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Enhanced CNN Model for Cardiovascular Disease Prediction Using ECG Signals

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Abstract: Cardiovascular Disease is one of the leading causes of death on a global scale. Heart related diseases account for 32% of all the deaths worldwide. Cardiovascular Disease Prediction (CDP) is crucial for early detection and prognostics of cardiac disorders. Timely detection of heart related disorders like cardiac arrythmia can save millions of lives. Electrocardiogram (ECG) signal is a reliable tool which is prominently being used to analyze the functionality of the heart and diagnose the disorders. To automate the task of ECG analysis, Deep Learning (DL) based models have exhibited significant potential. This paper proposes a novel deep learning based prediction system namely, HeartNet which is an enhanced CNN Model to predict four types of Arrhythmias. It resamples the data, then the resampled data is fed to the CNN layers for feature extraction, and then the extracted features are fed to LSTM layer for accurate arrythmia predictions. A combination of the publicly available datasets namely MIT-BIH Arrhythmia Database and PTB Diagnostic ECG Database is used for experimental study. The proposed model achieves the accuracy of 97.6% and Area Under the Curve (AUC) of 99.6%. The results are statistically compared with the existing base models from the literature in terms of accuracy. From the experimental results and statistical analysis, it can be concluded that the proposed HeartNet model has a significant potential to effectively detect Arrhythmia in humans from the ECG signals.

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1. Introduction

Cardiovascular disease is an important issue as it is associated with a high mortality rate globally. As per a report from World Health Organization (WHO), 37% of the worldwide fatalities are caused by the heart related disorders. Further, it is predicted that this will rise the global death rate [1]. An early detection of heart related disorders like Arrythmia can save lives. Arrhythmia is a condition where there is an issue with the rhythm of one's heartbeat. Arrhythmia may cause the heart to beat too quickly or too slowly. Not all arrythmia are fatal, but an early detection of Arrhythmia can be a potential help in saving millions of lives throughout the globe [2]. To detect Arrythmia, ECG is the most common signal which is used by cardiologists. ECG signals possess significant indicators and allow to monitor the functionality of the heart. But ECG recordings are long and contain complex patterns in relation with different arrythmia. Hence, manual analysis of ECG signals by a human is a challenging job. To assist the physicians and cardiologists in the analysis of ECGs, and to detect arrhythmia using the ECG signals, various Machine

Learning (ML) and Deep Learning (DL) have been developed [3,4]. The digital era has revolutionized day-to-day routine activities by deploying IoT, Sensors, ML and DL [5]. Existing Deep Learning (DL) models have made a huge contribution to classify heart disease from the healthy ones using ECG Readings [6]. Feature selection (FS) facilitates to enhance prediction accuracy by removing the non-contributing and irrelevant attributes [7]. Convolution Neural Network (CNN) has extensively been used to detect heart diseases [8]. Integration of CNN technique along with other techniques strengthens the prediction power of cardiovascular detection system [9]. This work contributes a novel CNN based HeartNet Model to predict heart disease in humans effectively.

1.1. Motivation

Cardiovascular diseases include a wide range of heart related problems. For early detection of heart disease, ECG analysis is the most convenient and reliable tool. Automation of ECG analysis for arrythmia detection can be modelled as a learning problem and hence machine learning and deep learning methods are suitable for early prediction of arrythmia [14]. Literature witnesses the significant potential of machine learning techniques like neural network [10], decision tree [11], support vector machine [12], ensembles [13] for accurate predictions from the previous recorded data. Deep learning techniques are also prominently being utilized for the heart disease prediction [14,20]. The optimization of learning algorithms on the criteria of data availability is reported as shown in Fig. 1. With the increasing availability of medical data due to advancement in IoT models and digitalization, Deep Learning (DL) architectures are widely being accepted for cardiovascular disease prediction [15].

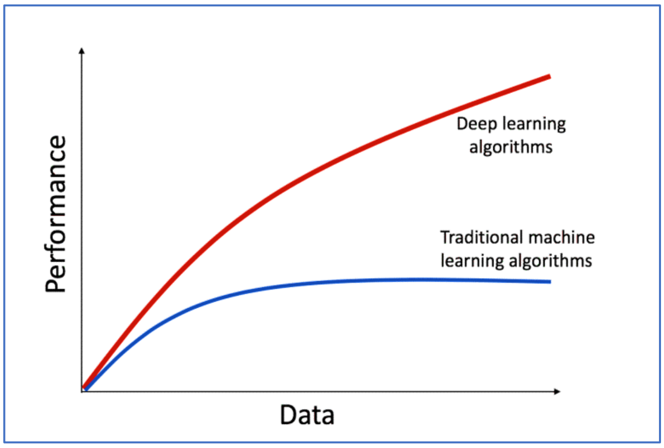

Figure 1. Performance of Learning Algorithms with Availability of Data [15]

Among deep learning architectures, Convolution Neural Network (CNN) is gaining popularity among the researchers [17-19]. Now-a-days, LSTM architecture is also attracting the researchers and academicians [20]. Studies from literature advocate that the resampling of data improves the accuracy of prediction models [21-24]. Cao et al. (2020) demonstrated a resampling method for data augmentation and attained high accuracy in prediction of cardio disease [21]. Mohapatra and Mohanty (2018) deployed resampling technique for arrythmia prediction and demonstrated a random forest model with pretty good performance [24]. This motivates the authors to utilize deep learning architecture with resampling of data at preprocessing.

