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# Deep Belief Neural Network Based Automatic NSTEMI CVD Prediction Using Adaptive Sliding Window Technique

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## Abstract

INTRODUCTION: Cardiac Vascular Disease (CVD) is determined to be the most prevailing disease all over the globe specifically in the case of elderly persons. Among various cardiac disease, CVD account for major mortality all over the globe. Diagnosis of cardiac disease at an early stage is mandatory to reduce the rate of mortality. Still, there is no availability of skilled specialists even in case of developed countries for accurate diagnosis.
OBJECTIVES: Achieving automated and accurate diagnosis, computer vision based methods that functions with the help of AI techniques are focused on by researchers. In this current research automated CVD prediction model is designed using a deep learning approach.
METHODS: ECG image dataset is utilized in this proposed CVD prediction model. Initially, the Non-ST-elevation myocardial infarction (NSTEMI) ECG data collected from the healthcare centre is taken as input. This input ECG image is converted into a signal and further, it is segmented using the sliding window segmentation technique. Then, using segmented signal QRS peak detection is achieved using Elephant Herd Optimization (EHO) algorithm. From the peak, detected signal features are extracted using Heart Rate Variability (HRV) analysis. Following that the extracted features are sent as input into the Deep Belief Network (DBN) classifier to predict CVD patients.
RESULTS: The proposed CVD prediction model is implemented and some of the performance metrics are calculated. Accuracy, error, precision, sensitivity and specificity attained by the proposed model using the second dataset are 95%, 5%. 96%, 94% and 96%. Results showed that the functioning of proposed CVD prediction model is better when compared with other existing techniques.
CONCLUSION: Based on this analysis it can be revealed that accurate and timely CVD prediction can be achieved with a lessor error rate. Further, this proposed model can be used in real time healthcare application by collecting NSTEMI ECG signal from patients.

**Keywords:** CVD prediction, ECG image, sliding window segmentation, QRS detection, elephant herd optimization; deep belief network

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## 1. Introduction

One of the biggest causes of death worldwide is Cardio Vascular Disease (CVD). Any disorder involving the cardiovascular system, including myocardial infarction, stroke, and fainting, is referred to as a cardiovascular event [1]. The American Heart Association estimates that 17 million people each year die from heart disease, a number that will rise to 23.6 million before 2030. This dreadful incident has the potential to completely wreck the patient's life for several minutes. Cardiac myopathy, congenital heart disease, arrhythmias, Coronary heart disease, etc are some of the

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different cardiac disorders that affect people [2, 3]. To raise people's standards of life, early diagnosis of heart disease is required. Medical devices like defibrillators can be used to minimise these cardiovascular episodes once they have been diagnosed. In the early days, the analysis of heart disease was achieved by means of some medical experts [4]. However, these kinds of analysis are quite complex and it is frequently prone to human error.

Within his context, the use of electrocardiograms is one of the most modern methods advocated for the prediction and diagnosis of heart disorders (ECG) [5]. The analysis of electrocardiograms (ECGs) has improved recently thanks to more advanced equipment and potent computer tools. Heart problems caused by cardiac pathology, such as conduction defects, valve defects, and coronary artery disorders, can be detected using this ECG test [6]. The presence of erratic QRS-complexes, erratic and chaotic F-waves in place of regular P-waves, and fluctuations in the RR-intervals, respectively, are the symptoms in the ECG signal [7]. However, there is still further data included in the signal, such as the ST segment, T wave, wave size and direction, rate, rhythm and smooth P waves, which has not yet been investigated to diagnose the disease [8].

Traditionally, the prediction of cardiac disease using ECG signal is achieved by means of visualization through specialist [9]. However it is quite complex to achieve accurate prediction using normal visualization due to presence of small amplitude and time varying signals. To address this issue developing of automated cardiac disease prediction model was at recent trend. To achieve automated cardiac disease prediction use of Artificial Intelligent (AI) system is recently focused by many researchers [10]. Machine learning algorithm is mostly widely utilized AI system for numerous prediction and diagnosis. Various machine learning algorithms such as Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF), Decision Tree (DT), etc. However extracting essential features from ECG signal is difficult which results in inaccurate prediction on using ML algorithm [11, 12]. To overcome this problem deep learning based CVD prediction is focused in this current research to achieve accurate prediction.

The main contribution of this work is listed below,

- Deep learning based automated cardiac disease prediction model is proposed to achieve accurate prediction and to decrease the mortality rate due to heart disease.
- NSTEMI ECG segment captured at different intervals consisting of P wave, Q wave, R wave, S wave and T wave is used to diagnose the heart disease. The presence of abnormal waves is the sign of heart disease in patients.
- Segmentation of NSTEMI ECG signal is achieved with the help of adaptive sliding window due to presence of non-transitional activity in NSTEMI ECG signal.
- Effective detection of QRS complex is attained using optimized peak threshold method. The threshold value is optimized using EHO algorithm. Fitness function provided for EHO algorithm is to maximise accuracy
- Features from the ECG signal is extracted using HRV technique. Using this technique both linear and non-linear features are extracted.
- DBN classifier is used to classify the disease patients from normal patients with the help of extracted features. Accurate prediction of CVD with less error is achieved using this proposed model.

The remaining portion of paper is organized as follows, section 2 includes the articles reviewed related to automated prediction of CVD using machine learning and deep learning approach. Section 3 encloses proposed automated CVD prediction model using DBN classifier. Section 4 encloses results obtained through implementing the proposed prediction model. Section 6 concludes the entire paper.

## 2. Literature review

Prediction of cardiac disease is considered as essential to reduce the rate of mortality due to heart disease as well as to improve their living standard. Traditional method through visualization is quite complex due to presence low amplitude ECG signal. To overcome this issue automated prediction model based on AI system was developed. Some of the automated cardiac disease prediction model is reviewed below.

Detection of coronary artery disease ECG signal and normal ECG signal was attained by Acharya et al. [13] using CNN. Normally the ECG signal was found to be non-linear and in some transitional disease it varied randomly with respect to time. Analysing ECG signal was quite complex, subjected to human errors and time consuming. To overcome this issue CNN which consist of four convolution layer and pooling layer and three fully connected layer was utilized to predict cardiac disease using ECG segment. Deep learning employed cardiac disease prediction was attained by Hasan and Bhattacharjee [14] using altered ECG signal. ECG signal was altered on applying intrinsic mode function and empirical mode functions. This modified signal was fetched as input into CNN in which softmax was used as activation function. CNN was found to be perform better with this modified ECG signal when compared to raw ECG signal.

One dimensional CNN was developed by Dai et al. [15] to predict six different cardiac disease from various interval of ECG signal. Here, the raw input signal was pre-processed using min-max normalization. Then, ten-fold cross validation technique was used to predict the cardiac disease from ECG signal observed at one second, two and three seconds. Three kind of support vector machine was developed by Abdar et al. [16] for achieving accurate prediction coronary artery disease. The performance of the classifier was enhanced through pre-processing the ECG signal with normalization and extracting with hybrid optimization algorithm namely particle swarm and genetic algorithm and then applying ten-fold cross validation.

Neural network based cardiac disease prediction model was developed by Suhail et al. [17] using ECG signal. Pre-processing of raw ECG signal was achieved using discrete wavelet transform and then training process of neural network was done using non-linear vector decomposition with thirteen features and these features were fed into neural network during testing process to predict cardiac disease. Optimized SVM based coronary artery disease prediction model was developed by Dolatabadi et al. [18] using ECG signal. Heart Rate variability features was extracted from ECG signal and then the dimension of the features was reduced using Principal component analysis and finally SVM was used to categorize features into cardiac disease and non-cardiac disease.

Hybrid CNN-LSTM based cardiac disease prediction model was developed by Tan et al. [19]. ECG signal was difficult to be analysed through visualization due to presence of low amplitude.to overcome this issue hybrid deep learning model using CNN and LSTM was developed to predict cardiac disease. Automated cardiac disease prediction model was developed by Raghavendra et al. [20] utilizing double density dual tree discrete wavelet transform. Using this transform the input ECG signal was decomposed into various sub bands and from these sub bands entropy features were extracted. Dimension of the extracted features was reduced using marginal fisher analysis. Finally prediction was achieved using linear discriminant analysis classifier.

One dimensional CNN model was designed by Yıldırım et al. [21] to predict cardiac arrhythmia disease using ECG segment acquired for long duration interval. In traditional heart disease prediction approach QRS complex detection and hand-crafted feature extraction technique was used. To perform both feature extraction and classification using single model deep CNN technique was utilized. Deep learning based cardiac disease prediction model was developed by Butun et al. [22] using ECG signal acquired at five and two second interval. Deep learning model used in this developed system was capsule network to categorize the ECG segments. Five-fold cross validation technique was utilized to evaluate the model.

