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Review

Bio-Signals in Medical Applications and Challenges Using Artificial Intelligence

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Abstract: Artificial Intelligence (AI) has broadly connected the medical field at various levels of diagnosis based on the congruous data generated. Different types of bio-signal can be used to monitor a patient's condition and in decision making. Medical equipment uses signals to communicate information to care staff. AI algorithms and approaches will help to predict health problems and check the health status of organs, while AI prediction, classification, and regression algorithms are helping the medical industry to protect from health hazards. The early prediction and detection of health conditions will guide people to stay healthy. This paper represents the scope of bio-signals using AI in the medical area. It will illustrate possible case studies relevant to bio-signals generated through IoT sensors. The bio-signals that retrospectively occur are discussed, and the new challenges of medical diagnosis using bio-signals are identified.

Keywords: artificial intelligence; signal processing; bio-medical signal processing; smart health devices; sensors; bio-signals

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1. Introduction

Artificial Intelligence (AI) was born from the idea of two great scientists—Herbert Simon and Allen Newell. In 1958, they proposed that various interdisciplinary departments and professional sectors cooperate and develop science and its applications [1]. AI started its journey from mathematical logic, knowledge, and reasoning concepts and became a branch of Computer Science by serving all other disciplines as per their needs and by producing useful products. The concepts of AI are built on knowledge base, algorithm design, and expert systems, and they include features such as Problem Solving, Perception, Natural Language Understanding, Logic Reasoning, Neural Networks, Machine Learning, and Learning. AI has emerged alongside new technologies in education, industry, finance, travel, automated industry, and the media sectors [2,3].

AI has also become a mandatory and intelligent approach to deal with issues in the healthcare industry. AI can be defined differently in different areas, and the best way to address this is for machine intelligence to imitate human intelligence. The biggest challenge in healthcare is that doctors cannot spend enough time on data analysis due to excessive workload. Data scientists can help in the processing and analysis of data, and in comparing the data of various diseases. A patient's medical records can be analyzed, and patterns can be detected and used to characterize the behavior of the disease. AI healthcare researchers are currently undertaking studies worldwide. Countries such as the USA, the UK, and

Israel are on the frontline of promoting research into AI, and the USA is currently ranked at number one, with 49 healthcare startups. The challenges of AI healthcare involve the achievement of high reliability and accuracy. These are required in order to supply services and maintain confidentiality and privacy of data [4].

Signal Processing is a subfield of electronic engineering that includes sound and images. It is also part of the medical imaging field and is utilized in X-rays, CT scans, and MRI. Digital signal processing is used to denoise the noise of speech signals. Bio-signals can be measured in many ways, including by electrooculogram (EOG), electroencephalogram (EEG), electromyogram (ERG), and electrocardiogram (ECG), which is an electronic amplifier used to find the difference between input voltages attached to the skin. The magnetic amplifier is a galvanic skin response [5].

Wearable Biosensors are used to monitor the subject's health using sensors or biomarkers. Bio-sensor devices can be used on the head or inside the oral cavity, or they can take the form of wristbands, textile devices, ear buds, finger rings, smart watches, skin mounted chips, gloves, or electronic chips. Different types of sensors, such as saliva-based sensors, implant sensors, sweat-based sensors, tear-based sensors, arm patches, oral cavity guards, or foot-mounted sensors are used for medical health monitoring. This author has previously discussed wearable devices that are non-invasive and practical and are scalable for commercial production [6].

Bio-medical signal processing is generally used to observe human body parts, tissues, protein sequences, gene structure, and organ images. Bio-signals will help to identify the internal details of organs. The observation is assessed by a biologist and radiologist, and the reports are verified by specialist doctors in order to identify the patient's illness. The bio-signal approach helps in monitoring the patient during the investigation, throughout the progress of treatment and at every stage of the disease. A bio-medical instrument is used to send data to or receive data from the body. Sampling instruments, such as BMI measuring instruments, audiometers, blood cell counters, BP meters, blood flow meters, and GSR meters [7], and different types of bio-signals and their usage, are shown in Figure 1.

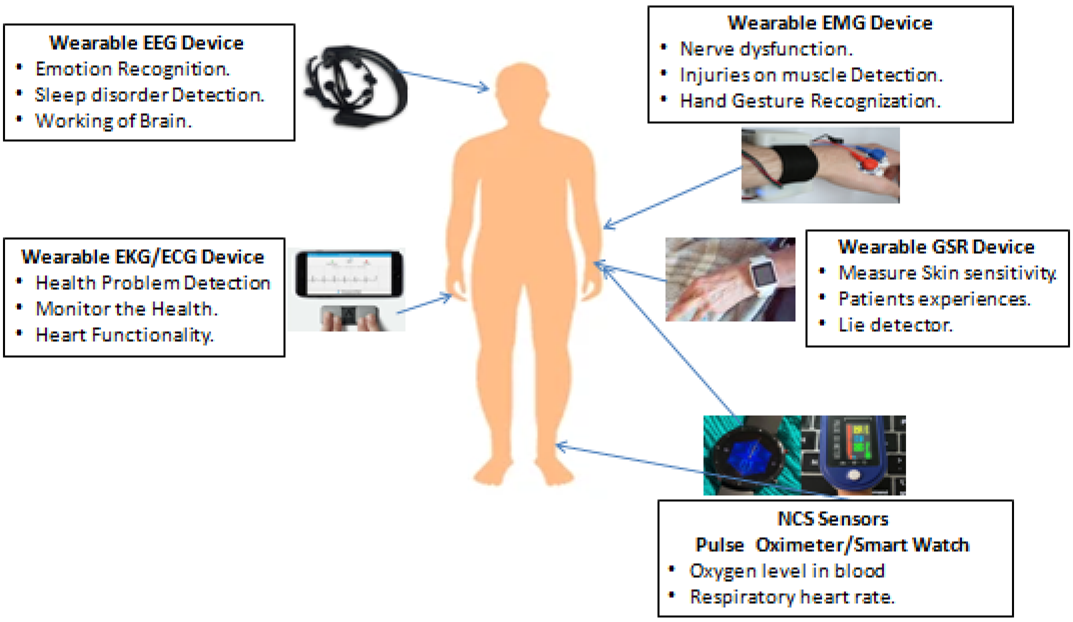


Figure 1. Different types of wearable bio-signal devices and utilities.