Further, appropriate feature selection at data preprocessing phase contributes to enhance the prediction power of deep learning model by eliminating the redundant and non-significant features [25,26]. Alonso-Atienza et al. (2013) demonstrated that how the appropriate selection of features enhanced the performance of arrythmia detection model

[27]. Pandey and Janghel (2020) extracted four features from ECG recordings namely- wavelets, HOS, R–R intervals, and morphological descriptors for arrythmia detection and exemplified that feature selection strengthens the prediction power [28]. The studies Kim et al. (2018) and Chen et al. (2020) commended a combination of CNN and LSTM models for cardio disease prediction with better accuracy [29,30].

The existing studies utilized resampling, feature selection, and a variety of deep learning architectures. But to the best of authors' knowledge, none of these utilized resampling technique, feature selection technique and combination of deep learning architecture altogether.

This work contributes an enhanced CNN model naming HeartNet with better accuracy for arrythmia detection from ECG recordings. For this agenda, three-fold strategy has been developed. First up, data preprocessing is done utilizing bootstrap resampling of data. Second, CNN model is deployed for feature extraction from the ECG recordings. Third, LSTM model is used for detecting the arrythmia from the extracted features.

1.2. Contribution

This work contributes an enhanced prediction model based on deep learning architecture deploying resampling method and feature selection technique to detect arrythmia from ECG. To carry out the research streamlined, following research goals are established-

RG#1 To build an enhanced CNN model (HeartNet) for arrythmia detection utilizing resampling methods and LSTM layers

RG#2 To evaluate the performance of proposed model (HeartNet) empirically and compare with the base models.

RG#3 To establish the statistical validation of the work.

The above mentioned goals are followed to steer this research work. Next, the organization of the work is discussed.

1.3. Organization

The paper is organized as follows- the related literature work is discussed under Section 2. Then, Section 3 describes the experimental set-up along with the dataset details and methodology is also explained. Later, the results of experiments are analyzed, and discussion is made under Section 4. Finally, the work is concluded with remarks on the future scope under Section 5.

2. Literature Work

This section brings a survey on the work carried out in the field of cardiovascular disease prediction deploying learning techniques. Deep Learning (DL) based classification models are prevailing in the domain of arrythmia detection. It is observed that few studies exemplified feature selection, and some demonstrated resampling methods in association with learning methodologies. The survey is summarized as Table 1.

The information is segregated under following heads of the table- name of the study along with the year of work published, the datasets used, techniques utilized in the study, and the evaluation criteria adopted to measure the performance of the work. The last head in the table shows the inferences drawn by the authors of this paper about the study under consideration.

Table 1. Related work in literature

S. No.	Study	Dataset Used	Technique Used	Evaluation Criteria	Inference Drawn by Goyal et al. (2022)
1	*Zhou et al. (2018) [17]*	MIT-BIH	CNN	Sensitivity, Specificity, Accuracy	1-D Convolutional net is promising to detect arrythmia from ECGs.
2	*Ferriti et al. (2021) [18]*	MIT-BIH	CNN	Accuracy	2-D Convolutional net is promising to detect arrythmia from ECGs.
3	*Shao (2022) [19]*	PhysioNet and MIT-BIH	CNN	Sensitivity, precision, Accuracy	CNN has potential for multi-modal attention network for effective arrythmia detection
4	*Hariyanto et al. (2022) [20]*	MIT-BIH	LSTM	Sensitivity, precision, Accuracy, F1-Score, G-value	LSTM- single layer shows pretty good accuracy with ECG analysis.
5	*Cao et al. (2020) [21]*	CinC Challenge Dataset	LSTM	Accuracy, F1-score	2-Layer LSTM with data augmentation brings 78.34 % accuracy in arrythmia detection.
6	*Mohapatra and Mohanty (2018) [24]*	UCI Repository	Resampling and Random Forests	Accuracy	Random sampling along with Random Forest classifier brings 96% accuracy.
7	*Alonso-Atienza (2013) [27]*	PhysioNet Repository	Filter Feature Selection and Support Vector Machines	Sensitivity, Specificity	Filtered feature selection along with machine learning algorithms possess potential to detect arrythmia.
8	*Pandey and Janghel (2020) [28]*	MIT-BIH	LSTM	Sensitivity, Specificity, Accuracy, F1-score	LSTM promises to extract significant features for arrythmia prediction.
9	*Chen et al. (2020) [29]*	MIT-BIH	CNN and LSTM	Sensitivity, Specificity, Accuracy	Combination of CNN and LSTM is suitable for arrythmia prediction.