He et al. [23] proposed a framework for Dynamic Heartbeat Classification with Adjusted Features (DHCAF) and Multi-channel Convolution Neural Network (MCHCNN) for arrhythmia identification from IoT based ECGs. The two key components of this architecture were heartbeat classification and data cleansing. A new CNN model for the multi-class classification of diabetic eye illness was proposed by Sarki et al. [24]. An ophthakmologist annotated a variety of retinal fundus photos from the publicly accessible dataset and tested the suggested model on them. The maximum accuracy of this model was 81.33%. An EEG data analysis system with a multi-layer gated recurrent unit (GRU) for abnormalities detection was created by Alvi et al. [25]. On a publicly accessible EEG dataset, this approach was tested, and the accuracy rate was 96.91%. Real-time analysis of ECG data obtained from wearable ECG sensors employing two different types of first-order derivative filters, a max filter, and an effective R and QRS detection algorithm was developed by Bae et al. [26]. The suggested method combines the observed R points in each sliding window and detects the R point and QRS interval in units of a sliding window for real-time processing.

## 3. Proposed methodology

Strategical analysis conducted by world health organization showed that among various existing disease in India cardio vascular disorder is most common disease which causes around 30% of mortality. This cardio vascular disorder occur most frequently in men population rather than females. Early detection and diagnosis of CVD is essential to reduce the mortality rate as well as to improve the life of people suffering from the disease. However accurate detection of heart disease is not achieved by medical specialist even in developed countries. So, there is necessity for developing automated system to achieve accurate heart disease prediction. Existing automated prediction does not perform effectively in extracting features from NSTEMI ECG signal. Thus, in this current research automated CVD prediction is achieved using deep learning algorithm based on ECG signal. Figure 1 illustrates the architecture of proposed automated CVD prediction model.

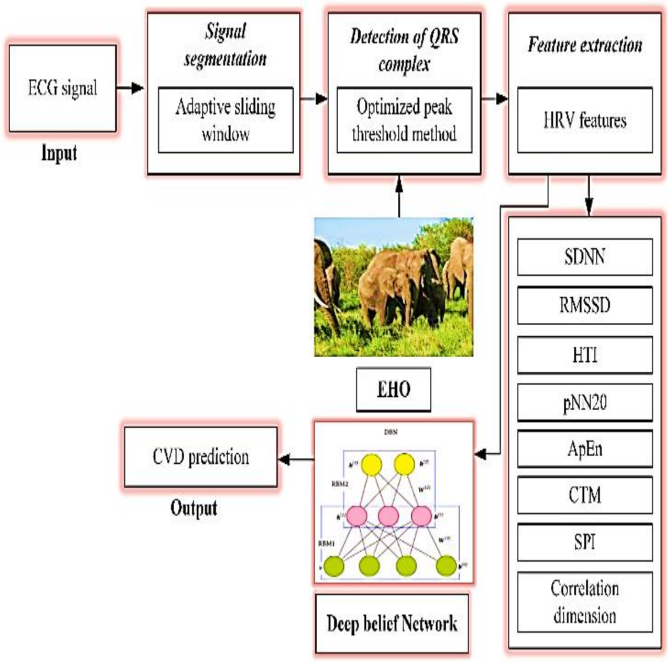



**Figure 1.** Architecture of Proposed Automated CVD Prediction Model.

Initially, collect the ECG signals from real time database which consist of different classes related to cardiac disease. The input signals are send to the segmentation process, the signals are segmented with the help of the adaptive sliding window. For efficient prediction of CVD, the QRS complex is detected using peak threshold method for identifying the variation of the NSTEMI ECG signals. In this step, the threshold value for effective QRS Complex detection is computed based on the EHO algorithm. Different features are extracted from the ECG signals with the help of HRV based feature extraction method. The selected features are sent to DBN classifier for prediction of the CVD from the ECG signals. Finally the effective prediction of CVD is achieved using the proposed model. Brief explanation regarding the proposed model is provided below.

## 3.1. Collection of ECG Data

Initially, the ECG signals are collected from the real time database which includes different classes such as mitochondrial (SDHB), Succinate dehydrogenase [ubiquinone] iron-sulfur subunit, Right Bundle Branch Block (RBBB), Left Bundle Branch Block (LBBB), Ventricular Flutter (VFL), Idioventricular rhythm (IVR), Ventricular tachycardia (VT), Bigeminy, Trigeminy, Premature Ventricular Contraction (PVC), Wolff Parkinson White syndrome (WPW), Supraventricular tachycardia (SVT), Atrial Fibrillation (AFiB), Atrial Flutter (AFl), Atrial premature Beats (APB), and Normal Sinus Rhythm (NSR). The acquired ECG signal is further sent for segmentation process.

## 3.2. Signal segmentation

Signal segmentation is considered as significant for selecting most appropriate window size in order to achieve effective classification of activity. In case of short windows size, the signal is cut into numerous window. Slicing the signal into short window is ineffective as essential information needed for classification is not obtained. Controversially, in case of large window size, multiple characteristic signal may be present and this led to misclassification. Generally, there exist two types of sliding window. One is fixed sliding window and another one is adaptive sliding window. The fixed sliding window is used for non-transitional signals whereas the adaptive sliding window is used for transitional. In this present work adaptive sliding widow is utilized as the ECG signal is found to be transitional.

### Adaptive Sliding Window

This adaptive sliding window technique begins with extracting the necessary features which is to be evaluated using transitional activity classifier and following that Probability Density Function (PDF) of the classified activity is calculated based on which the window segmentation is achieved.

Probability density function is estimated with the help of Gaussian distribution which helps in finding the correlation existing between the features and their relevant problem [27]. Let us considered d-dimensional data $X = \{x\}$ given with an activity $A_j$ and its corresponding probability density function is calculated using eqn (1)

$$p(X/A_j)\alpha\, p(X;\mu_j\Sigma_j) = \frac{1}{(2\pi)^{n/2}[\Sigma_j]^{1/2}} e^{\frac{1}{2}(x-\mu_j)^T\Sigma^{-1}(x-\mu_J)} \quad (1)$$

In eqn (1) $n$ represents the dimension of feature vector, $\mu_j$ signifies the mean matrix, $\Sigma_j$ represents the covariance matrix related to the extracted features from the window. Further the mean matrix and covariance matrix can be represented using eqn (2) and (3)

$$\mu_j = \frac{1}{N_j}\sum_{x\epsilon A_j} x \quad (2)$$

$$\Sigma_j = \frac{1}{N_j}\sum_{x\epsilon A_j} xx^T - \mu_j\mu_j^T \quad (3)$$

In eqn (2) and (3) $N_j$ represents the number of incidence belonging to the activity $A_j$. Initially the size of window is fixed and as iteration passes the window size is altered to achieve effective segmentation for better classification.

## 3.3. QRS complex detection

QRS detection is considered as significant for performing effective analysis of cardiac signals. Generally, the QRS complex in NSTEMI ECG is found to varying with time along with that it is prone to physical variation and also corrupted due to presence of noise [28]. The performance of QRS detection is greatly affected due to presence of noise source, artifacts because of power line interference or electrode motion, baseline drifts and waves with same characteristic such as P and T waves. To overcome this issue effective QRS detection approach must be developed. In this present work QRS detection is performed using optimized peak threshold method.

### Optimized peak threshold method

Considered a data point $x_a$ which is also referred to as peak of QRS complex. The obtained value must be positive on subtracting the current data point with next point which is represented as $x_{a+1}$. Following that the obtained value must be greater than zero on subtracting the current data point with previous data point $x_{a-1}$. Then, the current data point must be greater than the threshold value. Schematic representation of QRS complex detection using peak threshold method is given in figure 2. The mathematical expression used to represent peak threshold method is displayed in eqn (4), (5), (6).

$$x_a - x_{a-1} > 0 \quad (4)$$

$$x_a - x_{a+1} > 0 \quad (5)$$

$$x_a > Threshold \quad (6)$$

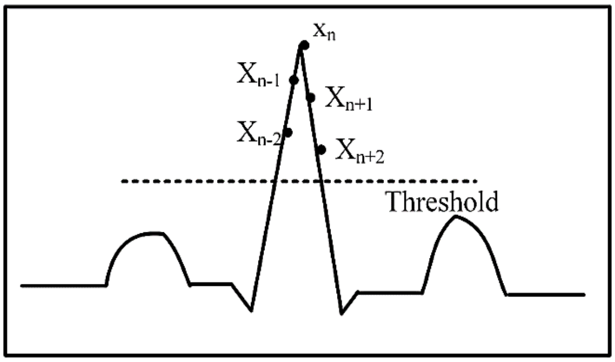



**Figure 2.** Detection of QRS Complex Using Peak Threshold Method.

In order to achieve effective QRS complex detection the threshold value is optimized in this present work using meta-heuristic algorithm namely elephant herding optimization. The mathematical model of elephant herding optimization and its application in threshold value estimation is given below.

### Elephant Herding Optimization

Elephants are living creatures that exists in herds consisting of calves and females. Matriarch is generally considered as the head of the elephant and this elephant clan includes many number of elephants. Male elephant members were found to live separately anywhere whereas the female elephants live along with their family [29]. If the elephants left their family entirely then they will become independent. Through learning the natural behaviour of elephant Wang et al., got inspired and introduced elephant herding optimization. Some of the assumptions made in EHO is given below.

- Number of elephants is fixed in certain clans and this constitute the population of elephants.
- In case of every generation accurate number of male elephant member get detached from their family found to live separately away from the main elephant herds
- Matriarch is found to be the leader of every clan.