The organization of the paper is as follows: Section 1 introduces the paper, and the concept of bio-signals is discussed. An exhaustive literature survey on bio-signals and their applications is carried out in Section 2. In Section 3, different AI methods are used to process input and help to decide on the application. In Section 4, different AI algorithms are discussed that can be applied to applications to improve. In Section 5, the latest treads in bio-signals application in the medical industry are discussed. In Section 6, challenges in bio-signals are discussed.

2. Role of Bio-Signals in Medical Applications

2.1. Bio-Signals with Artificial Intelligence

There have been great success stories about the reach and advancements of AI technology in the medical area. Some of the applications, such as smart watches and wearable devices, are used to sense the pulse rate and irregularity in monitoring through algorithms and in the prediction of heart stroke. They will monitor the activity of a person. As per the authors, it was proven that the size of the brain is larger than the common size for those with heart stroke. The life of the brain will also reduce by 1.1 years of the average lifetime of the brain. It will work one hour more than the regular brain capacity. Echocardiography examination can predict a person's cardiac attack up to two weeks prior to the event [8].

Sleep detection with a bio-signal AI application is used to detect the sleep stages of the person using AI with asleep analysis algorithm, which uses the concepts of pattern recognition and rule evaluation [9]. Bio-signals help in perceiving the emotions of a person while they are returning home from the office. It is possible to know the pulse rate of a person while walking. If at all the pulse rate crosses a limit, only then will the device send a message to the person's family. It also helps us to know the actual mindset of a person's emotions [10].

Another application with bio-signal recognition is to know the emotions of a car racer while driving a car in a car racing competition. It can be evaluated using the intelligent emotion reorganization algorithm. This system will read the values from the wearable device to send the signals to the reorganization module and then classify the results based on an adaptive neuron fuzzy inference system [11]. A severe infection, such as cancer, can easily be identified with blood investigation using the total tally counter to count the first leucocytes and then parasites under high power fields (HPF).

This count is directly recorded in CSV files, having no scope for human error. TTC counts outside of the range signify that some infection or cancer exists in the blood. It is a very simple, easy, and low-cost investigation [12].

AI in wearable devices use bio-signals, and literature work reveals that AI concepts can be used to predict heart diseases at early stages, but applying AI on wearable devices is the proposed model by the author. Cardiovascular-related diseases can be monitored through a digital setting on devices. Atrial fibrillation detection was performed using a forest plot using the R Package. Deep learning methods are used on the bio-signal values recorded by wearable device data, such as ECG and PPG Bio-signals [13].

Bio-signals Processing Architecture: Bio-signals are used in the medical field to assess the environment. This technology is used for the better detection, diagnosis, and treatment of many life-threatening diseases. Figure 2 will explain the signal processing flow. The steps include selecting the dependent variables, analysis, type of sensor that needs to be used, observing input signal, collecting the data, and visualizing. Finally, we can analyze the input using technical and efficient algorithms to classify, predict, and find a correlation or covariance, etc.

The data have been collected from various types of biosensor wearable devices. Different types of Bio-signals are recorded through these devices and stored on the device. The simulator/application use dynamic data that can be updated on the cloud. The data storage format can be in different modes, but we preprocess the data and perform different analytics or statistical approaches. The processed data are sent to the application engine to apply AI concepts and the results are extracted. The generated reports are viewed over different report generation tools such as data visualize, tabular tool, mat plots, etc. The notification is generated on the event generator, effectors are reacted to the environment, and agents perform assertion.

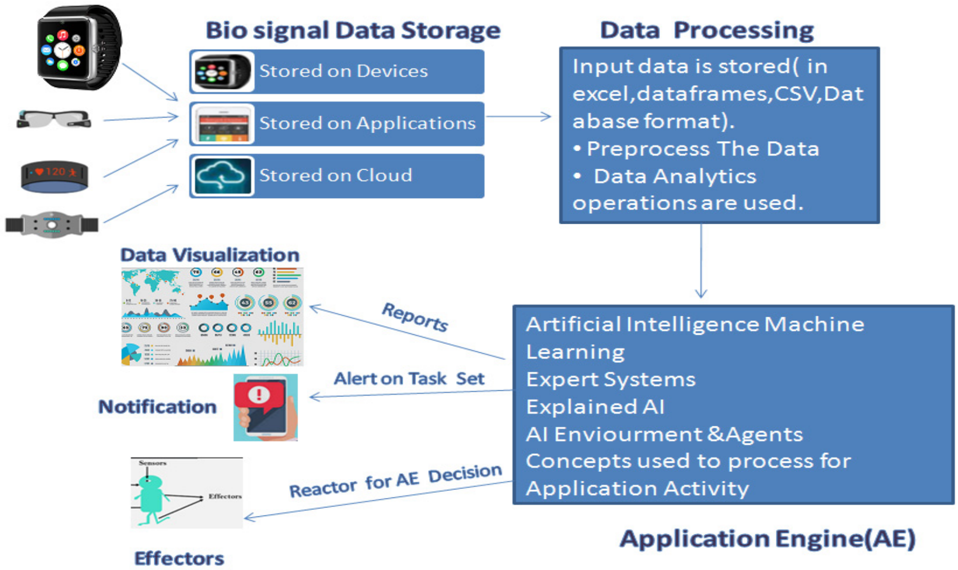


Figure 2. Architecture diagrams of bio-signals processing environment.

2.2. Basic Concepts and Applications in the Medical Industry

AI has taken the lead over the biomedical discipline in the detection of various diseases. Accurate identification of medical and health complications can be completed. The most common approaches in medical imaging are used for preliminary suspects and investigation. This method will process images with the help of different AI techniques and as per the observations made concerning the applications, results are found. A three-dimensional brain MRI scan is used to create a three-dimensional image view of the brain to detect lesions and find any faults that exist on the tissue (such as tissue stiffing, infection on tissue, nerve damage, etc.). The segmentation of lesions using the concept analysis will observe images of the white and gray matter and cerebrospinal fluid. It computes the feature using SVM, where lesions exist only in white matter, and the result was observed that there is an increase in performance in compression with previous methods. Sensitivity is 99%, specificity is 80% and accuracy is 99% [14].