10	***Kim et al. (2022) [30]***	MIT-BIH, CinC Challenge	SMOTE and LSTM	Sensitivity, Specificity, Accuracy, F1-score	Class imbalance impacts the classification performance. SMOTE is effective for handling class imbalance to predict arrythmia effectively utilizing LSTM.

3. Research Methodology

This section discusses the research methodology adopted for this work including the research questions, proposed model, and experimental set-up along with the methods.

3.1. Research Questions

In this paper, an enhanced CNN model-HeartNet is developed to effectively predict the arrythmia from ECG recordings with three key features- 1) Resampling and Normalization of data, 2) CNN for feature Extraction, and 3) LSTM for prediction from trained model. To achieve HeartNet Model with high performance matrix, following Research Questions (RQs) are addressed-

RQ#1 Does the proposed model (HeartNet) utilizing resampling methods and LSTM layers, predict the arrythmia effectively from ECG recordings?

This question focuses on the evaluation of the performance of the proposed model empirically. To evaluate the performance, the model is to be developed and the performance is to be recorded on the selected evaluation criteria which are confusion matrix, ROC curve, AUC and Accuracy.

RQ#2 Whether the proposed model (HeartNet) empirically performs better than the base prediction models?

This question deals with the effectiveness of the proposed model in comparison to the base models already available from the literature. To answer this question, three studies from literature are selected (Chen et al. (2020) [29], Cao et al. (2020) [21] and Ferriti et al. (2021) [18]) in order to draw comparison in terms of Accuracy-performance evaluation criteria with that of the proposed model (HeartNet).

RQ#3 Whether a statistical proof exist for the validation of the answers to the above-mentioned research question (RQ#2)?

It is observed that each learning model has its own capabilities and limitations while predicting arrythmia from ECGs. This question is to seek confirmation to the answers to the above stated research question taking into consideration the statistical tools. To answer this question, Friedman Statistical Test is to be conducted to ensure that the proposed model outperforms the selected base models from the literature.

Next, we describe the methodology adopted to find answers to the Research Questions (RQs). First up, the datasets are described along with their characteristics. Then, the proposed model and methods are explained.

3.2 Experimental Set-up

For experimental set-up, Windows™ 10 Pro computer with Intel® Core™ i5-8265U CPU @1.60 GHz 1.80 GHz (64-bit processor) and 8 GB of RAM are used. The proposed experimental design is evaluated by running k-fold cross validation with 10 as the value of k for the replication and randomization purposes.

3.2.1. Datasets Used

The dataset used is a combination of two popular datasets, the first being Physionet's MIT-BIH Arrhythmia Dataset and the second one being the Physionet's PTB Diagnostic Database [31]. The MIT-BIH Arrhythmia Dataset consists of 109446 samples having 5 categories and the sampling frequency of 125Hz. The PTB Diagnostic ECG Database consists of 14552 samples having two categories and a sampling frequency of 125Hz. The overall dataset consists of a series of CSV files. Each of the CSV files consists of a matrix in which the rows represent samples from the dataset. The last element of each row represents the class to which the sample belongs. The signals in the dataset correspond to Electrocardiogram shapes of the heartbeats for arrhythmias as well as for the normal cases. The dataset has the signals pre-processed as well as segmented. In the dataset each of the segments refers to a heartbeat. There are a total of 5 classes in the dataset which are as follows-

Class 1: 'N' -> 0 -> Normal Beats.

Class 2: 'S' -> 1 -> Supraventricular Ectopic beats.

Class 3: 'V' -> 2 -> Ventricular Ectopic beats.

Class 4: 'F' -> 3-> Fusion Beats.

Class 5: 'Q' -> 4 -> Unknown Beats.

The combined dataset has 4 varieties of diseases. The normal and abnormal diseases are shown in Figure 2 and Figure 3.

