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# HybDeepNet: A Hybrid Deep Learning Model for Detecting Cardiac Arrhythmia from ECG Signals

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The problem to be addressed is the high mortality rate of heart disease and the need for reliable and early detection techniques to prevent fatalities. Several clinical tests, including electrocardiogram (ECG) signals, heart sound signals, impedance cardiography (ICG), magnetic resonance imaging, and computer tomography can be used to determine whether an individual has heart disease. In this research, three deep learning models - Multi-layer Perceptrons (MLPs), Deep Belief Networks (DBNs), and Restricted Boltzmann Machines (RBMs) - were used to detect heart disease by using the electrocardiogram (ECG) signal as the primary source. The publicly available datasets MIT-BIH and PTB-ECG were used to train and validate the proposed model. The results showed that the proposed hybrid model achieved the best performance compared to existing models, with an accuracy of 98.6%, 97.4%, and 96.2% on the MIT-BIH dataset, and 97.1%, 96.4%, and 95.3% on the PTB-ECG dataset, respectively. Furthermore, the model had excellent F1-score and AUC values, indicating the robustness of the proposed approach.

**KEYWORDS:** Deep learning, heart disease, ECG signal, Generative Adversarial Networks, Deep Belief Networks.

## 1. Introduction

Cardiovascular disease (CVD) is a widespread non-communicable illness that is a major cause of death worldwide. It can result from any anomaly in the cardiovascular system and can manifest in a number of forms such as heart failure, heart attacks, traumatic strokes, infarction strokes, and other arrhythmia and heart muscle-related disorders [4]. According to the World Health Organization, an estimated 16.9 million people die from CVD every year, and it accounts for 29% of all deaths worldwide. Developing nations are particularly affected, with 78% of deaths from CVD occurring in these countries. It is projected that by 2035, the number of annual deaths from CVD will reach 24 million [1]. The main contributing factors are hypertension, an irregular heartbeat, hyperlipidemia, hypoglycemia, and elevated blood pressure. The linked risk factors that may cause CVD are psychological trauma, lack of exercise, tobacco usage, alcoholism, overweight, genetic factors, poor diets, and a lack of physical workouts. The linked risk factors that may cause CVD are psychological trauma, lack of exercise, tobacco usage, alcoholism, overweight, genetic factors, and poor diet [12].

Coronary artery disease (CAD) is one of the most frequent kinds of CVD. This happens due to the abnormality in minimum one of the left anterior dorsal, left circumflex, and right arteries [28]. In CAD, interfacial tissue in the epithelium of the coronary arterial wall mixes with low-density lipoprotein, exposing them to additional lipid modification and aggravation, which causes poor vascular lesions. As irritation progresses, cell interfacial fatty accumulation induces apoptosis in the vascular system, causing high magnesium deposition and ulceration. The carotid arteries' thrombus expands, leading to myocardial luminal blockage, which limits blood circulation and provides the heart with enough blood and oxygen, thus leading to hypoxia in the muscles [13].

Despite having stiffening and fibro muscular coverings, atherogenesis nodules with significantly tiny hydrophobic cores can slowly produce infarction due to progressive atherosclerotic volume increase that infringes the cardiac channel radius [14]. On the other hand, specific liposome arterial plaques have wider cores and weaker fibrous coverings that are prone to collapse, in which the fluids rapidly leak into the myo-

cardial stream, causing the emboli to develop. This development could obstruct the inflow of cerebral hypoxia in the cardiomyopathy resulting in Thromboembolic lesions. In this condition, an individual's cardiac muscles perish due to oxygen deprivation for longer [6].

Myocardial infarction is a type of CVD caused due to hypo-perfusion, which harms the heart muscles. Chronic recurrent infarction might result in deleterious reconfiguration of the right atrium and diminished heart muscle contraction [26]. Additionally, physiological consequences of MI, such as rheumatic heart disease, decrease efficiency or breach the posterior segment and atrial septal region, aggravating cardio humiliation and resulting in heart attacks. Timely diagnosis of myocardial infarctions is crucial for the early intervention and prevention of the potential onset of cardiovascular diseases [23].

Cardiovascular disease (CVD) diagnosis involves diagnostic procedures like coronary angiography and screening tests. Additionally, alternative passive cardiac testing methods are also available that have other limitations ranging from uncertainty in detecting appropriate order, duration of the results, and selection of proper cardiac imaging procedures [8]. Further, additionally, other assessments include cardiac neuroimaging or echocardiogram. The cost of echocardiograms and the need for qualified specialists to examine the neuroimaging results are among the limitations of these diagnostic tests. Machine learning techniques have recently been applied more successfully to classify CVDs.

The most prevalent type of CVDs is cardiac arrhythmia, which can be correctly identified from electrocardiogram (ECG) records. The ECG signal detects the irregularity of the heart to identify cardiac arrhythmia. An essential medical tool for automatically detecting CVD is the ECG, which documents the features of cardiac contraction, healing, and susceptibility. Finding abnormal cardiac rhythms in the ECG readings is crucial. Manual examination, which is laborious and time-consuming, is necessary to interpret the ECG recording. As a result, many Machine learning techniques have been used to identify cardiac arrhythmias from ECG signals automatically. The main process control methods needed by convention-

al ML systems are feature engineering, pattern discovery, feature representation, and classification [29]. The main limitation of such systems is the selection of accurate features using the correct elements from the ECG signals to detect CVD. In recent times, applications requiring prediction and classification tasks have greatly benefited from the use of Deep Learning approaches, as these models do not suffer from the risk of selecting and extracting features [18]. However, because of the ECG signal's weak amplitude, doctors frequently miss its abnormalities. Therefore, creating trustworthy DL-based models for CAD early detection and robust classification is a difficult challenge. On the identification and categorization of CVD, numerous investigations have been conducted and reported in the literature [10].

