which are used to evaluate the machine learning models on the limited samples. Root mean square error and mean absolute error were used in 6 and 5 studies, respectively. These are methods which are used in case of prediction tasks to check the error percentage, they are used mainly in the studies related to the blood disorders for predicting the systolic and diastolic pressure value. Other measures like negative predictive rate, false positive rate, false negative rate, goodness of fit index are used in less than 5 studies. There are studies which have also used evaluation measures which are not mentioned here but they are based on some medical standards. Those standards define the range of predicted value and the error rates. Table 3 summarizes shows the ranges of various evaluation criteria along with their units and some references from the studies.

**TABLE 3.** Evaluation criteria value range.

| Metric | Ranges reported in studied literature | Unit | Example reference |
|---|---|---|---|
| Accuracy | 70%-99% | [%] | References: [13] [32] [3] [14] [45] [49] [64] |
| Sensitivity | 69%-98% | [%] | References: [5] [63] [21] [11] [28] [38] |
| Specificity | 72%-99% | [%] | References: [22] [40] [52] [44] [29] |
| Precision | 70%-99% | [%] | References: [9] [37] [58] [57] [18] |
| F-score | 68%-98% | [%] | References: [14] [65] [59] [25] |
| K-fold cross validation | 5-20 folds | Folds | References: [33] [38] [59] [66] [5] [51] [38] [67] |
| Area under receiver operating curve | 77%-99% | [%] | References: [13] [43] [58] [38] |
| Root mean square error | 3.09-33.90 | Residuals | References: [31] [29] [42] [20] |
| Mean square error | 5.01-41.345 | Residuals | References: [49] [42] [38] [40] |
| Negative predictive value | 90%-100% | [%] | References: [58] |
| False positive rate | 4%-12% | [%] | References: [22] [11] |
| False negative rate | 0%-3% | [%] | References: [22] |
| Goodness index | 0-1 | Model fit | References: [32] |

### *E. CUMULATIVE OVERVIEW*

Figure 8 shows the cumulative diagram of the study. It comprises five blocks, each of which represents the process followed for obtaining the information from the raw healthcare data.

The first block is **Signal types** which represents the signals which are used in the studies, these signals are corresponding to some chronic diseases such as diabetes, heart disease, blood disorder, Parkinson, infection related disease, brain

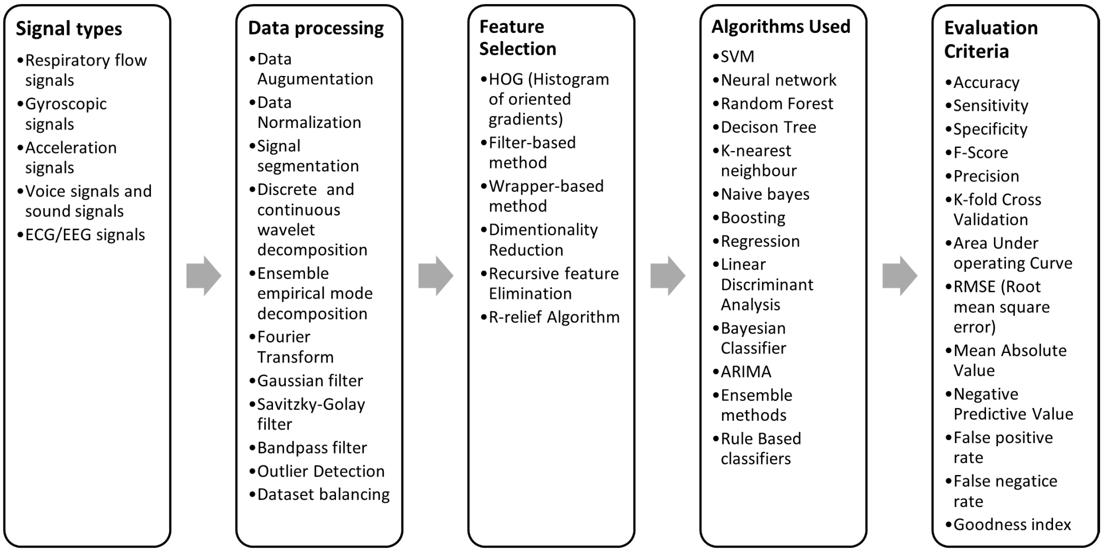


**FIGURE 8.** Cumulative diagram of studies.

disorder, or stroke. Some of these signals are respiratory flow signals, gyroscopic signals, acceleration signals, voice and sound signals, EEG/ECG signals.