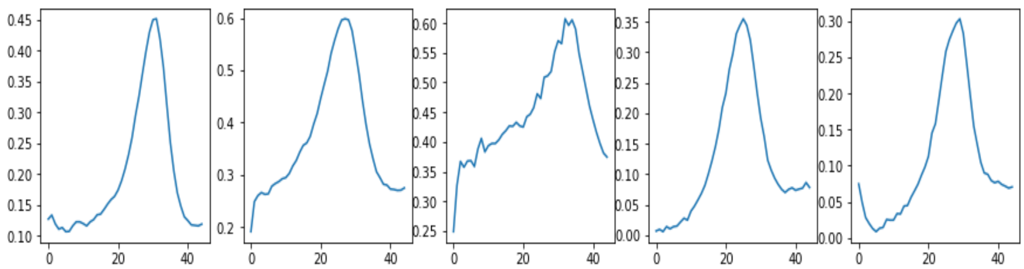

Figure 2. Normal ECG

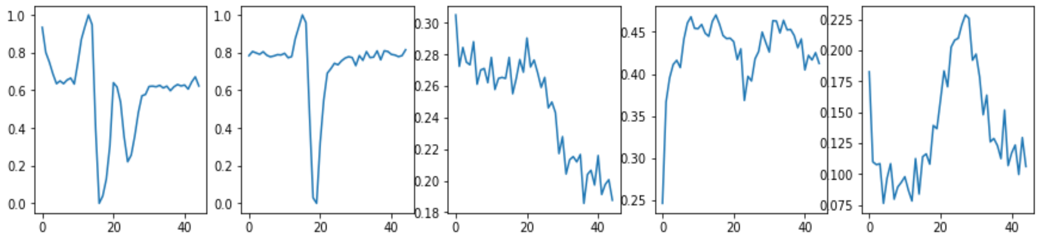

Figure 3. Abnormal ECG

The dataset consists of enough amount of data to train a deep learning model. The dataset is not equally distributed, Normal beats contribute 82.8% of the dataset followed by unknown beats contributing 7.3% followed by Ventricular Ectopic beats contributing 6.6% followed by Supraventricular Ectopic beats contributing 2.5% and lastly Fusion beats contributing 0.7% in the Dataset.

3.2.2. The Proposed Model-HeartNet Model

The arrythmia detection is formulated as a classification problem. The dataset possesses five classes corresponding to the four diseases and one for the normal ECG. Hence, it is 5-class classification problem. The dataset is split in the ratio of 80%-20% for training and testing respectively. The training data is pre-processed with bootstrap resampling and then normalization. The preprocessed data is then fed to the CNN Feature Extractor Block. Later, the LSTM predictor Block makes the predictions which are outputted with SoftMax Layer. The output can be one of the five classes. The predictions are tested against the test bench. The performance of the model is evaluated over the selected criteria namely- ROC, AUC and accuracy. The proposed model is depicted as under Figure 4.

Data Pre-Processing

As there is unequal distribution of data in the dataset, the model could become bias, to remove biasness we used data augmentation using the resampling technique. The resampling was done in a consistent way to handle the class imbalance in the dataset. The data was split into train and test sets with 80% of the data belonging to train set and the rest 20% of the data belonging to the test set. Further, Normalization is done using equation (1) and equation (2)-

$$\mu' = \frac{(\mu - E[\mu])}{\sqrt{var(\mu)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$\mu'' = \gamma \times \mu' + \beta \quad \ldots\ldots\ldots\ldots (2)$$

Where γ *and* β are learned per layer and make sure that batch normalization can learn the identity function and $\mu'$is the new value of the single component.

The Batch Normalization layer in the model ensures that the mean output is close to zero and the standard deviation of the output is close to one.

CNN Feature Extractor Block

The proposed CNN model would generate the prediction results. We applied a one-dimensional CNN model therefore firstly we needed to reshape our data to apply one dimensional CNN model. The model is a sequential model with a plain stack of layers in which each layer has one input and one output tensor. The one-dimensional convolution kernel gets convolved with the input of the layer over a single dimension. The activation