Six different pieces of information collected from the patients are used to identify cardiac arrhythmia [25]. These diagnostic tests' characteristics include Electrocardiogram, heartbeat sound, Flow cytometry, MRI, and CT. These six different patient signals can be used for diagnostic purposes. However, each method has advantages and disadvantages for diagnosing cardiac arrhythmia [21]. The main emphasis of this paper is the development of suitable CAD detection models using the participants' ECG signals as input. In light of this, a review of the cardiovascular disease literature has been conducted with a focus on the material relating to ECG-based Cardiac arrhythmia identification [22]. To have a better understanding of the current stream of research on Cardiac arrhythmia, a small number of pertinent recent findings employing different kinds of signals and features are also examined [9]. This work proposes a novel hybrid model based on deep learning to identify cardiac arrhythmia. Three deep models, such as Multilayer Perceptrons (MLPs), Deep Belief Networks (DBNs), and Restricted Boltzmann Machines (RBMs), are combined to diagnose cardiac arrhythmia from ECG signals effectively.

### 1.1. Contributions to the Existing Work

The main contributions of this work are as follows:

- 1 To employ a combined version of Multilayer Perceptrons for hyperparameter optimization, Restricted Boltzmann Machine for feature extraction, and Deep Belief Network for performing classification between normal and affected patients by Cardiac Arrhythmia.

- 2 To evaluate the performance of the proposed Hyb-DeepNet model by applying it to two ECG signals-based datasets such as MIT-BIH and PTB-ECG and compare the model's performance to check the consistency of the model in making predictions for both datasets.

### 1.2. Organization of the Paper

The remainder of the paper is organized as follows. Section 2 reviews the existing works related to cardiovascular disease prediction. Section 3 outlines the proposed hybrid deep neural network model. Section 4 discusses the results of performing experiments using the datasets. Section 5 concludes the current research work

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## 2. Related Works

The state-of-the-art studies in the existing literature for cardiovascular disease prediction are discussed briefly in this section. Several articles published between 2014 and 2022 are chosen to review the works carried out by several authors for the problem taken. It was discovered that most of the results used signals such as heart sound, Radiography, and Optical coherence tomography. Research on the papers gathered from various sources shows that different forms of pulses from the human body have been used as input to perform cardiovascular disease classification methods.

Sinus arrhythmia was directly determined in [27] using a Recurrent neural network. Accuracy of 97.6% and 98.55% are claimed to be obtained for 30 participants using 10-fold cross-validation and for ten participants using blindfold validation. The deep learning technique based on bi-LSTM is utilized in [30] to categorize the ECG signal. The median filter analysis in the study is used to retrieve the secondary signal's bands, followed by using it in the deep neural networks as input. A 98.54% recognition rate has been achieved for the suggested method. Using coupled CNN and LSTM models, the ECG signal has been detected in [31]. In the initial layers, the CNN is utilized to extract features, and the LSTM learning algorithm is then further employed for classification using the features that the CNN has removed. According to reports, the combined technique offers a better accuracy rate [11].

In [16], four different characteristics are extracted from the ECG signal before input into the LSTM model for diagnosis. The experiments conducted through simulation produce a reasonable level of precision, accuracy, and F1-score. The authors in [25] describe the development of an attributes-based bi-LSTM model for classifying arrhythmia from ECG data. The work in [21] reports on the localization of cardiac rhythm using a temporal LSTM network. It is demonstrated that the suggested paradigm offers convincing performance. Using GAN, suppression of noises in CT has been accomplished in another intriguing research [25]. The simulation study used unbalanced CT data, and the GAN approach's successful application in reducing the noise component was demonstrated. In [17], a mixed hybrid model is proposed, exhibiting an enhanced performance and noise reduction in CT images. The CVD categorization based on Convolutional Neural Networks is claimed to produce an altered ECG signal before feeding it to the CNN model. Moreover, it incorporates Short Time Fourier Transform for preprocessing [3, 20].

Support vector machine (SVM) was used by the authors of [32] as a classifier to identify CAD. The optimization algorithms such as genetic and binary PSO have been used to choose the features. The suggested model is trained and tested using the 10-fold validation. It is shown that the proposed strategy performs

better prediction performance while requiring less complexity than the SVM model used without optimization [26]. Table 1 provides a comparative analysis of the existing methods in the literature for cardiovascular disease diagnosis.

## 2.1. Research Gap and Motivation of Research

From the perspective of health care, reliable, precise, and quick detection of cardiovascular diseases is the highest priority. Additionally, it is true that the Deep learning-based detection of Heart diseases generally provides more excellent performance in contrast to the Machine learning techniques. Further, it is observed that in most existing works for heart disease prediction, only one dataset has been utilized to evaluate the effectiveness of the various models for classification. The conclusion drawn from one dataset's findings may not apply to other datasets. Hence, there is necessary to test and assess the performance of the proposed models with at least two standard datasets.