Medical Imaging is a highly active field of research in the biomedical industry. AI algorithms are used to process digital images and classify various diseases. In a previous study, 80 MRI images were referred from the Harvard Medical School database. The study was on various methods to classify diseases such as Pick's, Huntington's, cerebral calcinosis, and Alzheimer's using Otsu's thresholding. We use Euclidean distance methods to analyze the clusters of classes with the histogram binning approach. The similarity can be measured using a base of Euclidean distance value. The classifications of classes are carried out using the binary threshold method and dendrograms [15].

Bio-signals are used in various applications using intelligent devices such as the electrocardiogram (ECG). This ECG can have low power consumption and low data loss features. It can not only work with low-energy wireless communication protocols, but also use a smart phone for the display of ECG output. ECG is used for synthetic waveform, which monitors the heart behavior, such as excitement assessment, recovery rate, etc. The author's latest intelligent proposal is that an ECG waveform is given as input, and with the help of ADS, we convert an analog signal to a digital signal. MSP is used for data processing, BLE is used for transmission, and data are collected on a smart phone using Bluetooth technology. The results obtained in the above process are that the loss rate of ECG packets has reduced from 13.26% to 0.63% and no packet transmission over time has risen from 98 to 633 packets with the new intelligent ECG system [16].

Vital signals are important parameters to check the basic health profile of the subject, which includes blood pressure, blood oxygen, respiration rate, and temperature and pulse rate being the basic biomarkers to check the fitness of a subject. Electrodes and pulse sensors are used to sense the ECG signals, pulse rate, humidity and temperature. This information is sent to an app, web browser or the local web browser [17].

Bio-signals are used in electrocardiogram (ECG) for cardiology examination used for heart regularization. It helps us to find out the damage in the heart and the size and location of holes in the heart. These signals may have noise issues, or they have unacceptable ECG waveforms for the investigation process. Deep learning methods are used to classify the ECG waveform as acceptable or not. Four conventional neural networks are used to be defined with a different number of layers, kernels, learning rate, etc., in architecture models. The results in the above models with a cutoff value of 0.05 have an 88% success rate in the detection of unaccepted ECG waveforms [18]. Takumi Toya et.al. [19] use a 12-lead ECG in the medical area of peripheral micro vascular endothelial function for an index of vascular ageing. An AI algorithm is trained to estimate age and sex, determining age and chronological age (Δ age). Additionally, the hazard ratio was 4.72; 95% CI, 1.24–17.91; $p = 0.02$AI. Δ age was significantly associated with an increased risk, which is consolidated in Table 1.

Electroencephalogram (EEG) is a bio-signal used to observe brain activity by attaching a small disc of electrodes to the scalp of the head. The brain cells communicate with an outside monitoring system using electrical impulses at all times, even while sleeping. This examination is used to know the patterns of the brain and test any head injuries, tumors, dizziness, seizures, and sleeping disorders. EEG investigation will not have any side effects. EEG bio-signal methods will assess the sleep stage scoring, seizure detection, mental workload, and emotional detection. The motor imaginary movement method will find the movement of the tongue/limbs. CNN architecture was designed as an efficient method in comparison with LSTM and RNN networks. EEG data are used to measure mental stress and complexity task performance. The SAE model with new architecture is doing well in comparison with other models. Sleeping stages are stage 1, 2, 3, and 4 [20].

Tremors and epileptic seizures are disorders of the neural system. Early diagnosis always helps in giving better treatment and results. EEG signal capture will help to monitor the functionality of the brain. This author uses the Bonn dataset; the Tunable Q wavelet transform (TQWT) method preprocesses the EEG signal. The feature extraction is performed using fuzzy entropy methods, feature reduction is used in auto encoders, and classifications are performed using fuzzy and non-fuzzy algorithms, ANFIS-BS, able to achieve an accuracy of 99.79% [21].

Electroencephalogram (EEG)bio-signals are used in real-time applications to know whether a person addresses questions with positive or negative mental pressure. The analysis of mental pressure helps us to know the facts of problem solving. This approach uses unsupervised learning in the classification of the classes. The preprocessing of EEG signals is performed based on the division of data, and feature selections are applied. The classification of the obtained dataset is applied. Feature selection is obtained using forward greedy attribute selection and gain ratio feature selection methods. Clustering analysis is conducted using two approaches; one is personal data analysis and the other is channel data analysis. The survey gives solutions for two problems. One of the most effective features is classification, and extra knowledge is used to classify the classes [22]. Another application is predicting children's grade failures using an ML model, which is used to classify (KNN algo) based on three variables, and the results showed that poor performance in math is 55% and language is 74%. The overall failure rate depends on the above reasons, discussed in Table 1.

Electromyography (EMG) is a bio-signal used to examine if the muscles respond to the nervous system properly or not. It helps in the detection of diseases, disorders, neural problems, or damages in the neural system. The various diseases used to detect using EMG include nerve injuries, degenerative conditions of the nerve. The procedure for the EMG test will use a needle electrode inserted into the muscles, which is used to record the muscles' functionality. EMG examination is carried out in COVID-19 patients after detecting negatives to discover any blocks in the nervous system and to check whether they have been exposed to fatigue, dizziness, calf cramping, or exhaustion under stress. This study was a study of three COVID-19 patients kept under observation with mild health issues. Cases 1 and 2 could tolerate but case 3 was not able to tolerate the needle electrodes in the muscles. The result of the EMG examination was able to find an inference pattern. Case 1 and case 2 were able to perform due to the short duration, low amplitude of motor unit action potential, and myalgia. In case 3, the EMG test was unable to be performed due to muscle pain while going through the procedure [23].

Hand recognition and gesture recognition are more challenging, especially in contactless health treatments such as for COVID-19. Contactless treatment, service in the hospital and quarantine need some actions for basic needs and response to the doctors. Some gestures, such as feeling good or require something, can be standardized by the hospital. EMG signals are used to recognize the gestures of hands or fingers. Electrodes are fixed to the hand, wrist and fingers. The time division features are extracted and machine algorithms are used for the classification of type of gesture. An ANN-based classifier achieved 0.940 accuracy [24].