Two major steps are involved in EHO which are clan operator and separating operator. The mathematical model enclosed in these steps is explained as follows,

Clan operator: The elephants in every clan is leaded by matriarch according to usual behaviour of elephants. Thus, new position of every elephant present in the clan ai is fixed by the matriarch ai of the clan. For instance the position of elephant j within clan ai can be updated based eqn (7).

$$y_{new,ai,j} = y_{ci,j} + \alpha \times \left(y_{best,ci} - y_{ci,j}\right) \times r \quad (7)$$

Where, $y_{new,ai,j}$ represents the updated position of elephant $j$ within clan $ai$, $y_{ci,j}$ signifies the old position of elephant in clan, $y_{best,ci}$ signifies the matriarch $ai$ that represents the fittest elephant member within the clan $ai$, $\alpha \in [0,1]$ signifies the scale factor which predicts the effect of matriarch $ai$ on $y_{ci,j}$ and $r \in [0,1]$. The position of fittest elephant in every clan is updated based on eqn (8)

$$y_{new,ai,j} = \beta \times \left(y_{center,ai}\right) \quad (8)$$

Here, $\beta \in [0,1]$ signifies the factor which finds the effect of $y_{center,ci}$ upon $y_{new,ai,j}$. Further the new member represented in the above equation is created based on the data acquired from every elephants in clan $ai$. This $y_{center,ai}$ signifies the centre of the clan $ai$ and in case of $d-th$ dimension it can represented using eqn (9)

$$y_{center,ai,d} = \frac{1}{n_{ai}} \times \sum_{j=1}^{n_{ai}} x_{ai}, j, d \quad (9)$$

Here, $1 \leq d \leq D$ signifies the $d-th$ dimension and in which $D$ represents the entire dimension and $x_{ai}, j, d$ signifies $d-th$ of individual elephant member $x_{ai}, j$. The centre of clan $ai$ through D can also be calculated based on above equation.

Separating operator: As the male elephant member lives away from their family group and this separation process is modelled into separating operator while solving the optimization issues. In every generation the individual elephant with worst fitness is considered for separating operator and it is given using eqn (10)

$$y_{worst,ai} = y_{min} + (y_{max} - y_{min} + 1) \times rand \quad (10)$$

Here, $y_{max}$ represents the upper bound position of elephant member and $y_{min}$ represents lower bound position of elephant member, $y_{worst,ai}$ signifies the worst elephant individual within the clan $ai$ and $rand$ represents the stochastic and uniform distribution which exist in the range between 0 as well as 1.

### EHO Based Threshold Value Selection

Steps involved in EHO based threshold value selection in order to achieve effective ORS complex detection is explained as follows.

Step 1 Initialization: In this stage the population necessary for the analysis get initialized. Normally, the variables corresponding to the problem is named as candidate solution or else population. The variables considered in this current research for optimization is threshold value. Formula used to denote population initialization is given in eqn (11)

$$TH = \{th_1, th_2, \ldots . th_n\} \quad (11)$$

Step 2 Fitness function According to the above mention variable the fitness function can be illustrated as in eqn (12) and (13)

$$fitness = \max(acc) \quad (12)$$

$$accuracy = \left(1 - \frac{F_P + F_N}{Total\ beat}\right) \times 100 \quad (13)$$

Where, $F_P$ represents the quantity of non-QRS complex detected as QRS and $F_N$ represents the quantity of undetected QRS complex.

Step 3 Updating: The threshold value get updated according to eqn (7) for every iteration in order to obtain best solution from the entire search space.

Step 4 Termination: The iteration get terminated when the satisfaction condition is reached.

Through optimal selection of threshold value effective QRS complex detection is achieved using peak threshold method. The detected QRS complex wave is further sent for feature extraction process. The flow of EHO based threshold value estimation is given in figure 3.

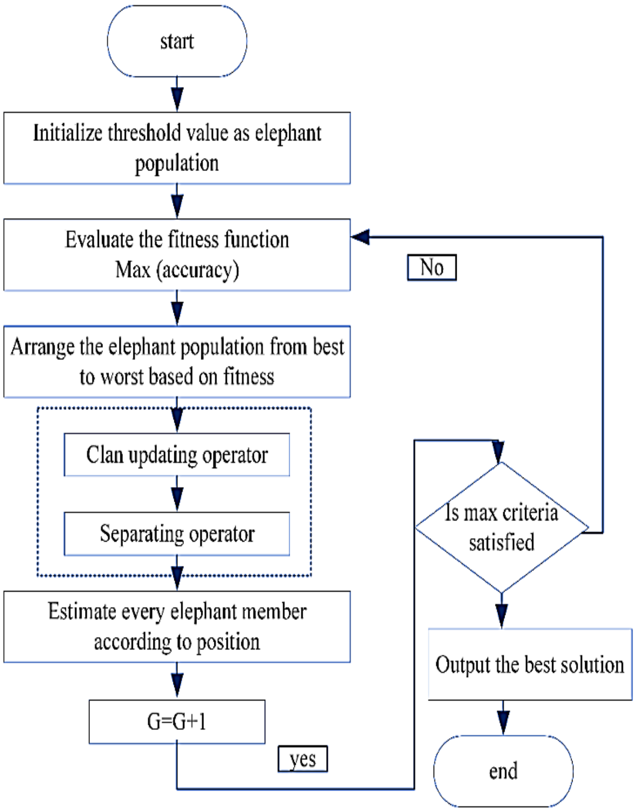



**Figure 3.** EHO Based Threshold Value Estimation.

## 3.4 Feature extraction

In this step the features essential for prediction is extracted from the ECG waveform. Here both linear and non-linear features are extracted. In this present work both linear and non-linear features are extracted effectively using HRV method. Description regarding HRV based feature extraction from NSTEMI ECG waveform is explained as follows.

### Heart Rate Variability Features

HRV is used to analyse the variation experienced within the sequence of cardiac interbeat interval. It generally calculates the spontaneous rate of heartbeat for a patient. This HRV analysis is performed with the help of NSTEMI ECG recording. It also helps in detecting the variation of heart rate in the presence of cardiovascular disease [30]. The detection of HRV reduction in patients predicts the presence of coronary issues. The concept of non-linearity was introduced into HRV analysis because of the non-linearity of heart rhythm. In this work four HRV features are extracted out of which three are statistical and one is geometric features. Some of the linear features extracted from NSTEMI ECG signal are Standard Deviation from NN interval (SDNN), Root Mean Square Standard Deviation (RMSSD), HRV Triangular Index (HTI) and Pnn20. Following that non-linear features include Central Tendency Measure (CTM), Spatial Filling Index (SFI), approximate entropy (ApEn) and correlation dimension $D_2$. Mathematical expression to represent both linear and non-linear features is discussed below.

(a) Central tendency measure

CTM is a kind of quantitative measure which is used to calculate the variability of second order difference plot. As it a non-linear measure it determine the concentration of points within the second order difference diagram and it is not suitable for phase space diagram. The chaotic characteristic of the system which highly represent the behaviour of non-linear system can be visualized accurately using this kind of diagram. CTM for E dimension can be represented according to following eqn (14)

$$CTM = \sum_{t=1}^{N-E} \delta(d(t)) \qquad (14)$$

Where,

$$\delta(d(t)) = \begin{cases} 1, & \sqrt{(x(t+T)-x(t))^2 + \cdots + (x(t+ET)-x(t+(E-1)T))^2} < r \\ 0 & other\ wise \end{cases} \qquad (15)$$

Here, $N$ represents number of R-R intervals which is analysed, $T$ denotes number existing between the two measured R-R intervals and then $r$ signifies the area of central radius.

(b) Approximate entropy

Statistical measure which is utilized to determine presence of regularities within the data without having the knowledge about the problem. Normally, it illustrates the probability that same pattern of observation is not repeated. Higher ApEn is found when there is presence of irregular pattern and complex time series. Mathematical expression used to represent ApEn is given in eqn (16)

$$ApEn(m, r, N) = \varphi^m(r) - \varphi^{m+1}(r) \qquad (16)$$

Here, the values for m and r parameter is fixed based on the problem. Normally the value for $m$ is taken from 1 and range of $r$ helps to notify variation in series complexity in case of presence of many number of point in the analysis.

(c) Correlation dimension

Correlation dimension is used to find whether the heart rhythm determine to possess stochastic or deterministic behaviour. Along with correlation dimension the attractor based reconstruction dimension is also examined. Normally the dimensional description of the approach is $d$ and then the attractor based correlation dimension is $D_2$. In case if the dimension of the system $d$ and correlation dimension $D_2$ come under saturation then the approach is taken to be deterministic. On the other hand in case of presence of noise in ECG therefore there is possibility for masking the attractor so the correlation dimension does not get saturated and the system is considered to be stochastic. The mathematical expression used for representing correlation dimension $(D_2)$ is given in eqn (17)

$$D_2 = \lim_{l \to 0} \frac{\log\left(\sum_{i=1}^{M(l)} p_i^2\right)}{\log l} \tag{17}$$

Here, $p_i$ signifies the probability of the attractors to come under the cell $i$, $l$ signifies the length of the cell and $M$ denotes the dimensional space of the system.