Additionally, it has been noted that the ensemble rendition of the best-performing models shows improved detection accuracy compared to the models employed individually. Several DL models, including MLP, RBM, and DBN, have only been utilized in a few studies. Hence, these models are combined in the present research to detect cardiac arrhythmia from ECG signals

**Table 1**

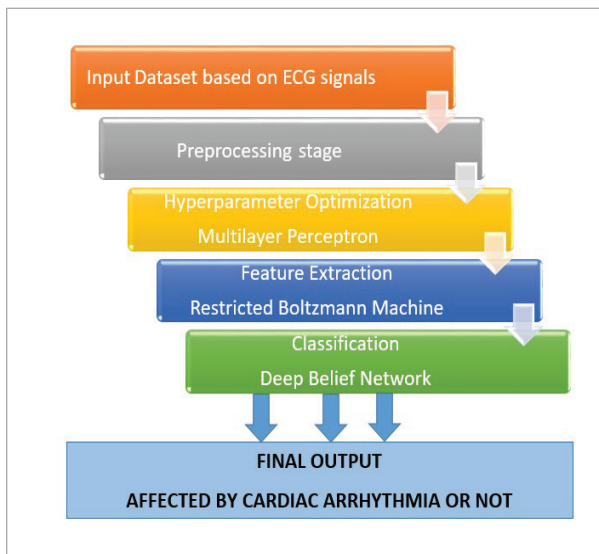
Comparative analysis of the existing methods for CVD diagnosis

Reference	Dataset	Type of CVD	Techniques	Inference	Limitations
[27]	PTB -XL	Myocardial infarction	ANN	Produced Accuracy of 85.2%	Data augmentation not performed
[30]	UCI dataset	Coronary Artery Disease	CNN	Produced Accuracy of 87.2%	Trivial dataset
[11]	Private	Congestive Heart failure	LSTM	Produced Accuracy of 87.8%	Not suitable for a dataset with more classes
[16]	PTB DB	Cardiac Arrhythmia	Random Forest classifier	Produced Accuracy of 78.6%	Less accurate prediction
[25]	MIT-DB	Cardiac Arrhythmia	ResNet and AlexNet	Produced Accuracy of 90.2%	Less reliable
[21]	Private	Congestive Heart failure	SVM	Produced Accuracy of 83.5%	Data augmentation not performed
[17]	MIT-DB	Myocardial infarction	bi-LSTM+ PSO	Produced Accuracy of 89.4%	Not suitable for datasets with more classes

### 3. Proposed Methodology

This section outlines the proposed methodology, which involves three deep learning models Multilayer Perceptrons, Restricted Boltzmann Machines, and Deep Belief Networks. These models are mainly developed for this research as these models have been rare for Cardiac arrhythmia prediction using deep learning. Moreover, to achieve high performance, instead of using these models independently, a hybrid approach is proposed to combine these models. MLPs are used to optimize the proposed model's hyperparameters, RBMs extract insightful features from the data, and further, the classification of whether the patient is affected by cardiac arrhythmia or not is performed using the DBNs. The architecture of the proposed hybrid model is presented in Figure 1.

**Figure 1**  
Proposed methodology



#### 3.1. Multilayer Perceptrons (MLPs)

The multilayer perceptron algorithm employs artificial neurons in several layers, including hidden layers. For problems requiring binary classification, these algorithms are used. Algorithms called multilayer perceptrons are derived from the concept of biological neurons. The structure of a Multilayer perceptron is depicted in Figure 2. They employ perceptrons, which are synthetic neurons. Each neuron in a perceptron has

an activation function. Each neuron's weighted inputs are mapped by the activation function, which also decreases the number of layers to only two. By changing the weights that are given to it, a perceptron evolves. The parameters that are set for the execution of the Multilayer perceptron algorithm are shown in Table 2.

**Table 2**  
Multilayer Perceptron Parameters

Parameter Name	Specification
Hidden Layers	Ranging between two to four
Number of epochs	1000
Bias Value	1.0
Weight value	0.1
Mode of Training	Batch Mode

The algorithm for the Multilayer perceptron is given in Algorithm 1.

#### Algorithm 1

Multilayer Perceptron Algorithm

Input: Nodes  $x_1, x_2, \dots, x_n$  in the input layer

Output: Nodes  $z_1, z_2, \dots, z_n$  in the output layer

Step 1: Initialize b as bias and w as weights

Step 2: For each weight  $w_{xy}$

Step 3:  $w_{xy} = w_{xy} + \delta(w_{xy})$

Step 4: For each bias  $\sigma_y$

Step 5:  $\sigma_y = \sigma_y + \delta(\sigma_y)$

Step 6: For each training sample s in N

Step 7: For each unit x in the input layer

Step 8:  $Out_x = In_x$

Step 9: For each unit y in the hidden layer

Step 10:  $Hid_y = \sum W_{xy} In_x + b_y$

Step 11:  $fn_{act} = \frac{1}{1 + e^{-x}}$

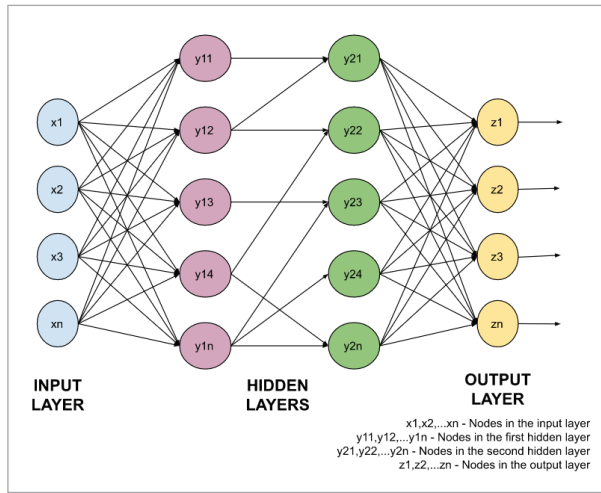
Step 12: For each unit z in the output layer