The second block represents the **Data processing** methods, used for obtaining the features like time-domain or frequency-domain features, time-series feature, spatio-temporal features, and other numerical feature values. The data processing methods used in most of the studies are signal segmentation, data augmentation, data normalization, wavelet decomposition [38], Fourier transforms, and ensemble empirical mode decomposition [65]. When the data is obtained from datasets [27] then other data processing methods are also used in the studies which includes outlier detection and database balancing.

The third block represents the **Feature selection/extraction** block. This blocks includes the algorithms used for selecting or extracting the features of most relevance and reducing the ones which are similar or are of less significance. Various methods used are filter-based methods, wrapper-based methods, and HOG (Histogram of oriented gradients), this is mostly used in case of image data. Dimensionality reduction is also used to transform the feature set into a low-dimension feature space so that it represents meaningful properties of data. Other methods also include recursive feature elimination and R-relief algorithm for selecting the features. Feature selection/extraction methods depends on the different data types.

The fourth block represents the next stage after feature selection that is analyzing the data using **Machine Learning Algorithms**. Various machine learning algorithms are used based on the classification, regression or prediction tasks. Models are created by fitting the data into it. Neural network algorithms and support vector machines are used predominantly, since the data obtained from the signals constitutes time and frequency domain values. For multiple type parameters, random forest algorithm and decision trees are used. CNN [64] and SVM [68] are also used for image classification task. These algorithms are also used to analyze the data from raw signals. ARIMA models are used for time-series data. Selection of algorithm also highly depends on the data and the tasks (classification, regression, prediction) to be performed.

The fifth block represents the **Evaluation criteria** used for evaluating the performance of the machine learning algorithms. Commonly used evaluation criteria in the studies for classification tasks are accuracy, precision, sensitivity, specificity, F-score, AUC and for prediction tasks RMSE and mean absolute error. Other criteria based on medical standards are also used in some studies.

## IV. DISCUSSIONS

This Systematic literature review examined the process of analyzing the digital health data by using the 67 studies obtained through a series of steps. This review explored different types of sensors which can be used for obtaining the health data. We also identified various types of signals that can be used to monitor the vital signs of some of the chronic diseases like diabetes, heart disease, blood disorder, Parkinson's disease, infection related disease, brain disorder, and stroke. The emphasis was given on the different type of data processing and analysis techniques used for analysing the digital healthcare data. The information obtained from the studies are summarized in the form of different types of bar graphs and pie charts for the comparative analysis.

We found that the most of the signals are obtained from the sensors such as accelerometers, gyroscopes, EEG/ECG monitors and smartwatches/wearables. The signals which are important for obtaining health parameters for nearly all of the chronic diseases are acceleration signals, gyroscopic signals, EEG/ECG signals. Moreover, there are other signals like respiratory flow signals, voice and sound signals that are also important for examining the parameters for lung diseases and infection related diseases.

This study revealed what are the different kind of feature types that can be extracted from these signals. It was found that the various types of features obtained include time domain and frequency domain features, images, raw signals, spectrogram, time-series data, and multiple type parameters. More than 23% of studies have used time-domain and frequency-domain features for analyzing the data obtained from these signals. A significant number of studies have also used numerical feature vectors. It has also been observed that 19% of studies have also used raw signals without any processing techniques. Studies have also used feature selection methods for selecting the feature of high relevance to obtain better detection/classification/prediction performance. For analyzing these features various machine learning algorithms were used. We explored that studies have used supervised machine learning algorithms for analysing the data. Most of the studies have performed classification tasks rather than prediction. Predominantly support vector machine, tree-based algorithms, boosting algorithms, neural network algorithms such as deep neural network and multilayer perceptron were used for analyzing the feature vectors. Convolutional neural network and support vector machine are also used for analysing the image and raw signal input. Time series data also constitutes an important part of eHealth data, ARIMA models and LSTM are used for analysing time series data. We found that in 28% of studies neural network algorithms have shown the best performance followed by support vector machines which have shown best performance in 27% of studies followed by random forest with best performance in 19% of studies. CNN and ANN are the algorithms that performed better within neural network algorithms.