(d) Spatial filling index

Spatial Filling Index (SFI) is used to describe the point density of an attractor through quantitatively. The mathematical expression used for representing SFI is given in eqn (18).

$$\eta = \frac{S}{n^2} \tag{18}$$

Where, $S$ signifies the combined factor related to the distribution of point within phase space and value of $S$ must be greater or equal to 1, $n$ denotes the number of squares used in the division of phase space totally and $\eta$ signifies the order of magnitude which is $10^{-3}$ and this get increased with respect to higher point concentration within some portion in an attractor.

(e) HRV triangular index

HTI is generally referred to as geometric measure of HRV. It is the ratio of integral of density distribution (number of R-R interval) to maximised density distribution. By means of utilizing R-R interval within discrete scale, the value of the measure is approximated. HTI measure can be represented according to eqn (19)

$$HTI = \frac{Toal\ number\ of\ R{-}R\ interval}{number\ of\ R{-}R\ interval\ within\ modal\ bin} \tag{19}$$

The value of HTI depend on the length of the bin. The length of the bin is generally referred to as sampling frequency related to ECG signal.

(f) pNN20

Generally, pNN20 is defined as the difference in number of successive R-R interval which are higher than 20 $ms$ divided to the total number of R-R interval. By means of using this pNN threshold value as 20 $ms$ or less the prediction between normal and diseased condition can be done effectively.

(g) SDNN

Standard deviation of R-R interval is a common HRV feature calculated in ECG record. The cyclic component that signifies the variability in the ECG record can be found effectively using this standard deviation. In case of long term recording the SD is calculated for 24 hrs and in case of short term it is calculated from 5 min recording.

(h) Root Mean Square Standard Deviation

The square root of mean squared difference related to N successive R-R intervals is defined as RMSSD. The mathematical expression used for calculating RMSSD is explained in eqn (20).

$$RMSSD = \frac{\sqrt{\sum_{i=1}^{N-1}(x_{i+1}-x_i)^2}}{N} \tag{20}$$

Here, $x_i$ represents the length related to R-R interval having index $i$ and $N$ represents the number of successive N-N intervals.

## 3.5. Classification of Cardiac Disease

Features that are obtained from previous step is fetched as an input into DBN for prediction. DBN is a kind of generative graphical model consisting of multiple layer and it is highly suitable for cardiac disease prediction. Mathematical model of DBN is given below.

### DBN

Using DBN, an unsupervised learning procedure is done through layer - by - layer mechanism. The network's weight will be pre-trained to the value that is initially provided. Each layer within that classifier must learn the features of the layer before it throughout the training process, starting with the feature of the lowest layer. The term "generative and probabilistic model" refers to this DFN [31]. They had various straightforward learning models and could reconstitute the input. Restricted Boltzmann Machines will be used for the training and testing process for each layer (RBM). A large number of RBM will connect to form a DBN. Figure 4 shows a diagrammatic representation of DBN.

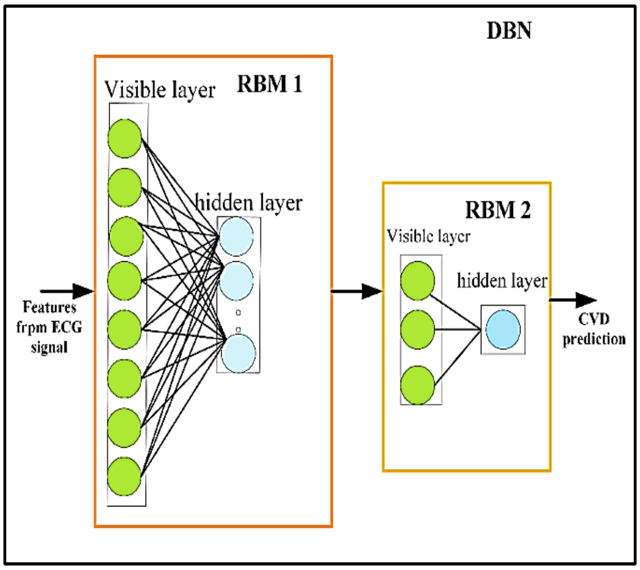



**Figure 4.** Diagrammatic Representation of DBN.

The bipartite graph is the name given to this RBM. In this, the hidden units are connected to the visible units, which signify the observation. The undirected weight connection is used in order to express the feature. There is no link between hidden-hidden and visible-visible. In RBM, the stochastic and binary units will be both visible and concealed. Every layer discovered later will be treated as a visible layer, while every layer discovered earlier will be treated as a hidden layer. This serves as the next layer's input. Every layer's nodes will be connected to those in the layer above it. The following list contains the key characteristics of DBN.

- It is possible to effectively learn, layer by layer, the top-down, generative constraints that specify how the variables in a single layer depend on the variables in the layer above.
- As multi-layered neural networks with information and output layers, deep conviction systems can also be thought of in this way. Each layer of hubs in deep learning is built utilising the clear yields from the preceding layer. We can notice more surprising highlights as we progress further into the system because our hubs sum and recombine highlights from the previous layer.
- It is profound learning systems' capacity to locate structures in unlabelled, chaotic data that gives them the greatest competitive edge. Images, sounds, and sound journals are a few examples of this basic information.

Gaussian-Bernoulli with real-value input is employed for the function. The hidden units in this case are discovered to be binary, and the input data are discovered to be linear with Gaussian noise. RBM has an efficient training methodology, which makes it an excellent tool for learning DBN. Utilizing a probability distribution based on the energy function, the joint state between the hidden and visible unit is defined. Equation provides the mathematical phrase for describing the joint state based on the energy function in binary form (21).

$$E(v,h;\vartheta) = -\sum_{i=1}^{V}\sum_{j=1}^{H} w_{ij}v_ih_j - \sum_{i=1}^{V} b_iv_i - \sum_{j=1}^{H} a_jh_j \tag{21}$$

Where $w_{ij}$ stands for the interaction between hidden unit $j$ and visible unit $i$ and $\theta = (b,a,w)$. The bias terms are represented by $a_j$ & $b_i$. The letters H and V stand for the quantity of hidden and visible units. Because there is no relationship between hidden-hidden and visible-visible, the conditional distributions $p(h{:}\,v)$ and $p(v{:}\,h)$ are shown as factorial. Equation provides the mathematical expression for a conditional distribution (22 and 23).

$$p(v_i = 1{:}\,h;\theta) = \sigma(\textstyle\sum_{j=1}^{H} w_{ij}h_j + b_i) \tag{22}$$

$$p(h_j = 1{:}\,v;\theta) = \sigma(\textstyle\sum_{j=1}^{V} w_{ij}v_j + a_i) \tag{23}$$

The updating rule for the weight is described in the following equation after the conditional distribution (24).

$$\Delta w \propto (v_ih_j)_{data} - (v_ih_j)_{model} \tag{24}$$

Where, $(v_ih_j)_{data}$ shows how often hidden and visible units work together in a training set. $(v_ih_j)_{model}$ indicates the same under the model-denoted distribution. The new updating rule is then shown in equation after this (25).

$$\Delta w \propto (v_ih_j)_{data} - (v_ih_j)_{recon} \tag{25}$$

Where, $(v_ih_j)_{recon}$ shows the distribution related to reconstruction. This is produced after initialising the data vector, followed by updates to the hidden unit, visible unit, and hidden unit once more. Similarly, a large number of RBMs that contain both visible and hidden units will be combined to generate the DBN.

## 4. Result and discussion

Simulation analysis on the proposed CVD prediction model is implemented in Matlab2020b software using following system configuration as Intel(R) Core(TM) i5-10300H processor, CPU @ 2.50GHz, NVIDIA GTX 1650 4Gb (GDDR6) GPU and 16.0 GB Memory (RAM). This current research utilize deep learning approach for finding the patients suffering from CVD. However to predict CVD patients image containing ECG signal is given as input. This ECG data is collected from healthcare centre. Two datasets are considered for this proposed approach. Both datasets contains ECG signals that are measured from two different wearable ECG devices in different timings for various set of people. One kind of portable ECG is the holter monitor. While the person are away from the doctor's office, it constantly records the electrical activity of the heart for 24 hours or longer. A benchmark or resting ECG is one of the quickest and easiest examinations to assess the heart. This ECG is carried out while the individual is still lying down and simultaneously records the electrical activity of the heart from 12 electrodes located on the chest, arms, and legs. These ECG database are collected by Dr.Sachin Patil, from Super specialist Hospital, Kolhapur, Maharashtra. Table 1 displays number of images in dataset 1 and dataset 2.

Table 1. Number of Images in Dataset 1 and Dataset 2.