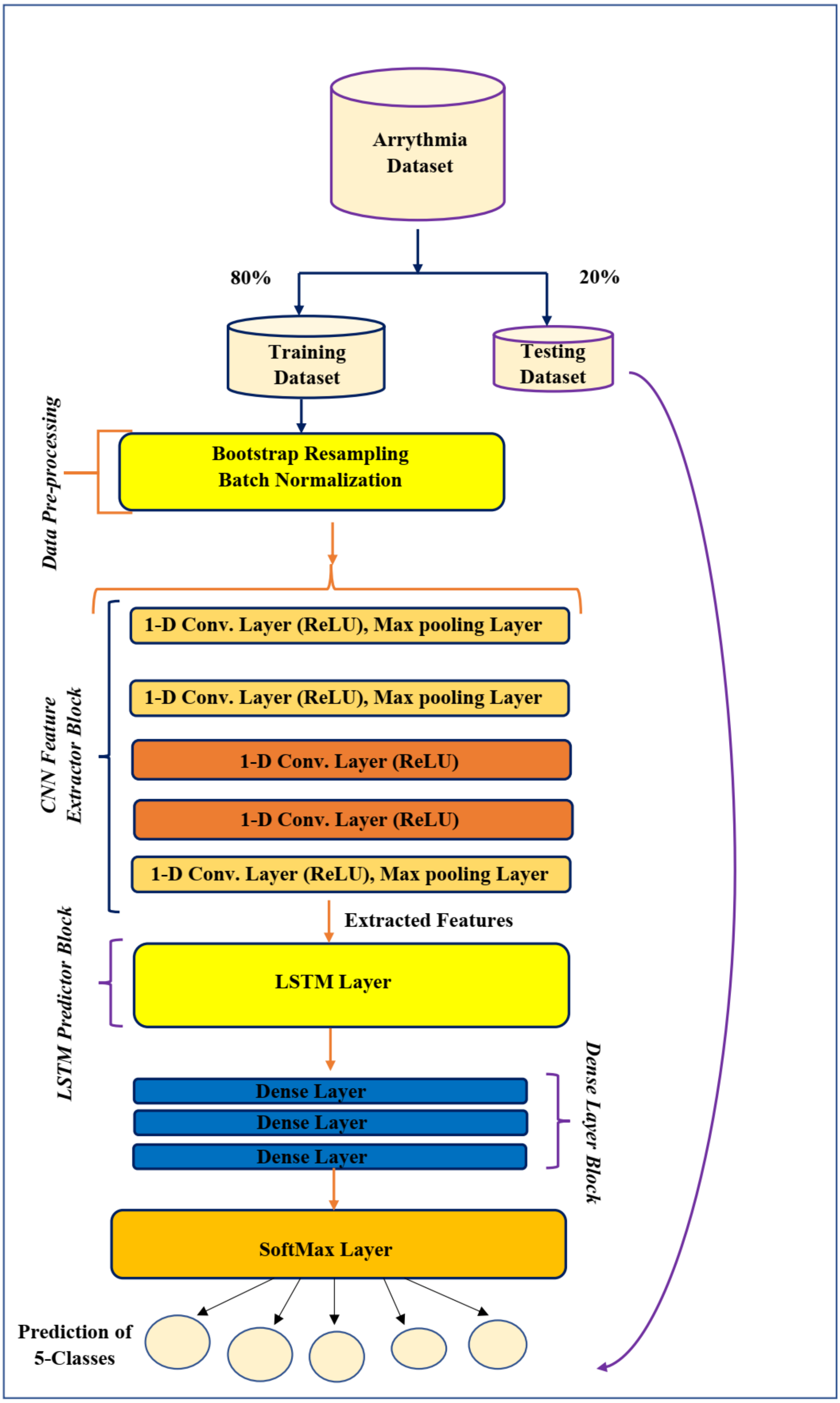

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Figure 4. Proposed HeartNet Model (Enhanced CNN Model) 228

function that is used between the layers is the "relu" or Rectified Linear Unit which returns the element wise maximum of the Input Tensor and zero. The "relu" function returns a tensor that represents the Input Tensor transformed by "relu", the returned Tensor has the same shape and data type as the input. The one-dimensional Max Pooling layer Down samples the inputs by taking the maximum value over the window of the pool size and the window gets shifted by the strides using Equation (3). The valid padding in the Max Pooling layer makes the output shape equal to the difference between the input shape and the pool size divided by the strides. The details of all the Net Layers are tabulated under Table 2.

$$\theta_s = (\lambda_s - \upsilon + 1) / \tau \ldots\ldots\ldots\ldots (3)$$

Where θ_s is the output shape, λ_s is the input shape, υ is the pool size, τ is the number of strides.

Table 2. Details of the Network Layers in Proposed HeartNet Model

LAYERS	TYPE	OUTPUT SHAPE	KERNEL SIZE
1	1D CONVOLUTION	45X96	11
2	1D MAX POOLING	22X96	2
3	1D CONVOLUTION	12X256	11
4	1D MAX POOLING	12X256	1
5	1D CONVOLUTION	10X384	3
6	1D CONVOLUTION	4X384	3
7	1D CONVOLUTION	1X256	3
8	1D MAX POOLING	1X256	1
9	LSTM	256	-
10	FLATTEN	256	-
11	DENSE	4096	-
12	DENSE	1000	-
13	DENSE	5	-

LSTM Predictor Block

The LSTM or Long Short-Term Memory Network is also added to the model. The features that are learned from the Convolution Layers is fed to the LSTM model. LSTM has a cell, a forget gate, an input gate, and an output gate. The cell unit remembers the values at a certain time interval and the rest of the gates are responsible for the management of the flow of information. The dropout layers are added to the model to prevent overfitting on the training data. If overfitting occurs, the model's performance against unseen data gets degraded. Therefore a 40% dropout is added in the model. The mathematical model is given with Equation (4), (5), (6), (7) and (8) as follows-

$$f_g = \alpha_g(\omega_f \times x_t + U_f \times \psi_{t-1} + \beta_f) \ldots\ldots\ldots (4)$$

$$i_g = \alpha_g(\omega_i \times x_t + U_i \times \psi_{t-1} + \beta_i) \ldots\ldots\ldots\ldots(5)$$

$$o_g = \alpha_g(\omega_o \times x_t + U_o \times \psi_{t-1} + \beta_o) \ldots\ldots\ldots\ldots(6)$$

$$c'_g = \alpha_c(\omega_c \times x_t + U_c \times \psi_{t-1} + \beta_c) \ \ldots.(7) \text{ and } \ c_g = f_g \times c_{t-1} + i_g \times c'_g \ldots\ldots (8)$$

Where f_g is the forget gate; i_g is the input gate; o_g is the output gate;

c_g is the cell state; ψ_t is the hidden state;

$\omega_f, \omega_i, \omega_o, \omega_c, U_f, U_i, U_o, U_c$ are weight matrices;

$\beta_f, \beta_i, \beta_o, \beta_c$ are biases.