This review has generated an overview of the state-of-art for current research field related to the analysis and processing of digital health data using machine learning algorithms. The results obtained from this review along with the knowledge obtained from the previous studies will be used for developing an automated system of healthcare for better detection of chronic diseases. Moreover the continuous nature of data will help in early detection and prevention of disease. Hence, the focus of this review is on important aspects like wearables/sensors or body area network and data analysis module, which are required for creating a connected/remote monitoring healthcare system. In addition to this, studies have also been identified related to the communication protocols like BLE for communication between various modules of remote monitoring healthcare system. Furthermore, this review is a part of the research work aiming to develop solutions for analysing varied forms of healthcare data using ML techniques and remote monitoring of healthcare parameters. Certain results which can be observed using this system will be:

1) Remote monitoring healthcare delivery system for continuous monitoring of vital signs.
2) Faster treatment time along with enhanced accuracy of diagnosis and health outcomes.
3) Reduced errors, duplication and delay in processing.
4) Common platform for analysing multiple types of sensor/wearable data.
5) This voluminous data obtained from the wearables can also be used for population pattern discovery which can prove useful in case of spread of infectious diseases.

Thus, this review provides important insights for developing a continuous multi-sensing remote monitoring healthcare system for active monitoring of patients having chronic diseases, by using wearable technology, IoT and Artificial Intelligence (AI), so that it can be used for the detection and prevention of any life-critical events.

## REFERENCES


[1] L. C. Fourati and S. Said, *Remote Health Monitoring Systems Based on Bluetooth Low Energy (BLE) Communication Systems*, M. Jmaiel, M. Mokhtari, B. Abdulrazak, H. Aloulou, and S. Kallel, Eds. Cham, Switzerland: Springer, pp. 41–54.

[2] A. Chocron, R. Efraim, F. Mandel, M. Rueschman, N. Palmius, T. Penzel, M. Elbaz, and J. A. Behar, "Digital biomarkers and artificial intelligence for mass diagnosis of atrial fibrillation in a population sample at risk of sleep disordered breathing," Jul. 2020, *arXiv:2007.14686*. [Online]. Available: https://arxiv.org/abs/2007.14686

[3] G. Mainenti, L. Campanile, F. Marulli, C. Ricciardi, and A. Valente, "Machine learning approaches for diabetes classification: Perspectives to artificial intelligence methods updating," in *Proc. 5th Int. Conf. Internet Things, Big Data Secur.*, vol. 1. Setúbal, Portugal: SciTePress, 2020, pp. 533–540.

[4] C. El-Hajj and P. A. Kyriacou, "A review of machine learning techniques in photoplethysmography for the non-invasive cuff-less measurement of blood pressure," *Biomed. Signal Process. Control*, vol. 58, Apr. 2020, Art. no. 101870.

[5] Y. Xia, N. Wulan, K. Wang, and H. Zhang, "Detecting atrial fibrillation by deep convolutional neural networks," *Comput. Biol. Med.*, vol. 93, pp. 84–92, Feb. 2018.

[6] A. Ed-daoudy and K. Maalmi, "Real-time heart disease detection and monitoring system based on fast machine learning using Spark," *Health Technol.*, vol. 10, no. 5, pp. 1145–1154, 2020, doi: 10.1007/s12553-020-00460-3.

[7] C.-H. Zhao, H.-T. Wu, H.-B. Che, Y.-N. Song, Y.-Z. Zhao, K.-Y. Li, H.-J. Xiao, Y.-Z. Zhai, X. Liu, H.-X. Lu, and T.-S. Li, "Prediction of fatal adverse prognosis in patients with fever-related diseases based on machine learning: A retrospective study," *Chin. Med. J.*, vol. 133, no. 5, pp. 583–589, 2020.

[8] D. Cacovean, I. Ioana, and G. Nitulescu, "IoT system in diagnosis of Covid-19 patients," *Inf. Economica*, vol. 24, no. 2, pp. 75–89, Jun. 2020.

[9] V. Skaramagkas, G. Andrikopoulos, Z. Kefalopoulou, and P. Polychronopoulos, "Towards differential diagnosis of essential and Parkinson's tremor via machine learning," in *Proc. 28th Medit. Conf. Control Autom. (MED)*, Sep. 2020, pp. 782–787.

[10] S. S. A. Alves, A. G. Matos, J. S. Almeida, C. A. Benevides, C. C. H. Cunha, R. V. C. Santiago, R. F. Pereira, and P. P. R. Filho, "A new strategy for the detection of diabetic retinopathy using a smartphone app and machine learning methods embedded on cloud computer," in *Proc. IEEE 33rd Int. Symp. Comput.-Based Med. Syst. (CBMS)*, Jul. 2020, pp. 542–545.