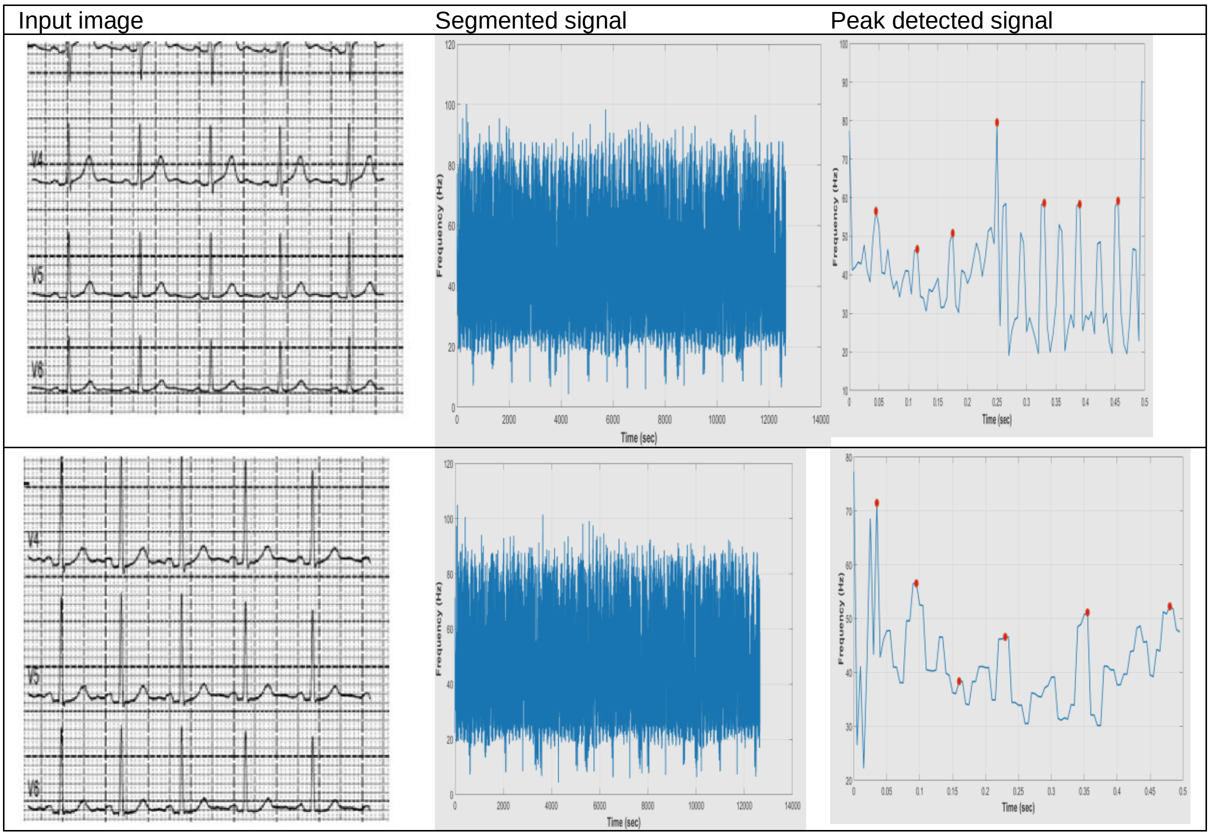
| | Class 1 | Class 2 | Total |
|---|---|---|---|
| Dataset 1 | 240 | 240 | 480 |
| Dataset 2 | 100 | 120 | 220 |

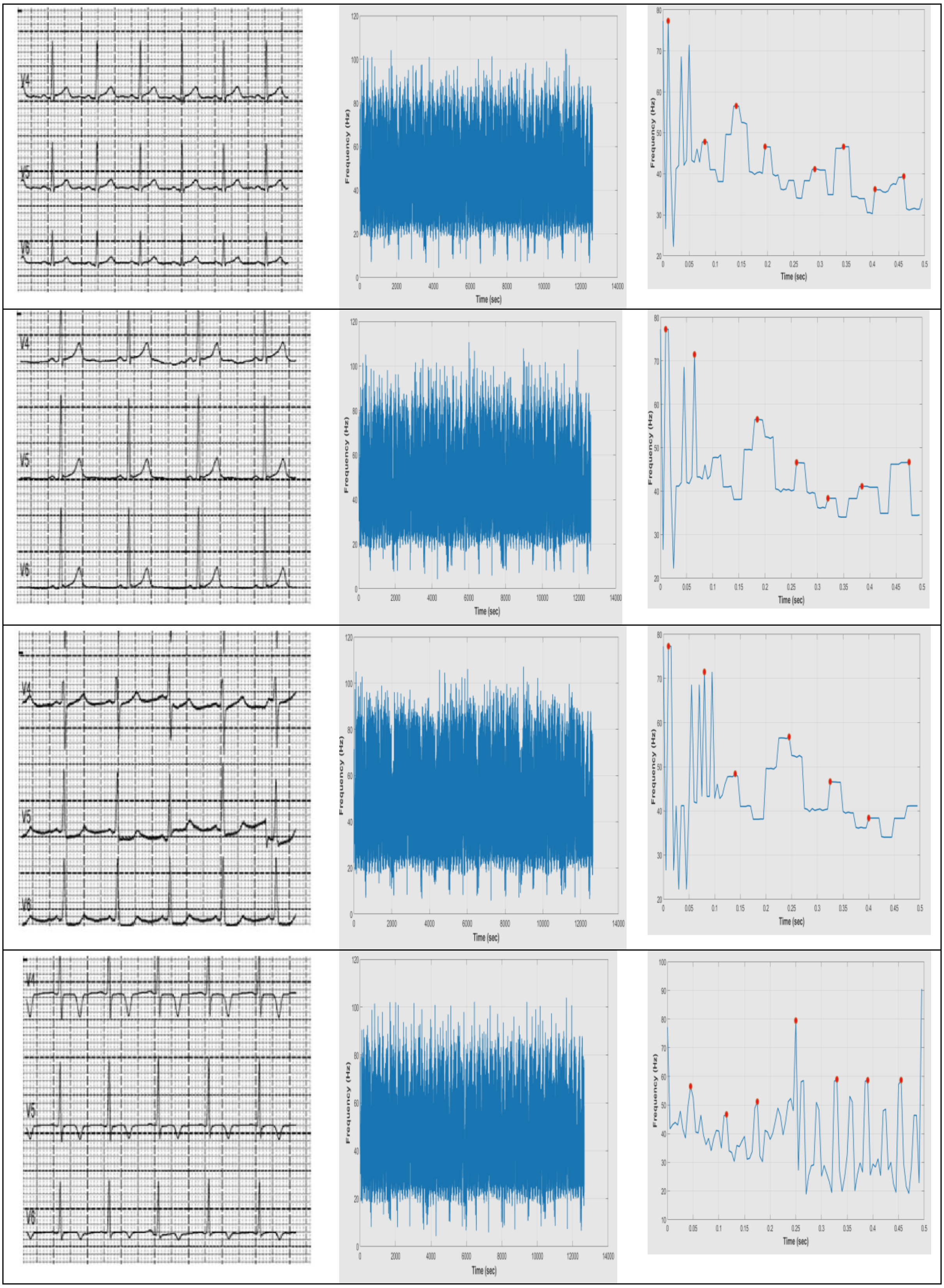
Following that the input image is converted into signal and further the obtained signal is segmented using sliding window segmentation technique. Then, from the segmented signal the detection of QRS complex peak is achieved using Meta-heuristic algorithm namely elephant herd optimization. After the detection of QRS complex the features from NSTEMI ECG signal is extracted using HRV analysis method. Then, the extracted features is sent as an input into DBN classifier to predict CVD and non-CVD individuals. Some of the simulation parameters considered in the proposed work is given in table 2.

Table 2. Simulation Parameter Considered For the Analysis.

| Parameters | Range |
|---|---|
| Batch size | 64 |
| Step ratio | 0.1 |
| DropOut Rate | 0.9 |
| Maximum iteration | 100 |
| Population size | 10 |
| Number of search agent | 4 |
| Number of elephants | 50 |
| Upper limit | 50 |
| Lower limit | 10 |
| Training data | 80 |
| Testing data | 20 |

Parameter considered in both DBN classifier and elephant herd optimization is explained above. Based on these parameter the functioning of both classifier and Meta-heuristic algorithm take places. The prediction of patients suffering from CVD disease is considered as significant for reducing the death rate of people as well as to improve and prolong their living standard. So, in this current research to achieve accurate CVD prediction from NSTEMI ECG input deep learning approach with improved segmentation, peak detection and feature extraction is proposed. Two sets of ECG data is collected which consist of two classes such as CVD diseased and non-diseased patients. The output result obtained after segmentation and peak detection from raw input image is given in figure 5




V4
V5
V6
Frequency (Hz)
Time (sec)