Step 13:  $E_x = O_z (1 - O_x) (D_z - O_x)$

Step 14: For each unit y in the hidden layer, moving from the final to initial layer in the hidden unit

Step 15:  $E_y = \sum_{i=0}^N Error(W_{xy}(i))$

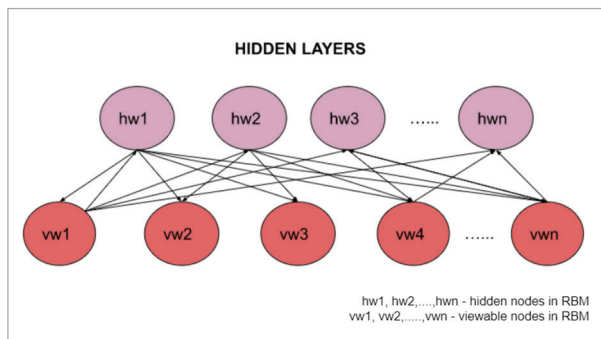
**Figure 2**  
Structure of Multilayer Perceptron



**3.2. Restricted Boltzmann Machines (RBMs)**

The Boltzmann Machine is a random probabilistic model stacked in two layers. This model's two layers are hidden and viewable in nature. The viewable layer includes a set of states. Similarly, the hidden layer is represented as, The states that relate these two layers are completely packed and interconnected. The structure of the RBM model is presented in Figure 3. The conditions are devoid of connections within themselves. This model is also known as a model based on energy. There exists a multiplicative type of energy between the layers. The model learns by altering this energy variant according to the requirement. The distribution of the probability-based function for the RBM model is denoted as in (1):

**Figure 3**  
Structure of Restricted Boltzmann Machine



$$prob(vw, hw) = \frac{1}{p} e^{-F(vw, hw)}. \tag{1}$$

Here,  $F(vw, hw)$  represents the multiplicative energy which is as shown in (2):

$$F(vw, hw) = \sum_{x=1}^N \sum_{y=1}^N w_{xy} h w_x v w_y - \sum_{y=1}^N m_y v w_y - \sum_{x=1}^N n_x h w_x. \tag{2}$$

Here,  $w_{xy}$  denotes the weight variable,  $m_y$  and  $n_x$  denotes the bias variables. The bias variable may be modified in order to train the model in a better way to improve the performance. The computational complexity of the system depends on number of layers and techniques used to implement features that are selected.

The probability for the minimal function for the viewable layers is computed as a sum function using Equation (3) as:

$$minProb(vw) = \sum_{i=0}^N \frac{1}{p} e^{-F(vw_i, hw_i)}. \tag{3}$$

Here, P is considered as a standardization component which is represented as in (4):

$$P = \sum_{i=0}^N v w_i, h w_i e^{-F(vw_i, hw_i)}. \tag{4}$$

In case of two states existence, there are two probabilities calculated assuming that one value is given using the transfer function denoted in (5):

$$\varphi(i) = \frac{1}{1 - e^{-i}}. \tag{5}$$

The first probability is computed as shown in (6) by assuming that the value of hw is given:

$$prob(vw | hw) = \varphi\left(m_y + \sum_{x=0}^N h w_x w_{xy}\right). \tag{6}$$

Similar to this, the second probability is computed as shown in (7) by assuming that the value of vw is given:

$$prob(hw | vw) = \varphi\left(n_x + \sum_{y=0}^N v w_y w_{xy}\right). \tag{7}$$

The weight matrix  $w_{xy}$  is modified as shown in (8) to improve the learning of the model:

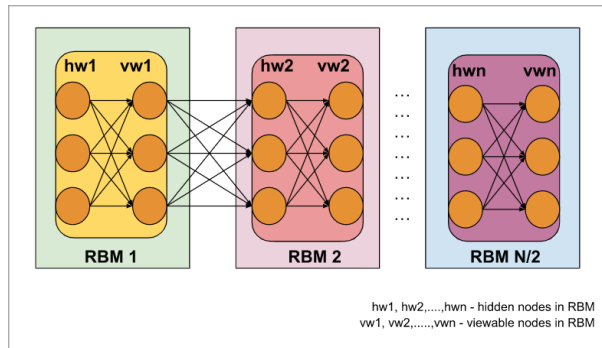
$$\delta w_{xy} = \sum_{x=0}^N \sum_{y=0}^N v w_y h w_x - \sum_{x=N}^{\infty} \sum_{y=N}^{\infty} v w_y h w_x. \quad (3)$$

### 3.3. Deep Belief Networks (DBNs)

Deep belief networks (DBN) are probability distribution models of numerous hidden layers. Adjusting the weights between nodes increases the likelihood that the whole model will be generated. The DBN's fundamental structure is depicted in Figure 4. It consists of a backpropagation (BP) neural network and several restricted Boltzmann machines (RBMs). RBM is a two different neural network with bidirectional connections, with its output being passed as input to the subsequent RBM. Thus, a continuous overlay of an inner layer structure is possible

Figure 4

Structure of Deep Belief Network



The loss function is optimized on the training data to achieve a nominal solution as shown in (9):

$$NS(\varphi, T) = -\frac{1}{K} \sum_{y=0}^N \log \left( K \left( v w_y \right) \right). \quad (9)$$

Here,  $k$  denotes the length of the data in the training examples. The weight and bias are further updated as shown in (10) to (12):

$$\log \left( K \left( w_{xy} \right) \right) = N_{prob} \left( v w_y h w_x \right) - G_{prob} \left( v w_y h w_x \right); \quad (10)$$

$$\log \left( K \left( h w_x \right) \right) = N_{prob} \left( h w_x \right) - G_{prob} \left( h w_x \right); \quad (11)$$

$$\log \left( K \left( v w_y \right) \right) = N_{prob} \left( v w_y \right) - G_{prob} \left( v w_y \right). \quad (12)$$

The above equations,  $N_{prob}$  and  $G_{prob}$  denote the numerical and generative probability of the model. The DBN's training strategy is broken up into two phases. Each RBM is first trained from the ground up. The second stage involves top-down fine-tuning of the hyperparameters.