Tele rehabilitation is a traditional treatment that will be used to monitor the muscular activities of the patients and the effectiveness of home exercise. This application is most effective in physiotherapist treatments. The electromyography biofeedback system device helps to monitor the patients at remote places. It helps to monitor muscular activity after injuries and major surgeries. AI is added to support the medical industry with technology. This device has five module roles Module1: accept the input through EMG electrodes for sensors; Module2: biofeedback device gadgets are designed along with two mobile phones with designed applications, and Modules 3,4, and 5 are used to implement a check of EMG signal [25].

Electroencephalograms (EEG) are used in the medical industry to identify disorders and changes in behavior and to monitor the activity of the brain. It is observed generally in liver transplant and heart transplant patients. EEG is an examination performed through an external metal disc attached to the scalp. It has no side effects. EEG is also used to authenticate a person's identity. There are many biometric methods used to identity authentication, such as DNA, face reorganization, fingerprint, hand geometry, typing rhythm, and voice. In biometric reorganization, many considerations should be satisfied; for example, every person should have distinct characteristics, invariant over time, and this should be measurable. This examination has three stages of study. Stage one—we perform four tasks: person to relax, close eyes, and be still. The next task is to take the observation of limb movement activity without moving the limbs. Another task is to generate finger rotation activity. The next stage is feature extraction and finally, classification rules are applied using a support vector machine algorithm to calculate the false acceptance rate and false rejection rate, and 100% accuracy has been improved using the voting rule [26].

AI is used to classify the EEG collected data for application in very short-term memory assessment. Short-term memory can remember the small visual details of an image or picture at one sight. Some details include color, shape, location, and characteristics of the image. Short-term memory has two limitations: capacity of memory and time limit. The brain will see, observe and try to store in the memory. This experiment was conducted with 12 patients showing two images, A and B. Later, we asked a few questions and calculated the order of display image, type of the image, and correctness of the answer, and classification was obtained using four methods of AI, which are SVM, KNN, Navi Bayesian, and Random Forest. The classification result declares that 90.12% of correct answers in the orders of the image shown are drawn from the persons. A total of 90.51% of emotional people can answer the time and type questions correctly [27].

Electrooculography (EOG)is a bio-signal used to observe eye movements and to record the cornea–retina potential difference. The electrodes are placed above and below the right side or left side of the eyes. Of two electrodes, one is positive and another one is negative. The eyes will move to either side, and we can record the position of potential difference between the electrodes. The real-time applications are implemented to guide wheelchair patients and HCI applications for people who suffer from brainstem strokes, injuries to the brain and spine, etc. The spectrum of studies is carried out on EOG bio-signals in medical areas such as cranial nerves (CN) to record the positive and negative waveforms. In this study, 18 patients who had brain surgery have kept practicing this technology [28].

Mechanical devices such as wheel chair, mechanical arms, aerial vehicles, and toys cars are controlled by neuroscience. The real-time bio-signals (EEG) of the human brain are recorded. These signals are processed on a Raspberry Pi3 circuit board. The open-source code used to process the signals include brain flow, sLORETA and TAPEEG. The artificial intelligence and machine learning are used to control the robots [29].

3. Data Sources

Data sources are taken from critical health issues. The eICU Research Institute maintains a collaborated database of patients [30]. It has a two-year track record of 2014 and 2015. It maintains the patient's history, ICU data and lab examination details. The link to the data site is shown in Table 1. The database contains patient details such as name, gender, joining date, discharge date, weight of patient at joining and discharge, patient status, etc., which are stored in tables. These data are used to analyze patient care. Munich Bio-voice corpus is used to record the voice of the human and record their pulse and project the complete treatment. The project details are directed through the link enclosed in Table 1. Bio-signals including pulse and voice recording analyze the data and predict the heart rate. The project works in two phases. Phase 1 uses regression and classification, and Phase 2 uses a diffusion map for feature extraction. The AUMC (Ajou University Medical Center) is used to record the ECG bio-signal details of patients and apply transfer learning for classification. We evaluate performance using mean squared error [31]. VitalDB consists of the example dataset containing bio-signal data. The EEG dataset is stored in a csv file in the public domain and contains almost 30 attribute values such as ECG, number of days in ICU, weight, gender values, etc. A Convolution Neural Network is used to classify and predict the mortality rate.

Table 1. The different data sources of medical applications using bio-signals.

Data Source Details	URL
The eICU Collaborative Research Database [32]	https://eicu-crd.mit.edu/gettingstarted/access (accessed on 27 December 2021).
Ajou University Hospital Biosignal database [33]	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7921576/ (accessed on 27 December 2021).
The Munich BioVoice corpus (MBC) [34]	https://sipl.eelabs.technion.ac.il/projects/heart-rate-measurement-from-human-voice (accessed on 27 December 2021).
VitalDB database [35]	https://github.com/vitaldb (accessed on 27 December 2021).

4. Methods in Artificial Intelligence and Machine Learning

Algorithms are used to achieve the targeted task in a step-by-step process. The Computer Science industry has taken the world to the next level by improvising their thinking and introducing AI algorithms, which have advanced features such as supporting large and complex data as input and fast execution, and an intelligent factor of these algorithms is that it can make decisions. The major concept of AI is to build the concept to make the machine think as humans do in decision making or behavior, and machine learning is a concept to learn from traditional and current data. It maintains a training dataset and makes a decision based on the historical dataset. AI algorithms are designed for different purposes, such as classification of data, regression analysis, and clustering of data [36,37].

4.1. AI Classification Algorithms

The classification of data is used to segregate data based on some common factors. Data can be of a structured or unstructured format [38]. Classification algorithms are used to build the model and to train the data into labeled classes. The trained model will help in predicting to which class the new entry belongs with respect to training the model. Classification can be binary, multiclass, or multilabel [39,40].