[11] A. Rghioui, J. Lloret, L. Parra, S. Sendra, and A. Oumnad, "Glucose data classification for diabetic patient monitoring," *Appl. Sci.*, vol. 9, no. 20, p. 4459, Oct. 2019.

[12] C. Caramia, D. Torricelli, M. Schmid, A. Muñoz-Gonzalez, J. Gonzalez-Vargas, F. Grandas, and J. L. Pons, "IMU-based classification of Parkinson's disease from gait: A sensitivity analysis on sensor location and feature selection," *IEEE J. Biomed. Health Informat.*, vol. 22, no. 6, pp. 1765–1774, Nov. 2018.

[13] L. Wang, Y. Mu, J. Zhao, X. Wang, and H. Che, "IGRNet: A deep learning model for non-invasive, real-time diagnosis of prediabetes through electrocardiograms," *Sensors*, vol. 20, no. 9, p. 2556, Apr. 2020.

[14] J. Kwon and K. Kim, "Artificial intelligence for early prediction of pulmonary hypertension using electrocardiography," *J. Heart Lung Transplantation*, vol. 39, no. 4, p. S13, Apr. 2020.

[15] V. Jahmunah, S. L. Oh, J. K. E. Wei, E. J. Ciaccio, K. Chua, T. R. San, and U. R. Acharya, "Computer-aided diagnosis of congestive heart failure using ECG signals—A review," *Phys. Medica*, vol. 62, pp. 95–104, Jun. 2019.

[16] C.-R. Phang, F. Noman, H. Hussain, C.-M. Ting, and H. Ombao, "A multi-domain connectome convolutional neural network for identifying schizophrenia from EEG connectivity patterns," *IEEE J. Biomed. Health Informat.*, vol. 24, no. 5, pp. 1333–1343, May 2020.

[17] S. G. Khalid, J. Zhang, F. Chen, and D. Zheng, "Blood pressure estimation using photoplethysmography only: Comparison between different machine learning approaches," *J. Healthcare Eng.*, vol. 2018, Oct. 2018, Art. no. 1548647.

[18] J. Dhanapal, B. Narayanamurthy, V. Shanmugam, A. Gangadharan, and S. Magesh, "Pervasive computational model and wearable devices for prediction of respiratory symptoms in progression of COVID-19," *Int. J. Pervas. Comput. Commun.*, vol. 16, no. 4, pp. 371–381, Jul. 2020.

[19] I. Tobore, A. Kandwal, J. Li, Y. Yan, O. M. Omisore, E. Enitan, L. Sinan, L. Yuhang, L. Wang, and Z. Nie, "Towards adequate prediction of prediabetes using spatiotemporal ECG and EEG feature analysis and weight-based multi-model approach," *Knowl.-Based Syst.*, vol. 209, Dec. 2020, Art. no. 106464.

[20] I. Rodríguez-Rodríguez, I. Chatzigiannakis, J.-V. Rodríguez, M. Maranghi, M. Gentili, and M.-Á. Zamora-Izquierdo, "Utility of big data in predicting short-term blood glucose levels in type 1 diabetes mellitus through machine learning techniques," *Sensors*, vol. 19, no. 20, p. 4482, Oct. 2019.

[21] M. Ijaz, G. Alfian, M. Syafrudin, and J. Rhee, "Hybrid prediction model for type 2 diabetes and hypertension using DBSCAN-based outlier detection, synthetic minority over sampling technique (SMOTE), and random forest," *Appl. Sci.*, vol. 8, no. 8, p. 1325, Aug. 2018.

[22] H. Yin, B. Mukadam, X. Dai, and N. Jha, "DiabDeep: Pervasive diabetes diagnosis based on wearable medical sensors and efficient neural networks," *IEEE Trans. Emerg. Topics Comput.*, early access, Dec. 17, 2020, doi: 10.1109/TETC.2019.2958946.

[23] S. Wan, Y. Liang, Y. Zhang, and M. Guizani, "Deep multi-layer perceptron classifier for behavior analysis to estimate Parkinson's disease severity using smartphones," *IEEE Access*, vol. 6, pp. 36825–36833, 2018.

[24] R. Alkhatib, M. O. Diab, C. Corbier, and M. E. Badaoui, "Machine learning algorithm for gait analysis and classification on early detection of Parkinson," *IEEE Sensors Lett.*, vol. 4, no. 6, pp. 1–4, Jun. 2020.