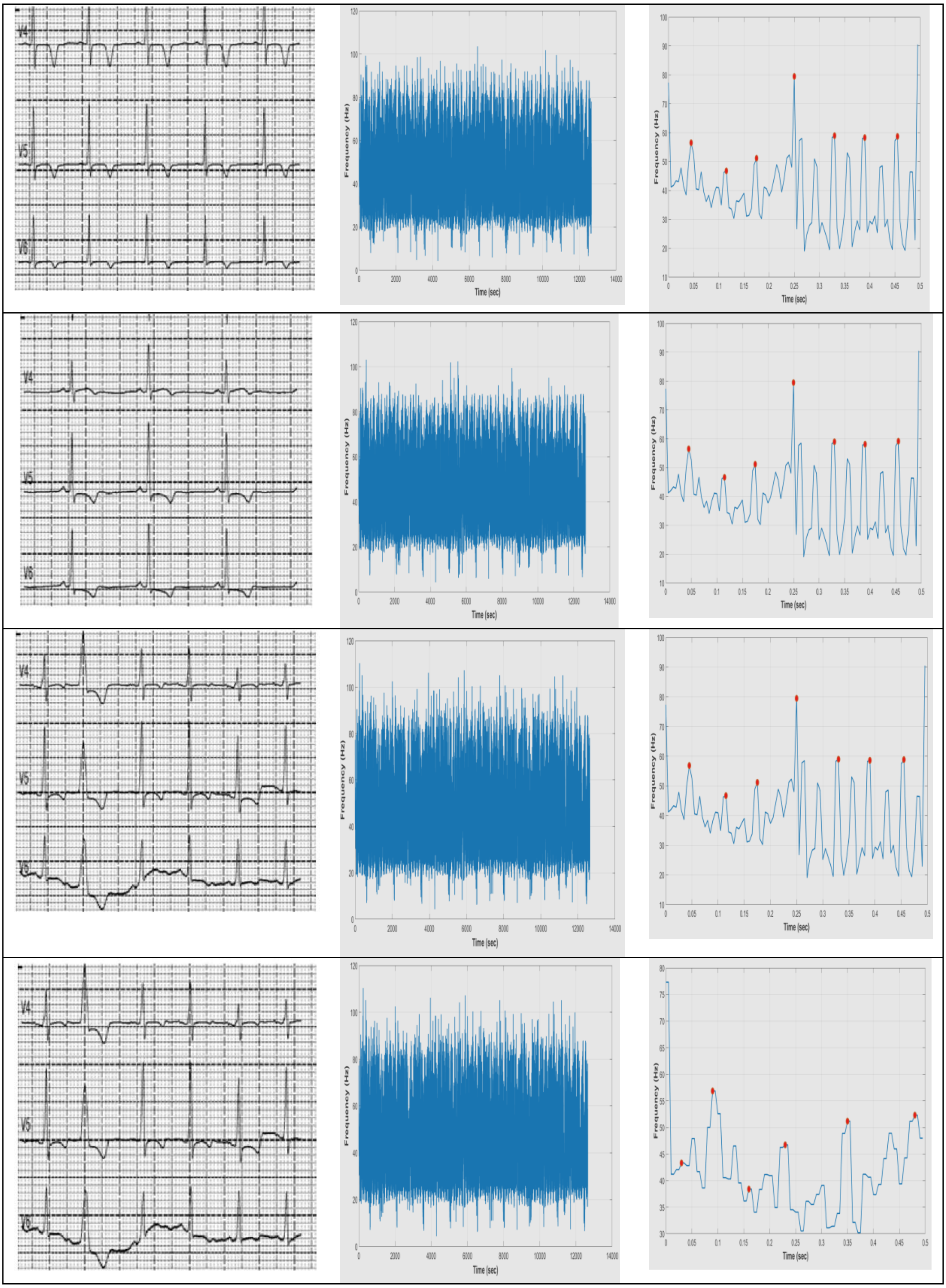



**Figure 5.** Output Result Obtained After Various Process

In the beginning of the process raw input image is given as input into the proposed model. Then the signals from the image is extracted and the signals are segmented using sliding window segmentation technique. The segmented signal is sent into QRS peak detection technique. In peak detection technique the threshold is optimized using elephant herd optimization algorithm. After that the peak detected signal is sent for feature extraction using HRV analysis. Finally, the extracted features is sent into DBN to classify the CVD patients. The classification output is given in table 3.

Table 3. Classification Output Attained Using The Proposed Model For Dataset 1 And Dataset 2.

| Actual & predicted label | True | False |
|---|---|---|
| Positive | 67 | 11 |
| Negative | 5 | 61 |

| Actual & predicted label | True | False |
|---|---|---|
| Positive | 32 | 2 |
| Negative | 1 | 31 |

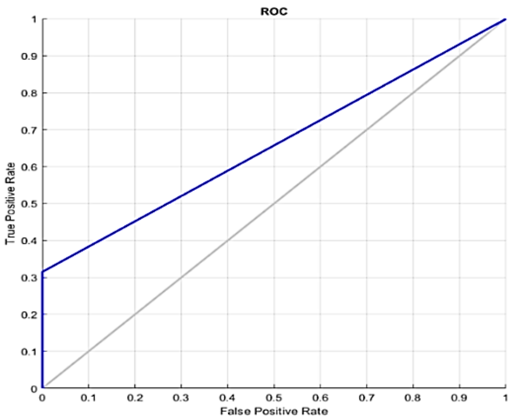



**Figure 6.** ROC plot for Dataset 1.

Figure 6 illustrates the ROC plot obtained for the first dataset. ROC curve is attained by means of plotting between both true positive rate and false positive rate. The area under the ROC curve (AUC) is determine to estimate the functioning of the proposed classifier. The classifier used in this proposed CVD prediction model is DBN classifier. Generally, for effective functioning of the classifier the value of AUC must be 1. If the value of AUC is lesser than 1 and nearer to 0 it shows the retarded functioning of the classifier. Proposed CVD prediction model attains AU C value of 0.96 for first dataset. Higher AUC value shows that the proposed classifier functions effectively on using first ECG image dataset.

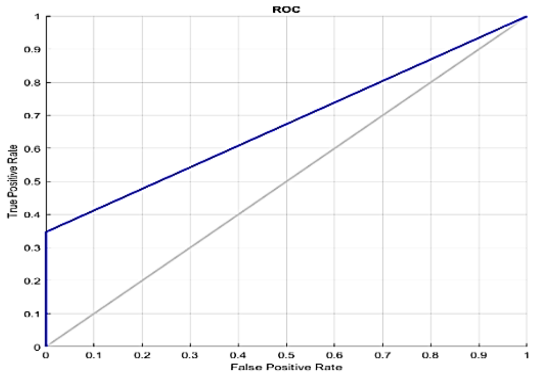



**Figure 7.** ROC plot for Dataset 2.

Figure 7 illustrates the ROC plot obtained for second dataset. The area under the ROC curve (AUC) is found to illustrate the performance of the classifier used in CVD prediction process. The classifier used for CVD prediction in this proposed work is DBN classifier. Generally, for achieved better performance of the classifier the value of AUC must be 1. If the value of AUC is lesser than 1 and nearer to 0 it shows the retarded functioning of the classifier. Proposed CVD prediction model attains AUC value of 0.98 for second dataset. AUC value nearer to 1 shows that the proposed DBN classifier functions better on using second ECG image dataset.

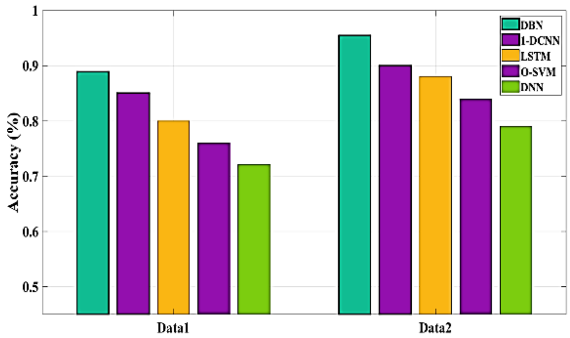



**Figure 8.** Accuracy Comparison using Proposed and Existing CVD Prediction Model.

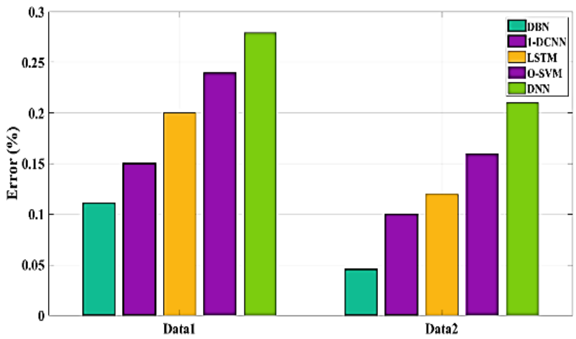



**Figure 9.** Error Comparison using Proposed and Existing CVD Prediction Model.

Accuracy comparison between proposed CVD prediction model and existing model is performed using dataset 1 and 2. This accuracy comparison graph is illustrated in figure 8. Using this accuracy metric number of classes that are correctly predicted in each dataset can be found. Accuracy value attained for the proposed CVD prediction model using DBN classifier for dataset 1 is 0.88 % and for dataset 2 is 0.95%. Similarly, accuracy value attained using other existing model such as 1—DCNN [32], LSTM [33], O-SVM [34] and DNN [35] for first dataset is 0.85%, 0.80 %, 0.76% and 0.72%. Subsequently, value of accuracy attained using some of the existing model such as 1—DCNN, LSTM, O-SVM and DNN for second dataset is 0.90%, 0.88%, 0.84 and 0.79%. Proposed and existing CVD prediction model is compared with some of the existing model using error metrics is given in figure 9. 0.12 % is the error value achieved for the proposed model using first dataset. For similar dataset the error value attained using other existing model such as 1—DCNN, LSTM, O-SVM and DNN is 0.15%, 0.20%, 0.24% and 0.28%. In case of second dataset the error value attained for the proposed CVD prediction model is 0.05%. Following that the error value for other existing model like 1—DCNN, LSTM, O-SVM and DNN is 0.10%, 0.12%, 0.16% and 0.21%. Based on this analysis it can be shown that accurate CVD prediction can be achieved using the proposed model.