The estimation of the distribution of RBM model is computed mathematically as shown in Equations (13)-(15):

$$w_a = \theta w_{a-1} + \varphi(v w_y h w_x); \quad (13)$$

$$m_a = \theta m_{a-1} + \varphi(h w_x); \quad (14)$$

$$n_a = \theta n_{a-1} + \varphi(v w_y). \quad (15)$$

In the above equations,  $\theta$  denotes the rate of learning by the model and  $\varphi$  is the coefficient representing the factor of momentum.

## 4. Results and Discussion

For the performance evaluation of the proposed model, experiments have been conducted using two publicly available datasets that comprise ECG signals. The data is preprocessed and fed into the deep hybrid models. A detailed description of the dataset, as well as the experimental findings, are discussed in this section.

### 4.1. Dataset Specification

The two datasets selected for the experimentation of the present research are MIT-BIH [11] and PTB-ECG [20] datasets. The details about the number of samples in the dataset and how it is utilized in this work are presented in Table 3. The total number of samples in the MIT-BIH dataset is 268, whereas in PTB-ECG is 200. Out of 268, 104 samples are for patients affected by cardiovascular disease, and 164 samples represent patients without the condition. Similarly, for the PTB-ECG dataset, the affected patient's count is close to 54, and the unaffected is 146. The dataset is split in the ratio of 75:25 for training and validation.

**Table 3**

Datasets Specification Details

Specification	MIT-BIH	PTB-ECG
Number of samples	268	200
Number of samples for affected individuals	104	54
Number of samples for unaffected individuals	164	146
Number of samples taken for training	201	150
Number of samples taken for validation	67	50

In that case, for the MIT-BIH dataset, 201 samples are taken for the training phase, and 67 are used for the validation phase. Considering the PTB-ECG dataset, 150 samples are taken for the training phase, and 50 are employed for validation.

#### 4.2. Performance Metrics

The performance of the models is evaluated using three different metrics such as  $model_{acc}$ ,  $model_{f1-s}$  and  $model_{auc}$  which are accuracy, F1-score, and Area under curve respectively. These metrics are technically represented as shown below.  $model_{tp}$ ,  $model_{tn}$ ,  $odel_{fp}$  and  $model_{fn}$  in Equations (16)-(17) represent true positive, true negative, false positive, and false negative values respectively.

##### a $model_{acc}$ :

This is a measure that represents the predictions that are made correctly as expected that is classifying positive predictions and negative predictions accordingly as per the actual results.

$$model_{acc} = \frac{model_{tp} + model_{tn}}{model_{tp} + model_{tn} + model_{fp} + model_{fn}} \quad (16)$$

##### b $model_{f1-s}$ :

This metric is a computation that is performed as a harmonic average value between sensitivity and specificity values.

$$model_{f1-s} = \frac{2 * model_{tp}}{2 * model_{tp} + model_{fp} + model_{fn}} \quad (17)$$

##### c $model_{auc}$ :

The relationship between accuracy and precision is plotted on the receiver operating characteristics (ROC) curve. It alludes to a binary classification assessment matrix. The ROC's AUC measures its capacity to differentiate between both positive and negative classifications. The performance of a classifier improves with increasing AUC values.

#### 4.3. Performance Evaluation

The performance of the proposed model for both the datasets, such as MIT-BIH and PTB-ECG, is presented in Table 4. The proposed model produces an accuracy of 98.6% for the MIT-BIH and 97.1% for the PTB-ECG dataset. The F1 Score for MIT-BIH is 97.4%, whereas for the PTB-ECG dataset is 96.4%. Similarly, the AUC value is 96.2% and 95.3% for the MIT-BIH and PTB-ECG datasets, respectively. It can be observed from the obtained results that there is only a slight difference between the performances exhibited by the proposed model for both datasets. The model works best in making cardiac arrhythmia predictions from both datasets.

**Table 4**

Performance Evaluation of the Proposed HybDeepNet model

Performance Metric	MIT-BIH	PTB-ECG
Accuracy	98.6 %	97.1 %
F1-score	97.4 %	96.4 %
AUC	96.2 %	95.3 %

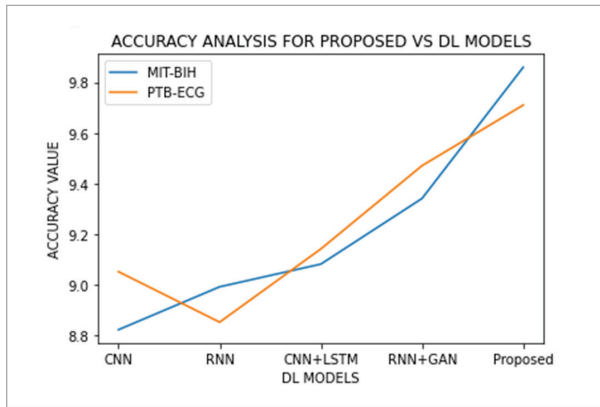
The performance of the proposed model is compared against various deep learning models, and the accuracy exhibited by each model is presented in Table 5 and graphically depicted in Figure 5. The Convolutional Neural Network model, when executed on the MIT-BIH dataset, showed an accuracy of 88.2%, and the same model for the PTB-ECG dataset showed 90.5%. This model showed better performance for the PTB-ECG dataset.