[25] T. J. Wroge, Y. Özkanca, C. Demiroglu, D. Si, D. C. Atkins, and R. H. Ghomi, "Parkinson's disease diagnosis using machine learning and voice," in *Proc. IEEE Signal Process. Med. Biol. Symp. (SPMB)*, Dec. 2018, pp. 1–7.

[26] H. Jeon, W. Lee, H. Park, H. J. Lee, S. K. Kim, H. B. Kim, B. Jeon, and K. S. Park, "High-accuracy automatic classification of parkinsonian tremor severity using machine learning method," *Physiol. Meas.*, vol. 38, no. 11, pp. 1980–1999, Oct. 2017.

[27] D. Dua and C. Graff, "UCI machine learning repository," School Inf. Comput. Sci., Univ. California, Irvine, Irvine, CA, USA, 2017. [Online]. Available: http://archive.ics.uci.edu/ml

[28] D. Rodriguez-Martin *et al.*, "Home detection of freezing of gait using support vector machines through a single waist-worn triaxial accelerometer," *PLoS ONE*, vol. 12, no. 2, pp. 1–26, 2017.

[29] A. Samà, C. Pérez-López, D. Rodríguez-Martín, A. Català, J. M. Moreno-Aróstegui, J. Cabestany, E. de Mingo, and A. Rodríguez-Molinero, "Estimating bradykinesia severity in Parkinson's disease by analysing gait through a waist-worn sensor," *Comput. Biol. Med.*, vol. 84, pp. 114–123, May 2017.

[30] A. C. A. de Araújo, E. G. da Rocha Santos, K. S. G. de Sá, V. K. T. Furtado, F. A. Santos, R. C. de Lima, L. V. Krejcová, B. L. Santos-Lobato, G. H. L. Pinto, A. dos Santos Cabral, A. Belgamo, B. Callegari, A. F. R. Kleiner, A. de Athayde Costa e Silva, and G. da Silva Souza, "Hand resting tremor assessment of healthy and patients with Parkinson's disease: An exploratory machine learning study," *Frontiers Bioeng. Biotechnol.*, vol. 8, p. 778, Jul. 2020.

[31] L. Yu, D. Xiong, L. Guo, and J. Wang, "A remote quantitative Fugl-Meyer assessment framework for stroke patients based on wearable sensor networks," *Comput. Methods Programs Biomed.*, vol. 128, pp. 100–110, May 2016.

[32] A. Czmil, S. Czmil, and D. Mazur, "A method to detect type 1 diabetes based on physical activity measurements using a mobile device," *Appl. Sci.*, vol. 9, no. 12, p. 2555, Jun. 2019.

[33] J. Costa, I. Sousa, and F. Soares, "Smartphone-based decision support system for elimination of pathology-free images in diabetic retinopathy screening," in *Internet of Things Technologies for HealthCare*, M. U. Ahmed, S. Begum, and W. Raad, Eds. Cham, Switzerland: Springer, 2016, pp. 83–88.

[34] J. Prince, F. Andreotti, and M. De Vos, "Multi-source ensemble learning for the remote prediction of Parkinson's disease in the presence of source-wise missing data," *IEEE Trans. Biomed. Eng.*, vol. 66, no. 5, pp. 1402–1411, May 2019.

[35] M. U. Ashraf, A. Hannan, S. M. Cheema, Z. Ali, K. M. Jambi, and A. Alofi, "Detection and tracking contagion using IoT-edge technologies: Confronting COVID-19 pandemic," in *Proc. Int. Conf. Electr., Commun., Comput. Eng. (ICECCE)*, Jun. 2020, pp. 1–6.

[36] R. Buettner, M. Hirschmiller, K. Schlosser, M. Rossle, M. Fernandes, and I. J. Timm, "High-performance exclusion of schizophrenia using a novel machine learning method on EEG data," in *Proc. IEEE Int. Conf. E-health Netw., Appl. Services (HealthCom)*, Oct. 2019, pp. 1–6.

[37] M. J. Tadi, S. Mehrang, M. Kaisti, O. Lahdenoja, T. Hurnanen, J. Jaakkola, S. Jaakkola, T. Vasankari, T. Kiviniemi, J. Airaksinen, T. Knuutila, E. Lehtonen, T. Koivisto, and M. Pänkäälä, "Comprehensive analysis of cardiogenic vibrations for automated detection of atrial fibrillation using smartphone mechanocardiograms," *IEEE Sensors J.*, vol. 19, no. 6, pp. 2230–2242, Nov. 2019.