Dense Layer Block

At the end of the blocks, a dense output layer is added with the activation function of "Softmax". The Softmax function at the output layer is used to predict the multinomial probability. As out dataset has multiple classes softmax is used in this multiclass classification problem of arrythmia detection. The layered view is given as in Figure 5. A sample code to generate the respective blocks is shown as in Figure 6.

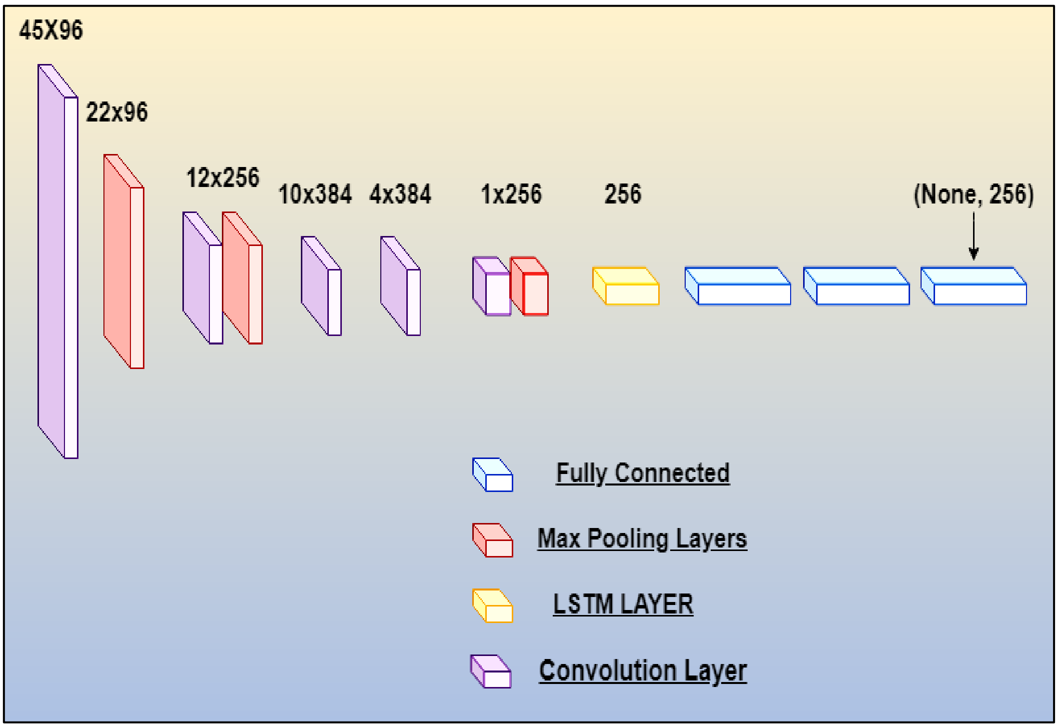

Figure 5. Layered View of Proposed HeartNet Model

```
# (3) Create a sequential model
model_a = Sequential()

# 1st Convolutional Layer
model_a.add(Conv1D(filters=96, input_shape=i_shape, kernel_size=11,\
 strides=4, padding='valid'))
model_a.add(Activation('relu'))
# Pooling
model_a.add(MaxPooling1D(pool_size=2, strides=2, padding='valid'))
# Batch Normalisation before passing it to the next layer
model_a.add(BatchNormalization())

# 2nd Convolutional Layer
model_a.add(Conv1D(filters=256, kernel_size=11, strides=1, padding='val
id'))
model_a.add(Activation('relu'))
# Pooling
model_a.add(MaxPooling1D(pool_size=1, strides=1, padding='valid'))
# Batch Normalisation
model_a.add(BatchNormalization())

# 3rd Convolutional Layer
model_a.add(Conv1D(filters=384, kernel_size=3, strides=1, padding='vali
d'))
model_a.add(Activation('relu'))
# Batch Normalisation
model_a.add(BatchNormalization())
```

Figure 6. Sample Code for Proposed HeartNet Model (in Python)

3.2.3. Evaluation Criteria Used

The performance of proposed HeartNet Model is evaluated using Confusion Matrix [16], ROC [22], AUC [23] and Accuracy measures [18,21,29].

4. Results and Discussion

The experimental results are reported in this section along with the inferences drawn after analysis. This section is dedicated to find the answers to the research questions formulated in Section 3.

#1. *Investigation into the effectiveness of proposed HeartNet Model to predict arrythmia-* ***Finding Answer to RQ1***

We investigate whether the proposed model has enough potential to effectively detect the arrythmia from ECG signals. To answer this RQ, we evaluate the performance of proposed model in terms of confusion matrix, ROC, AUC and Accuracy.

First up, the Confusion Matrix is recorded for all the classes of the dataset as shown in Figure 7. Next, the authors record the accuracy measure from the confusion matric which comes out to be 97.6%.