The Recurrent Neural Networks model made accurate predictions of 89.9% for MIT-BIH and 88.5% for PTB-ECG datasets. Though the accuracy is more for MIT-BIH for the RNN model, the difference is very marginal in this case. The ensemble models, like Con-



**Figure 5**

Proposed model Vs DL models



volutional Neural Networks with Long Short Term Memory Networks and Recurrent Neural Networks with Generative Adversarial Networks, were also validated for MIT-BIH and PTB-ECG datasets. CNN+LSTM combination produced an accuracy of 90.8% in making predictions for the MIT-BIH dataset and 91.4% for the PTB-ECG dataset. Similarly, the accuracy delivered by RNN+GAN for PTB-ECG is more than that of MIT-BIH, but the difference between them is negligible.

**Table 5**

Accuracy analysis of Proposed HybDeepNet model Vs Deep learning models

DL models	MIT-BIH	PTB-ECG
CNN	88.2 %	90.5 %
RNN	89.9 %	88.5 %
CNN+LSTM	90.8 %	91.4 %
RNN+GAN	93.4 %	94.7 %
<b>HybDeepNet model</b>	<b>98.6 %</b>	<b>97.1 %</b>

The proposed hybrid deep network model is also compared against existing hybrid models in [20], [32], [26], [7], and [5] as shown in Table 6. In [20], a hybrid model combining the CNN architectures such as ResNet50, AlexNet, and SqueezeNet has been proposed. In [32], an ensemble model with Deep Neural Networks, CNN, and LSTM is suggested. In [26], another ensemble model based on Self Organizing Maps

**Table 6**

Performance Comparison of Existing vs Proposed model

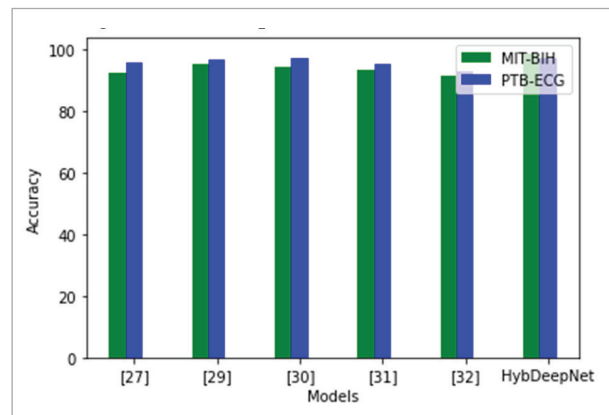
Existing/Proposed	Reference	MIT-BIH	PTB-ECG
Existing [20]	ResNet50, AlexNet, and SqueezeNet	92.4 %	95.8 %
Existing [32]	DNN, CNN, and LSTM	95.2 %	96.4 %
Existing [26]	SOM and AE ensemble model	94.3 %	96.8 %
Existing [7]	DBN and XGBOOST	93.4 %	95.2 %
Existing [5]	MobileNet v2-based DNN	91.2 %	92.8 %
Proposed	MLP, RBM, and DBN	98.6 %	97.1 %

and Autoencoders is developed for CVD diagnosis. Similarly, in [7], Deep Belief Networks along with XGBOOST are employed for heart disease prediction. In [5], authors have devised a deep learning model MobileNet v2-based DNN and utilized it for CVD research[2, 15, 19].

The hybrid model in [20] produces an accuracy of 92.4% for MIT-BIH and 95.8% for PTB-ECG. On the other hand, the ensemble model in [32] exhibits an accuracy of 95.2% and 96.4% for MIT-BIH and PTB-ECG datasets, respectively. The models proposed in [26] produce accurate predictions of 94.3% for MIT-BIH and 96.8% for PTB-ECG datasets. DBN

**Figure 6**

Existing Works vs Proposed Work



and XGBOOST combination in [7] works well to exhibit forecasts with an accuracy of 93.4% and 95.2% for MIT-BIH and PTB-ECG datasets, respectively. The model in [5] shows a lower accuracy than other models in the existing works taken for performance analysis. It exhibits 91.2% for the MIT-BIH dataset and 92.8% for the PTB-ECG dataset. However, the accuracy of all these models is lower than that of the proposed HybDeepNet model, as shown in Figure 6.

## 5. Conclusion

The proposed model, HybDeepNet, utilizes a unique hybrid approach for diagnosing Cardiac Arrhythmia using ECG signals. This includes the use of three different models: Multilayer Perceptrons for optimizing the model's hyperparameters, a Restricted Boltzmann Machine for feature extraction, and Deep Belief Networks for classification. The model is evaluated using two publicly available datasets, MIT-BIH and PTB-ECG. The proposed HybDeepNet model was compared to several deep learning models and two previous works in terms of performance. The results

show that the proposed model outperforms the others, achieving an accuracy of 98.6% on the MIT-BIH dataset and 97.1% on the PTB-ECG dataset. However, one limitation of this research is that the analysis was only conducted on consistent datasets. Further validation is needed using larger, more diverse datasets. Additionally, the computational requirements, specifically CPU time, for the hybrid model are relatively high. The proposed HybDeepNet model exhibited superior performance for diagnosing Cardiac Arrhythmia using ECG signals, but there is potential for further improvement. One potential approach is to integrate different types of classification techniques, such as nature-based optimization methods, to enhance the model's performance. Additionally, the same method could be adapted for detecting other diseases by using deep learning detection models. To aid remote patients, the technique could be implemented on an Internet of Things platform as a cloud service. Another area of focus for future work could be on increasing the operating speed of the model through fast convergence, which would enable real-time diagnosis. Finally, reducing implementation overhead for the developed strategy is another area where work can be done further.