[38] M. Kachuee, M. M. Kiani, H. Mohammadzade, and M. Shabany, "Cuffless blood pressure estimation algorithms for continuous healthcare monitoring," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 4, pp. 859–869, Apr. 2017.

[39] M. I. Vanegas, M. F. Ghilardi, S. P. Kelly, and A. Blangero, "Machine learning for EEG-based biomarkers in Parkinson's disease," in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Dec. 2018, pp. 2661–2665.

[40] G. A. Tadesse, H. Javed, N. L. N. Thanh, H. D. H. Thi, L. V. Tan, L. Thwaites, D. A. Clifton, and T. Zhu, "Multi-modal diagnosis of infectious diseases in the developing world," *IEEE J. Biomed. Health Informat.*, vol. 24, no. 7, pp. 2131–2141, Jul. 2020.

[41] W. Huo, P. Angeles, Y. F. Tai, N. Pavese, S. Wilson, M. T. Hu, and R. Vaidyanathan, "A heterogeneous sensing suite for multisymptom quantification of Parkinson's disease," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 6, pp. 1397–1406, Jun. 2020.

[42] Q. Zhang, D. Zhou, and X. Zeng, "Highly wearable cuff-less blood pressure and heart rate monitoring with single-arm electrocardiogram and photoplethysmogram signals," *Biomed. Eng. OnLine*, vol. 16, no. 1, p. 23, Dec. 2017.

[43] L. Han, M. Askari, R. B. Altman, S. K. Schmitt, J. Fan, J. P. Bentley, S. M. Narayan, and M. P. Turakhia, "Atrial fibrillation burden signature and near-term prediction of stroke," *Circulat., Cardiovascular Qual. Outcomes*, vol. 12, no. 10, Oct. 2019, Art. no. e005595.

[44] C. Fernandes, L. Fonseca, F. Ferreira, M. Gago, L. Costa, N. Sousa, C. Ferreira, J. Gama, W. Erlhagen, and E. Bicho, "Artificial neural networks classification of patients with Parkinsonism based on gait," in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Dec. 2018, pp. 2024–2030.

[45] S. Aich, J. Youn, S. Chakraborty, P. M. Pradhan, J.-H. Park, S. Park, and J. Park, "A supervised machine learning approach to detect the on/off state in Parkinson's disease using wearable based gait signals," *Diagnostics*, vol. 10, no. 6, p. 421, Jun. 2020.

[46] S. Tikka, B. Singh, S. Nizamie, S. Garg, S. Mandal, K. Thakur, and L. Singh, "Artificial intelligence-based classification of schizophrenia: A high density electroencephalographic and support vector machine study," *Indian J. Psychiatry*, vol. 62, no. 3, pp. 273–282, 2020.

[47] Yaseen, G.-Y. Son, and S. Kwon, "Classification of heart sound signal using multiple features," *Appl. Sci.*, vol. 8, no. 12, p. 2344, Nov. 2018.

[48] S. Argerich, S. Herrera, S. Benito, and B. F. Giraldo, "Evaluation of periodic breathing in respiratory flow signal of elderly patients using SVM and linear discriminant analysis," in *Proc. 38th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug. 2016, pp. 4276–4279.

[49] C. Devia, R. Mayol-Troncoso, J. Parrini, G. Orellana, A. Ruiz, P. E. Maldonado, and J. I. Egaña, "EEG classification during scene free-viewing for schizophrenia detection," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 6, pp. 1193–1199, Jun. 2019.

[50] M. D. Hssayeni, M. A. Burack, J. Jimenez-Shahed, and B. Ghoraani, "Assessment of response to medication in individuals with Parkinson's disease," *Med. Eng. Phys.*, vol. 67, pp. 33–43, May 2019.

[51] R. Z. U. Rehman, S. Del Din, J. Q. Shi, B. Galna, S. Lord, A. J. Yarnall, Y. Guan, and L. Rochester, "Comparison of walking protocols and gait assessment systems for machine learning-based classification of Parkinson's disease," *Sensors*, vol. 19, no. 24, p. 5363, Dec. 2019.