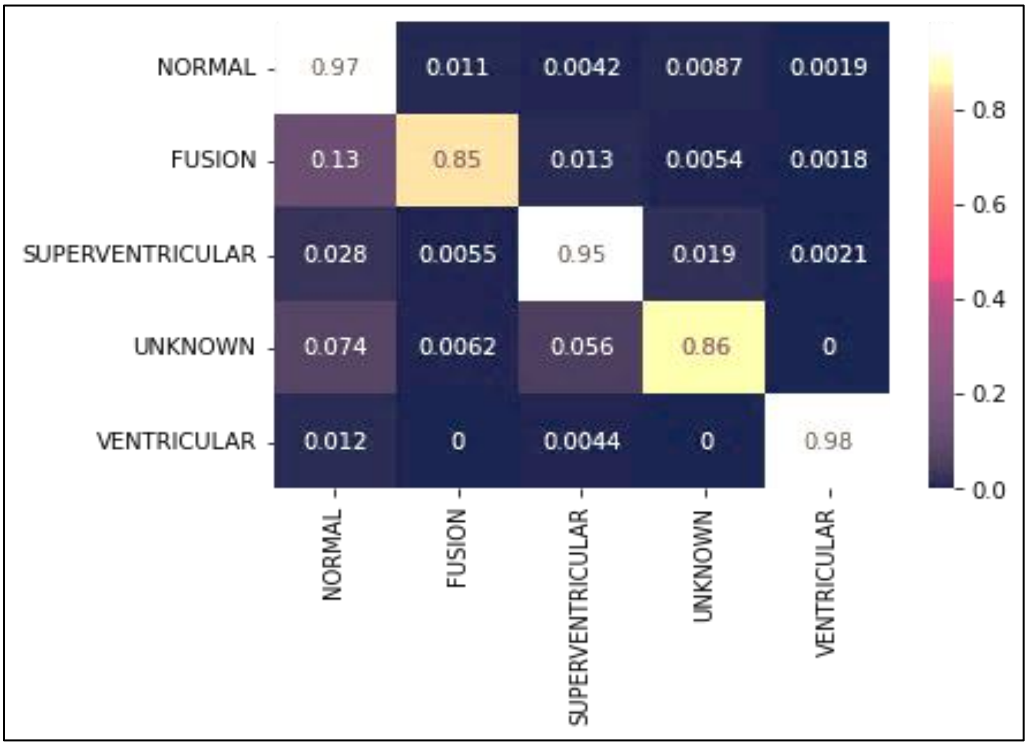

Figure 7. Confusion Matrix for all five classes of the Arrythmia Dataset

Next, ROC is considered for performance evaluation. The corresponding ROC plot is reported as Figure 8. It is observed that ROC curve is very close to top left corner of the unit square. The recorded value of Area Under the ROC Curve is recorded which is 99.6%.

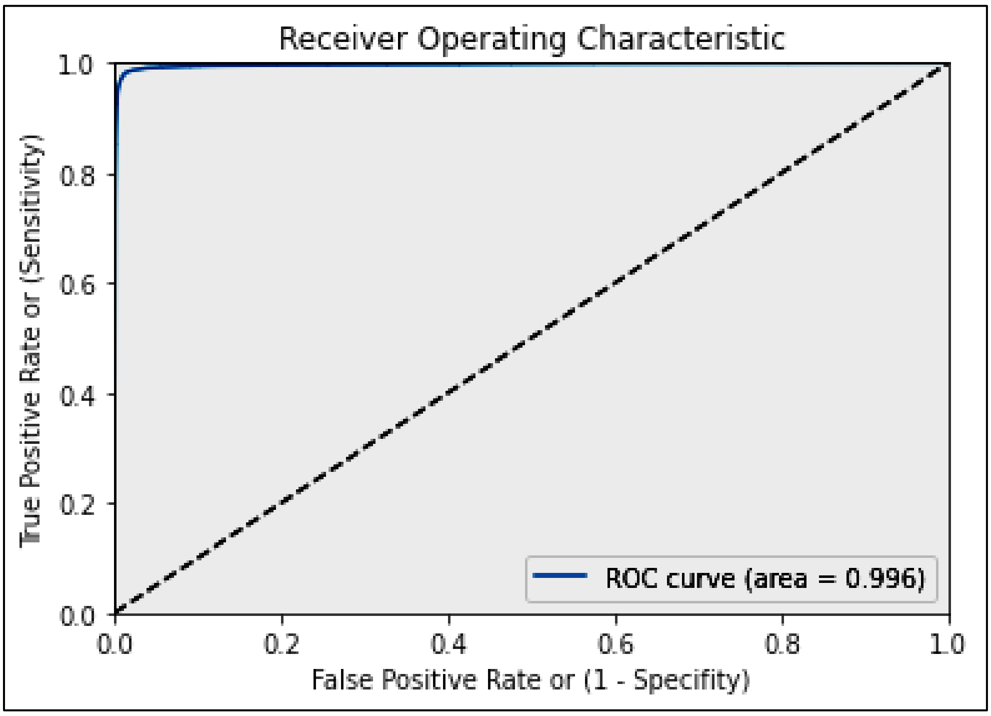

Figure 8. ROC Curve for Proposed HeartNet Model

From the experimental results, it can be inferred that proposed model has significant potential to detect the arrythmia from ECG recordings.