## References

1. Alizadehsani, R. Machine Learning-Based Coronary Artery Disease Diagnosis: A Comprehensive Review. *Computers in Biology and Medicine*, 2019, 111, 103346. <https://doi.org/10.1016/j.combiomed.2019.103346>
2. Beritelli, F., Capizzi, G., Lo Sciuto, G., Napoli, C., Woźniak, M. A Novel Training Method to Preserve Generalization of RBPNN Classifiers Applied to ECG Signals Diagnosis. *Neural Networks*, 2018, 108, 331-338. <https://doi.org/10.1016/j.neunet.2018.08.023>
3. Budholiya, K., Shrivastava, S. K., Sharma, V. An Optimized Xgboost Based Diagnostic System for Effective Prediction of Heart Disease. *Journal of King Saud University - Computer and Information Sciences*, 2022, 34(7), 4514-4523. <https://doi.org/10.1016/j.jksuci.2020.10.013>
4. Carnevale, L., Celesti, A., Fazio, M., Bramanti, P., Villari, M. Heart Disorder Detection with Menard Algorithm on Apache Spark. In *European Conference on Service-Oriented and Cloud Computing*, Springer, 2017, 229-237. [https://doi.org/10.1007/978-3-319-67262-5\\_17](https://doi.org/10.1007/978-3-319-67262-5_17)
5. Chen, J., Valehi, A., Razi, A. Smart Heart Monitoring: Early Prediction of Heart Problems Through Predictive Analysis of ECG Signals. *IEEE Access*, 2019, 7, 120831-120839. <https://doi.org/10.1109/ACCESS.2019.2937875>
6. Choi, R. Y., Coyner, A. S., Kalpathy-Cramer, J., Chiang, M. F., Peter Campbell, J. Introduction to Machine Learning, Neural Networks, and Deep Learning. *Translational Vision Science and Technology*, 2020, 9(2), 1-12.
7. Devi, R. L., Kalaivani, V. Machine Learning and IoT-Based Cardiac Arrhythmia Diagnosis Using Statistical and Dynamic Features of ECG. *Journal of Super Computing*, 2019, 1-12. <https://doi.org/10.1007/s11227-019-02873-y>
8. Faust, O., Barika, R., Shenfield, A., Ciaccio, E. J., Acharya, U. R. Accurate Detection of Sleep Apnea with Long Short-Term Memory Network Based on RR Interval Signals. *Knowledge Base Systems*, 2021, 212, 106591. <https://doi.org/10.1016/j.knosys.2020.106591>