4.1.1. Navi Bayes (NAB) Classifier Algorithm

This is one of the most popular algorithms used for the supervised learning approach and it is based on the Bayes theorem, which helps in handling classification problems in data partition [41]. It will build the most efficient machine learning model to predict correctly based on the training model. Most population applications built using the NAB algorithm are email filtering, text analysis, and research data. NAB is based on Bayes law and is used to determine the posterior probability. The NAB approach is the first step to convert the dataset into a tally table or frequency table. The next step calculates the probability of features and finally calculates the posterior probability using Bayes law and applications, which is discussed in Table 2 [42].

$$\mathbf{P}(\mathbf{A}|\mathbf{B}) = \frac{\mathbf{P}(\mathbf{B}|\mathbf{A})\mathbf{P}(\mathbf{A})}{\mathbf{P}(\mathbf{B})} \tag{1}$$

P (**A** | **B**) is a Posterior probability (**B** | **A**) is likelihood probability
P (**A**) is Prior Probability (**B**) is marginal probability.

Table 2. Applications of bio-signals.

Broad Area of Data Processing Approaches and Applications in Bio-Signals				
Data Processing Concepts	**Techniques**	**Approach of Algorithm**	**Expected Output**	**Sample Applications**
Binary Classification	Logistic Regression [43]	Supervised Classification, based on probability.	True/False Class	predict mortality in injured patients
	k-Nearest Neighbors [44]	Supervised Classification and regression problem Calculate K-Nearest and sort.	A most frequent class of these rows as predicted	Speech Recognition and Image Recognition
	Decision Trees [45]	Supervised Learning Algo was used to create a training database and predict the target variable. Decision rules inferred the class.	Categorical variable and continuous variable	Law and engineering
	Support Vector Machine [46]	Liner Classification, use hyperplane to divide from two sections	Divide the class and also find outliers	Facial Expression
	Naive Bayes [47]	It is a collection algorithm and every pair of the feature is classified independently.	Probability Yes or NO	Spam Filtering
Multi-Class Classification	k-Nearest Neighbors [48]	More than two classes for classification, uses proximity of each other.	Classification into more than two classes	Image processing
	Decision Trees [49]	More than two classes for classification, GINI index	Classify into defined classes	Vehicle driving alcohol percentage
	Naive Bayes [50]	More than two classes for classification, probabilistic classifiers	Classify into defined classes	Plant species classification
	Random Forest [51]	More than two classes for classification, hyperparameter	Classify into defined classes	Face classification
	Gradient Boosting [52]	More than two classes for classification, loss functions	Classify into defined classes	Optical character recognition.
Multi-Label Classification	Multi-label Decision Trees [53]	generalization of multiclass classification, BR-DT Pru algorithm	Classify into defined classes	Fraud detection.
	Multi-label Random Forests [54]	Problem Transformation Adapted Algorithm Ensemble approaches	Classify into defined classes	Outlier detection.
	Multi-label Gradient Boosting [55]	Hamming loss, predictive performance.	Classify into defined classes	Medical diagnostic tests.

4.1.2. Decision Tree Algorithm (DTA)

The approach used to help the statistical approach to decide on information and available data exists in the system. Classification has a learning phase and predication phase in machine learning. DTA is a supervised learning algorithm that can solve classification and regression problems. The attribute is arranged into a tree-like structure from the parent node to child nodes till it reaches conclusion leaf nodes. The general tree classification structure is shown in Figure 3. Decision trees are of two types: categorical variable decision tree and continuous variable decision tree. Categorical values have only one dependency variable, but continuous variable has more than one dependency variable. Some algorithms are designed based on the decision tree concept. Algorithms are Chi-square automatic interaction detection and perform multi-level splits when computing classification trees, ID3, C4.5, CART, and MARS [56].

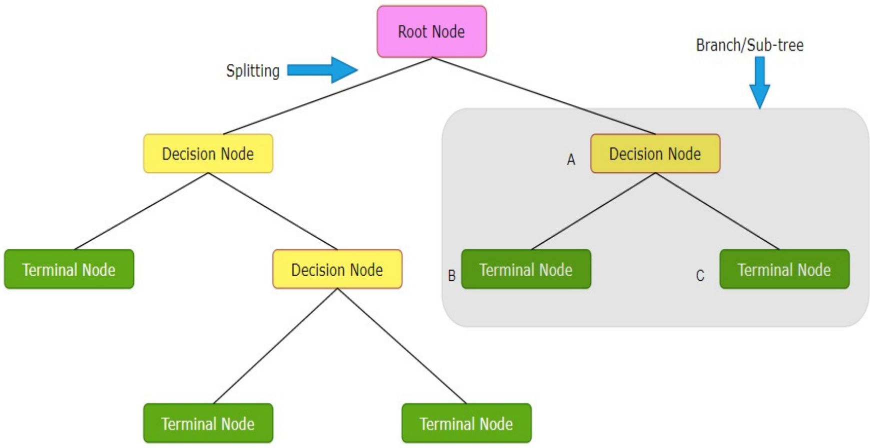


Figure 3. Model Diagram for Decision Tree Algorithm.

Attribute selection measures are shown in Table 3. Let us consider a dataset that has N-variables, and we need to decide the attribute to be placed in the root node and internal nodes. Another possibility is to arrange the nodes randomly. It was proven that results are very low in this possibility in terms of accuracy. Some calculations are performed to calculate information gain, Chi-square, reduction in variance, entropy, gain ratio, and Gini Index. The maximum attribute values are placed on the root node and other attributes are placed on different sub-levels in ascending order [57].

Table 3. Different attribute selection types for DTA.

Attribute Selection Measures for Decision Tree Algorithm			
Criteria	**Purpose and Process**	**Formula**	**Metric Measure**
Information gain	The statistical approach to decide the separation attribute for splitting.	$\text{Information Gain}(T,X) = \text{Entropy}(T) - \text{Entropy}(T,X)$	ID3 uses the highest information gain and smallest entropy.
Chi-square	The oldest method, calculating the sum of the square of actual values minus expected.	$x^2 = \sum \frac{(A-E)^2}{E}$	Higher deviation, splitting into subclasses.
Reduction invariance	It is a regression problem, check for the best split value.	$\text{varience} = \frac{\sum(X-X^{\cdot})^2}{n}$	Lower the variance value for splitting
Entropy E(Single/Multiple)	Measure the randomness of the information occurrence.	$E(s) = \sum_{i=1}^{c} -P_i \log_2 P_i$ $E(X,T) = \sum_{C \in X} P(C)E(C)$	In the ID3 algorithm, if the Entropy value is zero, this means it is a leaf node and greater zero means further splitting is needed.
Gain ratio	Splitting of attributes based on attribute has a large no of distinct values.	$\text{GainRatio} = \frac{\text{Informationgain}}{\text{SplitInfo}}$	C4.5 and improved ID3 uses the gain ratio and go to the next level.
Gini Index	Cost Function is used to evaluate split in the dataset. It subtracts sum of the square from one.	$\text{Gini} = 1 - \sum_{i=1}^{C} (P_i)^2$	Gini index values are binary 0 or 1. Higher gini values mean higher the heterogeneity