[52] H. Gokul, P. Suresh, B. H. Vignesh, R. P. Kumaar, and V. Vijayaraghavan, "Gait recovery system for Parkinson's disease using machine learning on embedded platforms," in *Proc. IEEE Int. Syst. Conf. (SysCon)*, Aug. 2020, pp. 1–8.

[53] E. Park, K. Lee, T. Han, and H. S. Nam, "Automatic grading of stroke symptoms for rapid assessment using optimized machine learning and 4-limb kinematics: Clinical validation study," *J. Med. Internet Res.*, vol. 22, no. 9, Sep. 2020, Art. no. e20641.

[54] T. Elhadd, R. Mall, M. Bashir, J. Palotti, L. Fernandez-Luque, F. Farooq, D. A. Mohanadi, Z. Dabbous, R. A. Malik, and A. B. Abou-Samra, "Artificial intelligence (AI) based machine learning models predict glucose variability and hypoglycaemia risk in patients with type 2 diabetes on a multiple drug regimen who fast during ramadan (The PROFAST–IT ramadan study)," *Diabetes Res. Clin. Pract.*, vol. 169, Nov. 2020, Art. no. 108388.

[55] Z. Liu, B. Zhou, Y. Li, M. Tang, and F. Miao, "Continuous blood pressure estimation from electrocardiogram and photoplethysmogram during arrhythmias," *Frontiers Physiol.*, vol. 11, p. 1126, Sep. 2020.

[56] S. Halloran, L. Tang, Y. Guan, J. Q. Shi, and J. Eyre, "Remote monitoring of stroke patients' rehabilitation using wearable accelerometers," in *Proc. 23rd Int. Symp. Wearable Comput.* New York, NY, USA: ACM, 2019, pp. 72–77.

[57] N. Tapas, T. Lone, D. Reddy, and V. Kuppili, "Prediction of cardiac arrest recurrence using ensemble classifiers," *Sādhanā*, vol. 42, no. 7, pp. 1135–1141, Jul. 2017.

[58] G. H. Tison, J. M. Sanchez, B. Ballinger, A. Singh, J. E. Olgin, M. J. Pletcher, E. Vittinghoff, E. S. Lee, S. M. Fan, R. A. Gladstone, C. Mikell, N. Sohoni, J. Hsieh, and G. M. Marcus, "Passive detection of atrial fibrillation using a commercially available smartwatch," *JAMA Cardiol.*, vol. 3, no. 5, pp. 409–416, 2018.

[59] U. Zalabarria, E. Irigoyen, and A. Lowe, "Diagnosis of atrial fibrillation based on arterial pulse wave foot point detection using artificial neural networks," *Comput. Methods Programs Biomed.*, vol. 197, Dec. 2020, Art. no. 105681.

[60] T. Pereira, C. Ding, K. Gadhoumi, N. Tran, R. A. Colorado, K. Meisel, and X. Hu, "Deep learning approaches for plethysmography signal quality assessment in the presence of atrial fibrillation," *Physiol. Meas.*, vol. 40, no. 12, Dec. 2019, Art. no. 125002.

[61] A. S. Ashour, A. El-Attar, N. Dey, H. A. El-Kader, and M. M. Abd El-Naby, "Long short term memory based patient-dependent model for FOG detection in Parkinson's disease," *Pattern Recognit. Lett.*, vol. 131, pp. 23–29, Mar. 2020.

[62] J. Zhu, B. Shen, A. Abbasi, M. Hoshmand-Kochi, H. Li, and T. Q. Duong, "Deep transfer learning artificial intelligence accurately stages COVID-19 lung disease severity on portable chest radiographs," *PLoS ONE*, vol. 15, Jul. 2020, Art. no. e0236621.

[63] A. Prabha, A. Trivedi, A. A. Kumar, and C. S. Kumar, "Automated system for obstructive sleep apnea detection using heart rate variability and respiratory rate variability," in *Proc. Int. Conf. Adv. Comput., Commun. Informat. (ICACCI)*, Sep. 2017, pp. 1303–1307.

[64] C. M. J. M. Dourado, Jr, S. P. P. da Silva, R. V. M. da Nóbrega, A. C. da S. Barros, P. P. R. Filho, and V. H. C. de Albuquerque, "Deep learning IoT system for online stroke detection in skull computed tomography images," *Comput. Netw.*, vol. 152, pp. 25–39, Apr. 2019.

[65] Z. Yue and Z. Jinjing, "Atrial fibrillation detection based on EEMD and XGBoost," *J. Phys., Conf. Ser.*, vol. 1229, May 2019, Art. no. 012074.