9. Faust, O., Shenfield, A., Kareem, M., San, T. R., Fujita, H., Acharya, U. R. Automated Detection of Atrial Fibrillation Using Long Short-term Memory Network with RR Interval Signals. *Computers in Biology and Medicine*, 2018, 102, 327-335. <https://doi.org/10.1016/j.combiomed.2018.07.001>
10. Ganguly, B., Ghosal, A., Das, A., Das, D., Chatterjee, D., Rakshit, D. Automated Detection and Classification of Arrhythmia from ECG Signals Using Feature-Induced Long Short-Term Memory Network. *IEEE Sensors Letters*, 2020, 4(8), 1-4. <https://doi.org/10.1109/LS-ENS.2020.3006756>
11. Hasan, N. I., Bhattacharjee, A. Deep Learning Approach to Cardiovascular Disease Classification Employing Modified ECG Signal from Empirical Mode Decomposition. *Biomedical Signal Processing and Control*, 2019, 52, 128-140. <https://doi.org/10.1016/j.bspc.2019.04.005>
12. Jahmunah, V. Computer-Aided Diagnosis of Congestive Heart Failure using ECG Signals - A Review. *Physica Medica*, 2019, 62, 95-104. <https://doi.org/10.1016/j.ejmp.2019.05.004>
13. Lih, O. S. Comprehensive Electrocardiographic Diagnosis Based on Deep Learning. *Artificial Intelligence in Medicine*, 2020, 103. <https://doi.org/10.1016/j.artmed.2019.101789>
14. Mastoi, Q., Wah, T. Y., Gopal Raj, R., Iqbal, U. Automated Diagnosis of Coronary Artery Disease: A Review and Workflow. *Cardiology Research and Practice*, 2018, 2016282. <https://doi.org/10.1155/2018/2016282>
15. Naz, M., Shah, J. H., Khan, M. A., Sharif, M., Raza, M., Damaševičius, R. From ECG Signals to Images: A Transformation Based Approach for Deep Learning. *Peer Journal of Computer Science*, 2021, 7, e386. <https://doi.org/10.7717/peerj-cs.386>
16. Oh, S. L., Ng, E. Y., San Tan, R., Acharya, U. R. Automated Diagnosis of Arrhythmia Using Combination of CNN and LSTM Techniques with Variable Length Heart Beats. *Computers in Biology and Medicine*, 2018, 102, 278-287. <https://doi.org/10.1016/j.combiomed.2018.06.002>
17. Panigrahy, D., Sahu, P. K., Albu, F. Detection of Ventricular Fibrillation Rhythm by Using Boosted Support Vector Machine with an Optimal Variable Combination. *Computers and Electrical Engineering*, 2021, 91, 107035. <https://doi.org/10.1016/j.compeleceng.2021.107035>
18. Pławiak, P., Acharya, U. R. Novel Deep Genetic Ensemble of Classifiers for Arrhythmia Detection Using ECG Signals. *Neural Computing and Applications*, 2019, 32, 11137-11161. <https://doi.org/10.1007/s00521-018-03980-2>
19. Prakash, V., Jothi, Karthikeyan N. K. Dual-Layer Deep Ensemble Techniques for Classifying Heart Disease. *Information Technology and Control*, 2022, 51(1), 158-179. <https://doi.org/10.5755/j01.itc.51.1.30083>
20. Rath, A., Mishra, D., Panda, G., Satapathy, S. C. Heart Disease Detection Using Deep Learning Methods from Imbalanced ECG Samples. *Biomedical Signal Processing and Control*, 2021, 68, 102820. <https://doi.org/10.1016/j.bspc.2021.102820>
21. Saeidi, A., Almasganj, F. Cardiac Valves Disorder Classification Based on Active Valves Appearance Periodic Sequences Tree of Murmurs. *Biomedical Signal Processing and Control*, 2020, 57, 101775. <https://doi.org/10.1016/j.bspc.2019.101775>
22. Saeidi, A., Almasganj, F. Cardiac Valves Disorder Classification Based on Active Valves Appearance Periodic Sequences Tree of Murmurs. *Biomedical Signal Processing and Control*, 2020, 57, 101775. <https://doi.org/10.1016/j.bspc.2019.101775>
23. Salah, I. B., de la Rosa, R., Ouni, K., Salah, R. B. Automatic Diagnosis of Valvular Heart Diseases by Impedance Cardiography Signal Processing. *Biomedical Signal Processing and Control*, 2020, 57, 101758. <https://doi.org/10.1016/j.bspc.2019.101758>
24. Soh, D. C. K., Ng, E. Y. K., Jahmunah, V., Oh, S. L., Tan, R. S., Acharya, U. R. Automated Diagnostic Tool for Hypertension Using Convolutional Neural Network. *Computers in Biology and Medicine*, 2020, 126, 103999. <https://doi.org/10.1016/j.combiomed.2020.103999>
25. Tan, J. H., Hagiwara, Y., Pang, W., Lim, I., Oh, S. L., Adam, M., Acharya, U. R. Application of Stacked Convolutional and Long Short-Term Memory Network for Accurate Identification of CAD ECG Signals. *Computers in Biology and Medicine*, 2018, 94, 19-26. <https://doi.org/10.1016/j.combiomed.2017.12.023>
26. Tao, R., Zhang, S., Huang, X., Tao, M., Ma, J., Ma, S., Shen, C. Magnetocardiography-based Ischemic Heart Disease Detection and Localization Using Machine Learning Methods. *IEEE Transactions on Biomedical Engineering*, 2018, 66(6), 1658-1667. <https://doi.org/10.1109/TBME.2018.2877649>
27. Uddin, S., Khan, A., Hossain, M. E., Moni, M. A. Comparing Different Supervised Machine Learning Algorithms for Disease Prediction. *BMC Medical Informatics and Decision Making*, 2019, 19(1), 1-16. <https://doi.org/10.1186/s12911-019-1004-8>

28. Wang, H., Shi, H., Chen, X., Zhao, L., Huang, Y., Liu, C. An Improved Convolutional Neural Network Based Approach for Automated Heartbeat Classification. *Journal of Medical Systems*, 2020, 44(2), 35. <https://doi.org/10.1007/s10916-019-1511-2>
29. Yamamoto, K., Hiromatsu, R., Ohtsuki, T. ECG Signal Reconstruction via Doppler Sensor by Hybrid Deep Learning Model with CNN and LSTM. *IEEE Access*, 2020, 8, 130551-130560. <https://doi.org/10.1109/ACCESS.2020.3009266>
30. Yildirim, O., Talo, M., Ciaccio, E. J., Tan, R. S., Acharya, U. R. Accurate Deep Neural Network Model to Detect Cardiac Arrhythmia on More than 10,000 Individual Subject ECG Records. *Computers Methods and Programs in Biomedicine*, 2020, 197. <https://doi.org/10.1016/j.cmpb.2020.105740>
31. Yıldırım, O., Pławiak, P., Tan, R. S., Acharya, U. R. Arrhythmia Detection Using Deep Convolutional Neural Network with Long Duration ECG Signals. *Computers in Biology and Medicine*, 2018, 102, 411- 420. <https://doi.org/10.1016/j.compbimed.2018.09.009>
32. Zhang, Y.D., Dong, Z., Wang, S. H., Yu, X., Yao, X., Zhou, Q. Advances in Multimodal Data Fusion in Neuroimaging: Overview, Challenges, and Novel Orientation. *Information Fusion*, 2020, 64, 149-187. <https://doi.org/10.1016/j.inffus.2020.07.006>
33. Zhang, Y. D., Nayak, D. R., Zhang, X., Wang, S. H. Diagnosis of Secondary Pulmonary Tuberculosis by an Eight-Layer Improved Convolutional Neural Network with Stochastic Pooling and Hyperparameter Optimization. *Journal of Ambient Intelligence and Humanized Computing*. *Computing*, 2020, 1-18. <https://doi.org/10.1007/s12652-020-02612-9>
34. Zou, Z. Z., Xie, K., Zhao, Y. F., Wan, J., Lan, L., Wen, C. Intelligent Assessment of Percutaneous Coronary Intervention Based on GAN and LSTM Models. *IEEE Access*, 2020, 8, 90640-90651. <https://doi.org/10.1109/ACCESS.2020.2992578>