4.1.3. Random Forest Algorithm (RFA)

This approach worked with the supervised learning technique. It is used for regression and classification problems in machine learning. It is a group of leanings combined, and very complex problems are solved with multiple classifiers and the current problem is improved. In the random forest, there are multiple decision trees and we take the average and predict the accuracy. Random forest is most efficient for a large range of data items flowing into the decision tree [58]. We can eliminate the over fitting problem because we go for averaging values. The algorithm selects random samples from the dataset, a decision tree constructed for every training case, and predicts the results. The obtained results are obtained by the greatest possible value. This algorithm is also used for anomaly detection in the network. Random forests are frequently used for "black box" models in business models [59], and a sample general model is shown in Figure 4.

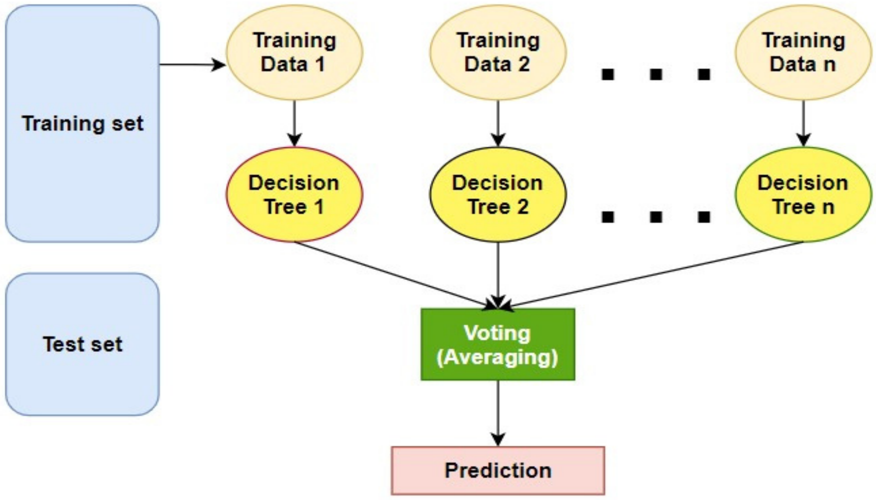


Figure 4. Random forest model algorithms.

4.1.4. Support Vector Machine (SVM)

This approach is a simple approach to solving the problem in the minimum number of steps. It helps to solve problems using classification and regression methods. It is the most frequently used for classification problems. SVM uses the N-hyper planes for defining N-features, which help to classify the data points. The separation of data points can be maximum minimum margins and a graph is shown in Figure 5. The support vector data points lie near the hyper planes, and finally, the gap between hyper planes is used to maximize and classify [60]. If the support vector data points are deleted, there is a possibility of changing the direction of the hyper plane. Hyper planes are named as positive hyper plane or negative hyper plane concerning the dividing margin based on the threshold function or cost function, and a graph of the hyper plane is shown in Figure 5. If the output of the squash function is less than the threshold, then it is a negative region, and if it is more than the threshold value, then it falls in the positive region. In a logistic regression problem, we obtain output from the linear function and sigmoid function. If the squash values are less than the threshold, then they are named as a class of zero, and those greater than the threshold are named as class one. SVM applications help in various medical industries in the classification of genes; their behavior is a specific disease and regression helps in the prediction of the future possibility of the disease [61].

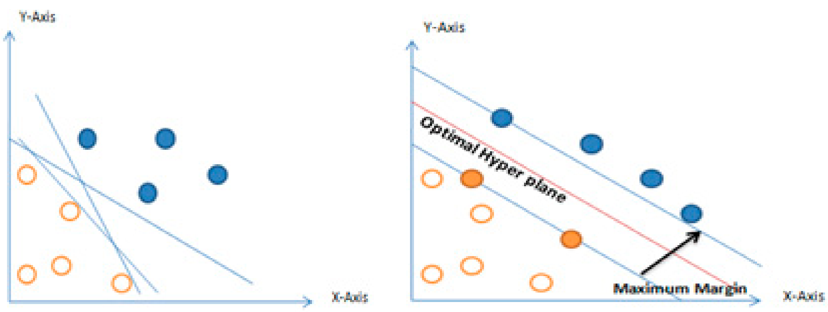


Figure 5. Support vector machine algorithm.

4.1.5. K-Nearest Neighbor Algorithm

KNN is also used to solve the classification and regression problem. This algorithm uses the supervised learning approach to train the application model. It is widely used to solve a problem such as prediction based on some feature learning [62]. It will classify the new-arrival case study with existing cases or find similarities among the available data classes. KNN has a lazy learner and a non-parametric algorithm as properties. Initially, it will not refer to the training set as a reference study. First, it will store it as a dataset, and then it will classify it later. Once the dataset is stored, it will then classify it as per the similarity among the class labels. A generalized graph is shown in Figure 6 [63].

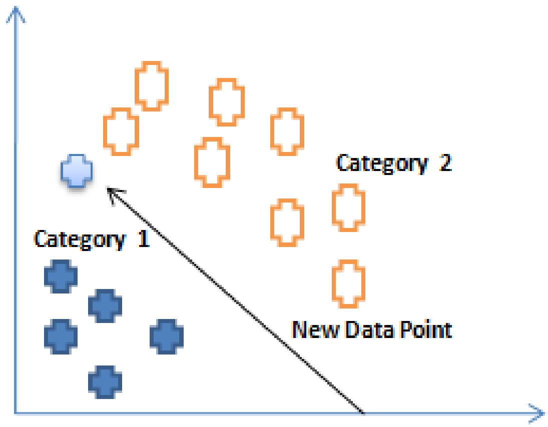


Figure 6. KNN machine learning algorithm.