[66] A. U. Haq, J. Li, J. Khan, M. H. Memon, S. Nazir, S. Ahmad, G. A. Khan, and A. Ali, "A new intelligent approach for effective recognition of diabetes in the IoT e-healthcare environment," *Preprints*, 2020, Art. no. 2020020462, doi: 10.20944/preprints202002.0462.v1.

[67] M. De Vos, J. Prince, T. Buchanan, J. J. FitzGerald, and C. A. Antoniades, "Discriminating progressive supranuclear palsy from Parkinson's disease using wearable technology and machine learning," *Gait Posture*, vol. 77, pp. 257–263, Mar. 2020.

[68] M. Lown, M. Brown, C. Brown, A. M. Yue, B. N. Shah, S. J. Corbett, G. Lewith, B. Stuart, M. Moore, and P. Little, "Machine learning detection of Atrial Fibrillation using wearable technology," *PLoS ONE*, vol. 15, pp. 1–9, Jan. 2020.

**ADITI SITE** received the B.E. degree in computer science and engineering in India and the master's degree in computer science, with a focus on big data analytics, from Vellore Institute of Technology, India. She is currently pursuing the Ph.D. degree with Tampere University. She has worked as a Software Development Engineer with Mcafee India Pvt. Ltd. She has working experience in developing machine learning models for malware detection, statistical analytics, data visualization, text summary, predictive analysis, and image classification applications. She has also worked as a Graduate Intern Technical at Intel India Pvt. Ltd. She has published research work on the topic hierarchical approach for finding the frequent closed item set in the distributed environment in *International Journal of Computer Applications*.

**JARI NURMI** (Senior Member, IEEE) received the D.Sc. degree in technonoly. He works as a Professor at the Electrical Engineering Unit, Tampere University, TAU (formerly Tampere University of Technology, TUT), Finland, since 1999. He is working on embedded computing systems, System-on-Chip, approximate computing, wireless localization, positioning receiver prototyping, and software-defined radio and software-defined networks. He held various research, education, and management positions at TUT, since 1987, (e.g., an Acting Associate Professor, from 1991 to 1994) and was the Vice President of the SME VLSI Solution Oy, from 1995 to 1998. Since 2013, he has also been a Partner and the Co-Founder of Ekin Labs Oy, a research spin-off company, now headquartered in Silicon Valley as Radiomaze, Inc. He has supervised 27 Ph.D. and over 140 M.Sc. theses, and been an opponent or a reviewer of 44 Ph.D. theses for other universities worldwide. He is a member of the Technical Committee on VLSI Systems and Applications at IEEE CAS. In 2004, he was one of the recipients of the Nokia Educational Award and a recipient of the Tampere Congress Award, in 2005. In 2011, he received the IIDA Innovation Award and the Scientific Congress Award, in 2013, and the HiPEAC Technology Transfer Award. He is a steering committee member of three international conferences (chairman in two). He has edited five Springer books and has published over 350 international conference and journal articles and book chapters. He is also an associate editor/handling editor of two international journals. He is the Director of the national DELTA doctoral training network of about 200 Ph.D. students, the Coordinator of the European doctoral training network APROPOS, and the Head of the A-WEAR European joint Ph.D. degree Program at TAU.

**ELENA SIMONA LOHAN** (Senior Member, IEEE) received the M.Sc. degree in electrical engineering from the Polytechnic University of Bucharest, in 1997, the D.E.A. degree in econometrics from Ecole Polytechnique, Paris, in 1998, and the Ph.D. degree in telecommunications from Tampere University of Technology, in 2003. She is currently a Full Professor at the Electrical Engineering Unit, Tampere University (TAU), and a Visiting Professor at the Universitat Autonoma de Barcelona (UAB), Spain. She is leading a research group on signal processing for wireless positioning. She is a Co-Editor of the first book on Galileo satellite system *Galileo Positioning Technology* (Springer), a Co-Editor of *Multi-Technology Positioning* (Springer), and the author or coauthor of more than 220 international peer-reviewed publications, and six patents and inventions. She is also an Associate Editor of *Journal of Navigation* (RIN) and *IET Radar, Sonar & Navigation*. She is currently coordinating the A-WEAR MSCA European Joint Doctorate Network in the field of wearable computing. Her expertise include signal processing for wireless positioning and navigation, multipath and interference mitigation, and RF fingerprinting.