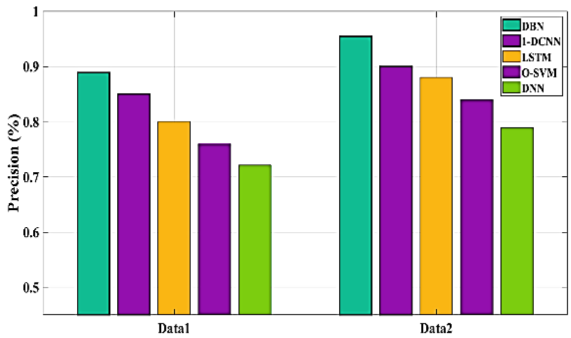



**Figure 10.** Precision Comparison using Proposed and Existing CVD Prediction Model.

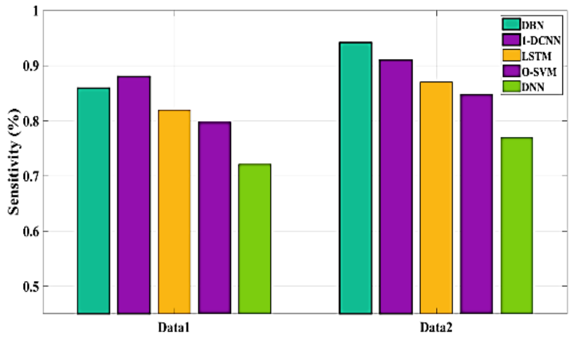



**Figure 11.** Sensitivity Comparison using Proposed and Existing CVD Prediction Model.

Proposed CVD prediction model is compared with some of the existing model like 1—DCNN, LSTM, O-SVM and DNN using precision metric is given in figure 10. The comparison study is done using two different datasets. As of first dataset is considered the value of precision attained by the proposed DBN model is 0.93% whereas the precision value achieved using other existing models such as 1—DCNN, LSTM, O-SVM and DNN is 0.90%, 0.86%, 0.81% and 0.72%. In case of second dataset value of precision attained by the proposed DBN model is 0.96% and following that precision value for other existing model such as 1—DCNN, LSTM, O-SVM and DNN is 0.91%, 0.89%, 0.83% and 0.75%. Comparison study done between existing and proposed CVD prediction model based on sensitivity metrics given in figure 11. Sensitivity value attained by the proposed model for first and second dataset is 0.85% and 0.94%. Subsequently the sensitivity value attained by other existing model such as 1—DCNN, LSTM, O-SVM and DNN for first and second dataset is 0.88%, 0.82%, 0.79%, 0.72% and 0.91%, 0.87%, 0.84%, 0.75%. Based on this analysis it can be shown that accurate CVD prediction from ECG image can be achieved.

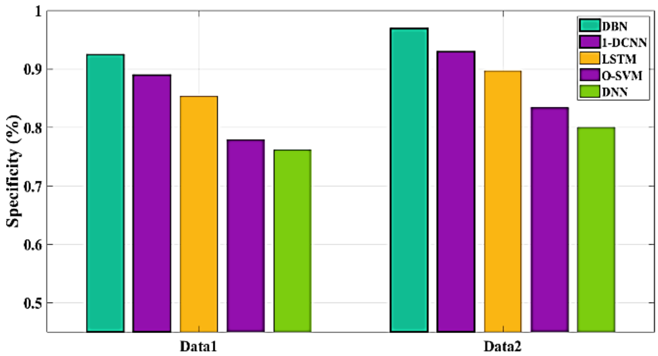



**Figure 12.** Specificity Comparison using Proposed and Existing CVD Prediction Model.

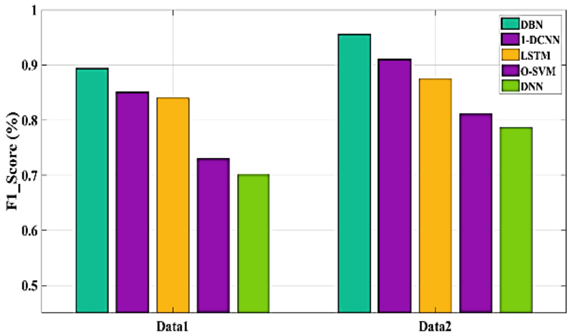



**Figure 13.** F1 score Comparison using Proposed and Existing CVD Prediction Model.

Figure 12 illustrates the comparison of specificity metric between proposed and existing CVD prediction model. Specificity value attained by the proposed model for first and second dataset is 0.93% and 0.97%. Subsequently, for other existing model such as 1—DCNN, LSTM, O-SVM and DNN the specificity value attained using first and second dataset is 0.89%, 0.85%, 0.78%, 0.76% and 0.93%, 0.89%, 0.83% and

0.80%. Following specificity comparison, F1 score comparison study between proposed and existing CVD prediction model is illustrated in figure 13. Value of F1 score attained by the proposed model for first dataset is 0.89% and for remaining existing model such as 1—DCNN, LSTM, O-SVM and DNN value of F1 score is 0.85%, 0.84%, 0.73% and 0.70%. Following that for second dataset F1 score value attained by the proposed model is 0.95%. On the other hand value of F1 score achieved using existing model such as 1—DCNN, LSTM, O-SVM and DNN is 0.91%, 0.87%, 0.81% and 0.78%. Based on this analysis it can be proven that enhanced prediction of CVD prediction can be achieved using proposed deep learning approach.

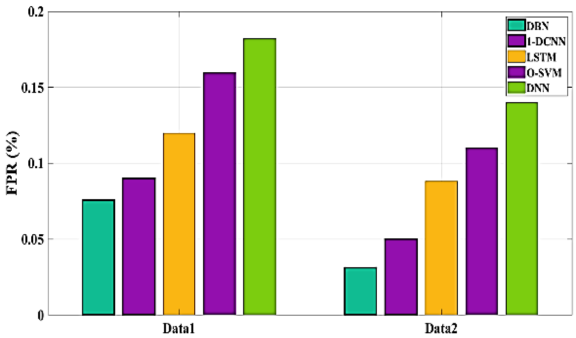



**Figure 14.** FPR Comparison using Proposed and Existing CVD Prediction Model.

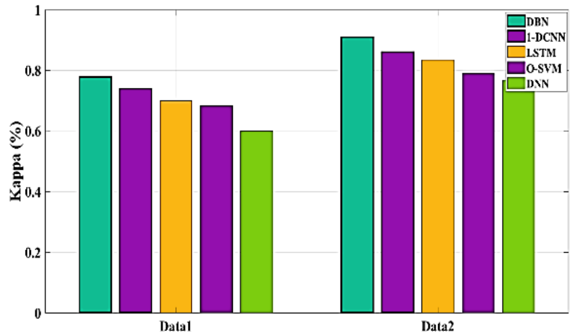



**Figure 15.** Kappa Comparison using Proposed and Existing CVD Prediction Model.

Comparison of FPR parameter between proposed CVD prediction model and existing model is given in figure 14. The FPR metric obtained for the proposed CVD prediction model using first dataset is 0.075% and for existing model such as DCNN, LSTM, O-SVM and DNN the value of FPR is 0.090%, 0.12%, 0.16% and 0.18%. After that FPR metric obtained for the proposed DBN based CVD prediction model using second dataset is 0.013% and for existing model such as DCNN, LSTM, O-SVM and DNN the value of FPR is 0.05%, 0.08%, 0.11% and 0.14%. Figure 15 illustrates the comparison of kappa metric between proposed and existing CVD prediction model. Value of kappa value attained by the proposed model using dataset 1 is 0.77%. For similar dataset the existing model such as DCNN, LSTM, O-SVM and DNN attains 0.74%, 0.70%, 0.68% and 0.60%. On the other hand kappa value attained by the proposed model using dataset 2 is 0.90% and for other existing model such as DCNN, LSTM, O-SVM and DNN is 0.86%, 0.83%, 0.79% and 0.76%. Based on this comparative analysis it can be concluded that enhanced and accurate CVD prediction can be attained using the proposed DBN model.

## 5. Conclusion

An automated CVD prediction model using a deep learning approach is designed in this current research. Diagnosis of patients suffering from CVD is considered as significant for reducing the death rate of cardiac disease patients as well as increasing their living standards. To achieve automated and accurate detection of CVD patients AI system is integrated into this proposed model. Within the AI system, the deep learning approach is focused on the detection of CVD patients. Prediction of CVD patients can be achieved using an ECG signal. At first, the signal is extracted from the image and then segmented using the sliding window segmentation technique. EHO based meta-heuristic algorithm is utilized for the detection of QRS complex in NSTEMI ECG signal. Then, the output signal obtained for the peak detection technique is sent into the feature extraction process in which the features are extracted using HRV analysis. The extracted features are sent as input into the DBN classifier to predict CVD disease patients. Then, the functioning of the proposed prediction model is simulated and statistical parameters are evaluated. Results showed that the functioning of the proposed CVD prediction model is better when compared with other existing techniques. Further, this proposed model can be used in real time healthcare applications by collecting NSTEMI ECG signals from patients. In future work, this research can be extended by predicting the level of CVD disease from patients' NSTEMI ECG signal.