4.2. Logistic Regression Algorithm

A regression algorithm is used to correlate the data points and to classify the data point into a set of classes. The medical applications for regression analysis for tumor characteristic analysis and classification is benign or malignant. Multi-linear classifications are used for stage detection of cancer. A linear regression function is used to predict hemoglobin deficiency or blood pressure based on age, weight, gender, etc. Lasso regression methods are used for predicting neonatal sepsis, radiological characteristics, and bipolar disorder [64]. Logistic regression is used to monitor health condition and improve healthy habits on feature selection based on the target set [65]. A multivariate regression algorithm is used to predict disease diagnosis based on the hidden rules in the medical area using clustering, DT, association rules, etc. [66]. Multiple regression algorithms were used for mean, median, and standard deviation value calculation. Different types of regression methods and their applications are consolidated in Table 4.

Table 4. AI Regression Algorithm.

Data Processing through AI Regression Algorithm		
Techniques	**Approach to Algorithm**	**Algorithm**
Linear Regression [67]	Prediction value based on independent variables, Gradient Descent.	Linear Line Show Dependent and Independent Variables.
Lasso Regression [68]	Eliminate irrelevant noises, feature selection.	Loss Function, Prediction, Grid Search
Logistic regression [69]	Obtain odds ratio, multiple linear regression An exception that the response variable is binomial	Logistic Function, Or A Sigmoid Function
Multivariate Regression algorithm [70]	One dependent variable and multiple independent variables	Feature Selection, Engineering, Normalizing, Loss Function, Hypothesis
Multiple Regression Algorithm [71]	Single dependent continuous variable and more than one independent variable	Statistical Technique, Relative Contribution of Each Independent Variable In The Total Variance.

4.3. AI Clustering Algorithm

The clustering algorithms are used to group the data based on similar patterns and the groups are created based on some specific criteria. The criteria are selected based on the priority and on the behavior of the data and future requirements for deep analysis. The clustering approach is an unsupervised classification of data into self-defined groups. Clustering will not predict any class, but it helps to classify the data. The outcome of clustering will result in knowledge discovery and help to frame the dynamic inferences from the results. The statistical calculations will find the similarities and dissimilarities among the data points to segregate the data into desired cluster groups. Python language will implement clustering algorithms using the Scikit-Learn package. The algorithms used are K-Means, Mixture of Gaussians, Mean Shift, Mini-Batch K-Means and Agglomerative Clustering methods, and applications are shown in a Table 5.

Table 5. Summary of various artificially intelligent algorithms.

Artificial Intelligence Concepts in Data Management				
Data Processing Concepts	**Techniques**	**Approach of Algorithm**	**Algorithm**	**Sample Applications**
AI Clustering Algorithm	K-means Clustering [72]	Iterative algorithm Partitioned into k clusters	Cluster with nearest mean	Customer segmentation
	Mean-Shift Clustering [73]	Non-parametric feature-space analysis local homogenization technique	maxima of a density function. so-called mode-seeking algorithm	Detection Toys in image
	Density-Based Spatial Clustering [74]	Unsupervised learning methods. distinctive groups/clusters in the data	Density-Based Spatial Clustering	COVID-19 case, over the world
	Gaussian Mixture Models (GMM) [75]	confidence ellipsoids for multivariate models	Bayesian Information Criterion to assess the number of clusters in the data	normally distributed Subpopulations within an overall population.
	Agglomerative Hierarchical clustering [76]	bottom-up approach each data point starts in its cluster	Agglomerative. Clustering and merging	DNA sequencing and hierarchical clustering to find the phylogenetic tree of animal

5. Latest Trends in Bio-Signal Application in the Medical Industry

The latest medical applications are using bio-signals for speech rehabilitation. Bio-signals can capture the air vibrations below the audible speaking mode. The speech can be captured using articulator, respiratory and laryngeal activities, brain activities, acoustic activity, and muscle activity, and are observed by bio-signals. The speech can be converted into artificial voice or text. Non-contact sensors are used to capture the image to predict the human facial expression and human observations on objects. Bio-signals help us to observe the emotions of a person while answering in the house of judgment. Another application health checkup needs to be performed for pilots before they take a flight for flying. Clinical observations were performed to check for drug and alcohol use and check for depression or anxiety. The near-field communication is very important for sending children to field trips, forest tracking, missing ships, missing flights and searching for people in a dense forest. It is also used to estimate the emotion of a sports person while participating in car racing and estimate the pressure of a student while taking an exam. The latest application and industry applicable details are discussed in Table 6.

Table 6. Latest Trends in Bio-signal Applications.

Latest Trends in Bio-Signal Applications in the Medical Industry			
Author	**Field of Application**	**Type of Signal**	**Concept of Application**
Tanja Schultz et al. [77]	Speech Rehabilitation	EMG, EEG, ECoG, fNIRS, US, PMA	Artificial Voice
Tourangeau et al. [78]	Facial Expression, Eye movement, and Skin Resistance	Video Camera Eye-tracking GSR measurements	Non-Contact Sensor
Akane Sano et al. [79]	Visual communication, automatic music selection, automatic metadata annotation	pulse wave, EMG, and acceleration sensors	Music play
Egon L et al. [80]	Unveiling Human Emotions through Bio-signals	EMG, EDA	classify the class of emotion
Suh, Y.A. et al. [81]	Existing Fitness for Duty: a worker's drug and alcohol level is taken, check for depression and anxiety	EEG indicators EEG indicators, ECG indicators, BVP, GSR,	Multi-Criteria Decision Making
Eduardo Coutinho et al. [82]	Estimating bio-signals using the human voice	HR and skin conductance	audio recordings, video recording
Yushou Tang et al. [83]	Emotion Recognitions like sadness, disgust, neutrality, fear, happiness	nelectroencephalography (EEG) signals	eye movements or physiological signals
Ken Yamashita [84]	Bio-signal Monitoring System with Near Field Communication	Antenna for NFC, Acceleration/Electrodes	Smart phones using Near Field Communication (NFC)

6. Challenges in Bio-Signals

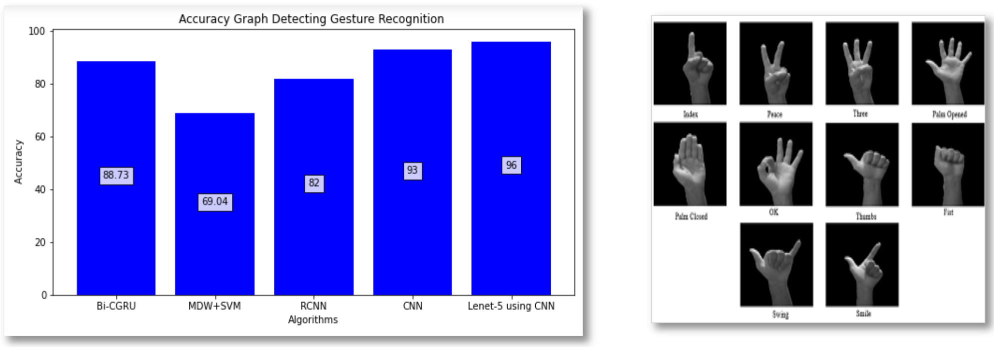
Medical applications are designed with technology to detect the expected scenarios, monitor the human health system, and predict life hazards; brain readings, etc., are some of the generalized challenges in the medical industry. There is also usage of wheel sensors, inclinometers, voltage meters, gyroscopes, and torque sensors in the feedback process between the nervous system and the human body parts. These sensors help to find any biological changes that occur in the human brain and find how they are received and reflected in terms of behavioral changes. Medical applications need to be developed to correlate the sensors with human brain connectivity. COVID-19 has changed human lives and style of living, and global awareness has changed the mindsets, behavior and the utilization of devices or resources in people. Using hepatic technology, we can eliminate human touch over resources and devices such as ATMs, lifts, etc. Another challenge in the COVID-19 pandemic is maintaining social distancing and creating an alarm system to give information to the police if social distancing is not maintained in a crowded area such as schools, colleges, parks, cinemas halls, etc., using a passive infrared (PIR) sensor with the geo tagging association. Doctors are facing medical challenges in treating COVID-19 patients; patients are isolated in a room and doctors and medical staff only visit patients for rotating checkups and emergency needs. COVID-19 patients are emotionally and mentally stressed and biofeedback monitoring is needed.

7. Summary and Results

Bio-signals are used to predict the activities of the patient and detect disease. The datasets available for different types of bio-signals to acquire and signal are processed using various AI approaches to classify and cluster. Regression analysis and learning algorithms are used to improve the efficiency and accuracy of the applications. Gesture recognition is an application to identify the need of the patients in the ICU. The accuracy percentage is show in Table 7 and different algorithm accuracies are reflected in the graph as shown in Figure 7a,b, which show the sample gestures. Surface electromyogram (EMG) signals were used and, they recorded the activity of the muscle. One medical application is for patients in the ICU that were physically disabled, and another application studied is the emotion of a person.

Table 7. Emotion of a person and hand gesture application.

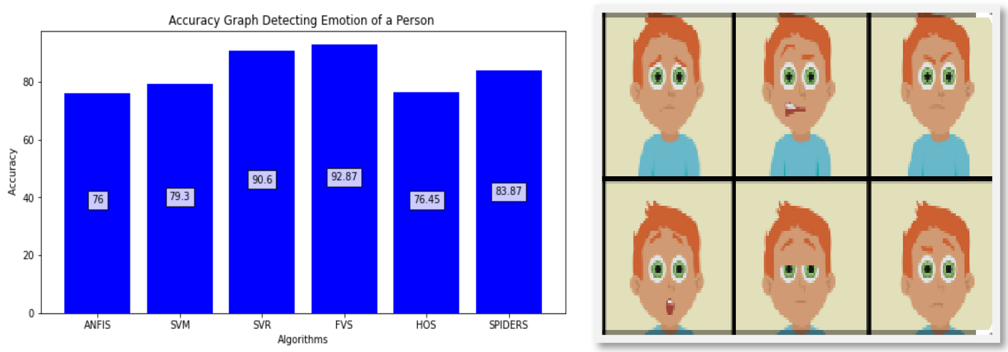
Author Details	Specialized Application	Objective of Research	Algorithm/Approach	Data Set Details	Findings/Results
Baao Xie et al. [86]	EMG Signal/Gesture recognition	Detection of hand Gesture of the Subjects	Bi-CGRU model, 17 hand gestures	NinaproDB5	88.73% Accuracy.
		Detection of Arm Gesture of the Subjects.	Multivariate Discrete Wavelet+ SVM.41 Movements		69.04% Accuracy
		Detection of Arm Gesture of the Subjects	Residual Convolution Neural Network 41 movements.		82% Accuracy
Ali Raza Asif et al. [87]		Hand Gesture of the Subjects.	Convolution Neural Network.	18 Subjects	93% Accuracy
Christos D. [88]	Facial EMG, ECG, EDAEmotion of a person	Car-Racing Drivers emotion Recognition	Adaptive Neuron-Fuzzy Inference System, Support vector machines	10 Subjects	ANFIS 76% Accuracy SVM.79.3% Accuracy
Jerritta Selvaraj [89]		Emotion State	Rescaled Range Statistics, Finite Variance Scaling, Higher Order Statistics	60 Participants	FVS92.87% HOS 6.45% Accuracy
Jingping Nie [90]		Shape of Eye.	SPIDERS Technology	6 People	83.87% Aaccuracy



(**a**) (**b**)

Figure 7. (**a**) Accuracy of gesture recognition, (**b**) hand gestures, reprinted with permission from [85].

The emotion of a person is recognized using different algorithms and its accuracy is measured in Table 7. The sample face expressions are shown in Figure 8b and graphical accuracy is shown in Figure 8a.



(**a**) (**b**)

Figure 8. (**a**)Emotion of a person accuracy, (**b**) emotion of a person.

8. Conclusions and Future Scope

Smart devices and wearable gadgets are embedded with bio-signals in the smart health care system. Some chronic diseases are not treatable and are only manageable. The smart health care system will help to monitor health changes and warn of a threat approaching. A smart device with the latest technology implementation success rate is not comparable with the old traditional system. The future scope is for the smart health care system to have wireless devices that will monitor the health of patients, and cloud data help to analyze the behavior of the medications and the recovery rate.

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