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### Conflict of Interest
The authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

### Availability of data and material
Thanks to Dr.Sachin Patil from Super specialist Hospital, Kolhapur, Maharashtra for providing me the ECG data's of a patients.

### Code availability
Not applicable

### Author contributions
The corresponding author claims the major contribution of the paper including formulation, analysis and editing. The co-author provide guidance to verify the analysis result and manuscript editing.

### Compliance with ethical standards

This article is a completely original work of its authors; it has not been published before and will not be sent to other publications until the journal's editorial board decides not to accept it for publication.

## References


[1] Chakraborty A, Chatterjee S, Majumder K, Shaw RN, Ghosh A. A comparative study of myocardial infarction detection from ECG data using machine learning. InAdvanced Computing and Intelligent Technologies 2022 (pp. 257-267). Springer, Singapore.

[2] Sree V, Mapes J, Dua S, Lih OS, Koh JE, Ciaccio EJ, Acharya UR. A novel machine learning framework for automated detection of arrhythmias in ECG segments. Journal of Ambient Intelligence and Humanized Computing. 2021 Nov;12(11):10145-62.

[3] Sheta A, Turabieh H, Thaher T, Too J, Mafarja M, Hossain MS, Surani SR. Diagnosis of obstructive sleep apnea from ecg signals using machine learning and deep learning classifiers. Applied Sciences. 2021 Jul 19;11(14):6622.

[4] Peimankar A, Puthusserypady S. DENS-ECG: A deep learning approach for ECG signal delineation. Expert systems with applications. 2021 Mar 1;165:113911.

[5] Mishra S, Khatwani G, Patil R, Sapariya D, Shah V, Parmar D, Dinesh S, Daphal P, Mehendale N. ECG paper record digitization and diagnosis using deep learning. Journal of medical and biological engineering. 2021 Aug;41(4):422-32.

[6] Ullah A, Anwar SM, Bilal M, Mehmood RM. Classification of arrhythmia by using deep learning with 2-D ECG spectral image representation. Remote Sensing. 2020 May 25;12(10):1685.

[7] Belo D, Bento N, Silva H, Fred A, Gamboa H. ECG biometrics using deep learning and relative score threshold classification. Sensors. 2020 Jul 22;20(15):4078.

[8] Rath A, Mishra D, Panda G, Satapathy SC. Heart disease detection using deep learning methods from imbalanced ECG samples. Biomedical Signal Processing and Control. 2021 Jul 1;68:102820.

[9] Mousavi S, Afghah F, Khadem F, Acharya UR. ECG Language processing (ELP): A new technique to analyze ECG signals. Computer Methods and Programs in Biomedicine. 2021 Apr 1;202:105959.

[10] Essa E, Xie X. An ensemble of deep learning-based multi-model for ECG heartbeats arrhythmia classification. IEEE Access. 2021 Jul 21;9:103452-64.

[11] Attallah O. ECG-BiCoNet: An ECG-based pipeline for COVID-19 diagnosis using Bi-Layers of deep features integration. Computers in biology and medicine. 2022 Mar 1;142:105210.

[12] Naik MS, Pancholi TK, Achary R. Prediction of congestive heart failure (chf) ecg data using machine learning. InIntelligent Data Communication Technologies and Internet of Things 2021 (pp. 325-333). Springer, Singapore.

[13] Acharya UR, Fujita H, Lih OS, Adam M, Tan JH, Chua CK. Automated detection of coronary artery disease using different durations of ECG segments with convolutional neural network. Knowledge-Based Systems. 2017 Sep 15;132:62-71.

[14] Hasan NI, Bhattacharjee A. Deep learning approach to cardiovascular disease classification employing modified ECG signal from empirical mode decomposition. Biomedical signal processing and control. 2019 Jul 1;52:128-40.

[15] Dai H, Hwang HG, Tseng VS. Convolutional neural network based automatic screening tool for cardiovascular diseases using different intervals of ECG signals. Computer Methods and Programs in Biomedicine. 2021 May 1;203:106035.

[16] Abdar M, Książek W, Acharya UR, Tan RS, Makarenkov V, Pławiak P. A new machine learning technique for an accurate diagnosis of coronary artery disease. Computer methods and programs in biomedicine. 2019 Oct 1;179:104992.

[17] Suhail MM, Razak TA. Cardiac disease detection from ECG signal using discrete wavelet transform with machine learning method. Diabetes Research and Clinical Practice. 2022 May 1;187:109852.

[18] Dolatabadi AD, Khadem SE, Asl BM. Automated diagnosis of coronary artery disease (CAD) patients using optimized SVM. Computer methods and programs in biomedicine. 2017 Jan 1;138:117-26.

[19] Tan JH, Hagiwara Y, Pang W, Lim I, Oh SL, Adam M, San Tan R, Chen M, Acharya UR. Application of stacked convolutional and long short-term memory network for accurate identification of CAD ECG signals. Computers in biology and medicine. 2018 Mar 1;94:19-26.

[20] Raghavendra U, Fujita H, Gudigar A, Shetty R, Nayak K, Pai U, Samanth J, Acharya UR. Automated technique for coronary artery disease characterization and classification using DD-DTDWT in ultrasound images. Biomedical Signal Processing and Control. 2018 Feb 1;40:324-34.

[21] Yıldırım Ö, Pławiak P, Tan RS, Acharya UR. Arrhythmia detection using deep convolutional neural network with long duration ECG signals. Computers in biology and medicine. 2018 Nov 1;102:411-20.

[22] Butun E, Yildirim O, Talo M, Tan RS, Acharya UR. 1D-CADCapsNet: One dimensional deep capsule networks for coronary artery disease detection using ECG signals. Physica Medica. 2020 Feb 1;70:39-48.

[23] He, J., Rong, J., Sun, L., Wang, H., Zhang, Y., & Ma, J. (2020). A framework for cardiac arrhythmia detection from IoT-based ECGs. World Wide Web, 23, 2835-2850.

[24] Sarki, R., Ahmed, K., Wang, H., Zhang, Y., & Wang, K. (2022). Convolutional neural network for multi-class classification of diabetic eye disease. EAI Endorsed Transactions on Scalable Information Systems, 9(4), e5-e5.

[25] Alvi, A. M., Siuly, S., & Wang, H. (2022, January). Developing a deep learning based approach for anomalies detection from EEG data. In Web Information Systems Engineering–WISE 2021: 22nd International Conference on Web Information Systems Engineering, WISE 2021, Melbourne, VIC, Australia, October 26–29, 2021, Proceedings, Part I (pp. 591-602). Cham: Springer International Publishing.

[26] Bae, T. W., & Kwon, K. K. (2019). Efficient real-time R and QRS detection method using a pair of derivative filters and max filter for portable ECG device. Applied Sciences, 9(19), 4128.

[27] Ma C, Li W, Cao J, Du J, Li Q, Gravina R. Adaptive sliding window based activity recognition for assisted livings. Information Fusion. 2020 Jan 1;53:55-65.

[28] Utomo TP, Nuryani N. QRS peak detection for heart rate monitoring on Android smartphone. InJournal of Physics: Conference Series 2017 Nov 1 (Vol. 909, No. 1, p. 012006). IOP Publishing.

[29] Ismaeel AA, Elshaarawy IA, Houssein EH, Ismail FH, Hassanien AE. Enhanced elephant herding optimization for global optimization. IEEE Access. 2019 Mar 12;7:34738-52.

[30] Jovic A, Bogunovic N. Electrocardiogram analysis using a combination of statistical, geometric, and nonlinear heart rate variability features. Artificial intelligence in medicine. 2011 Mar 1;51(3):175-86.
[31] Taji B, Chan AD, Shirmohammadi S. False alarm reduction in atrial fibrillation detection using deep belief networks. IEEE Transactions on Instrumentation and Measurement. 2017 Nov 28;67(5):1124-31.
[32] Kusuma, S., & Udayan, J. D. (2020). Analysis on deep learning methods for ECG based cardiovascular disease prediction. Scalable Computing: Practice and Experience, 21(1), 127-136.
[33] Islam, M. S., Umran, H. M., Umran, S. M., & Karim, M. (2019, May). Intelligent healthcare platform: cardiovascular disease risk factors prediction using attention module based LSTM. In 2019 2nd International Conference on Artificial Intelligence and Big Data (ICAIBD) (pp. 167-175). IEEE.
[34] Kumar, N. K., Sindhu, G. S., Prashanthi, D. K., & Sulthana, A. S. (2020, March). Analysis and prediction of cardio vascular disease using machine learning classifiers. In 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS) (pp. 15-21). IEEE.
[35] Alqahtani, A., Alsubai, S., Sha, M., Vilcekova, L., & Javed, T. (2022). Cardiovascular Disease Detection using Ensemble Learning. Computational Intelligence and Neuroscience, 2022.