Answer to RQ1- *"Yes, the proposed model (HeartNet) which is enhanced CNN model with extra glued LSTM layer has a significant potential to detect arrythmia from the ECG recordings."*

#2. Comparison of prediction power of proposed HeartNet Model over the selected baseline models to predict arrythmia- ***Finding Answer to RQ2***

It is to investigate into the effectiveness of the proposed model over the baseline models from the literature. To answer this RQ, a comparison is made of the proposed model with the existing models in literature. The three selected studies from literature are Chen et al. (2020) [29], Cao et al. (2020) [21] and Ferriti et al. (2021) [18] to draw comparison in prediction power of the selected baselines with that of the proposed model (HeartNet). For fair comparison, the studies are repeated with the same experimental set-up as mentioned in the selected studies.

First up, the comparison is made over Accuracy criteria and reported as in Table 3. It is observed that the proposed model shows the best performance in terms of Accuracy measure which is highlighted in Table 3 with bold entries.

Table 3. Comparison with the Selected Baseline Models over Accuracy

S. No.	Study	Technique Used	Reported Accuracy (in %)
1	Chen et al. (2020) [29]	CNN and LSTM	95.4%
2	Cao et al. (2020) [21]	LSTM	78.3%
3	Ferriti et al. (2021) [18]	CNN	95.0%
4	**Proposed HeartNet Model**	**CNN and LSTM**	**97.6%**

Next, the ROC curves are recorded, and AUC scores are computed. The ROC curves for all three baseline models and proposed model are plotted as Figure 9 for empirical-comparison. The AUC score for all the models is reported under Table 4. The best value is highlighted with bold entry. It is evident that the proposed model exhibits best performance and covers the largest area under the ROC curve among all the candidate models.

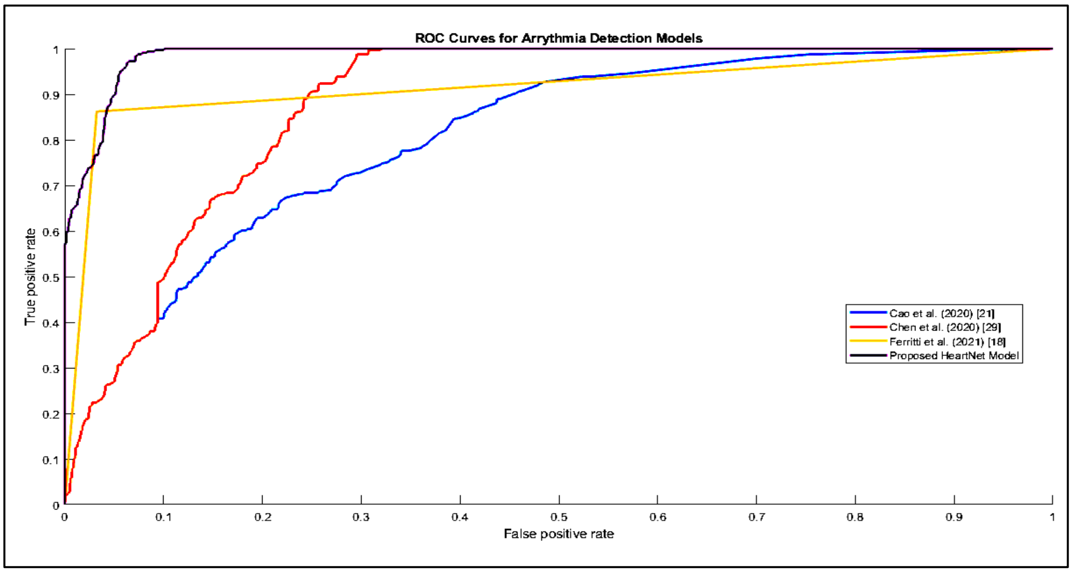

Figure 9. Comparison with Baseline Models over ROC Curve

Table 4. Comparison with the Selected Baseline Models over AUC

S. No.	Study	Technique Used	Reported AUC (in %)
1	Chen et al. (2020) [29]	CNN and LSTM	82.6%
2	Cao et al. (2020) [21]	LSTM	79.5%
3	Ferriti et al. (2021) [18]	CNN	91.8%
4	**Proposed HeartNet Model**	**CNN and LSTM**	**99.6%**

Further, the result for all the models for Accuracy and AUC measure are graphically given as Figure 10. From the experimental results, it is seen that the proposed HeartNet model shows the best values for AUC score and Accuracy measure in comparison to the selected baselines from the literature.

Answer to RQ2- *"Yes, the proposed model (HeartNet) empirically performs better than the selected baseline models for arrythmia prediction."*

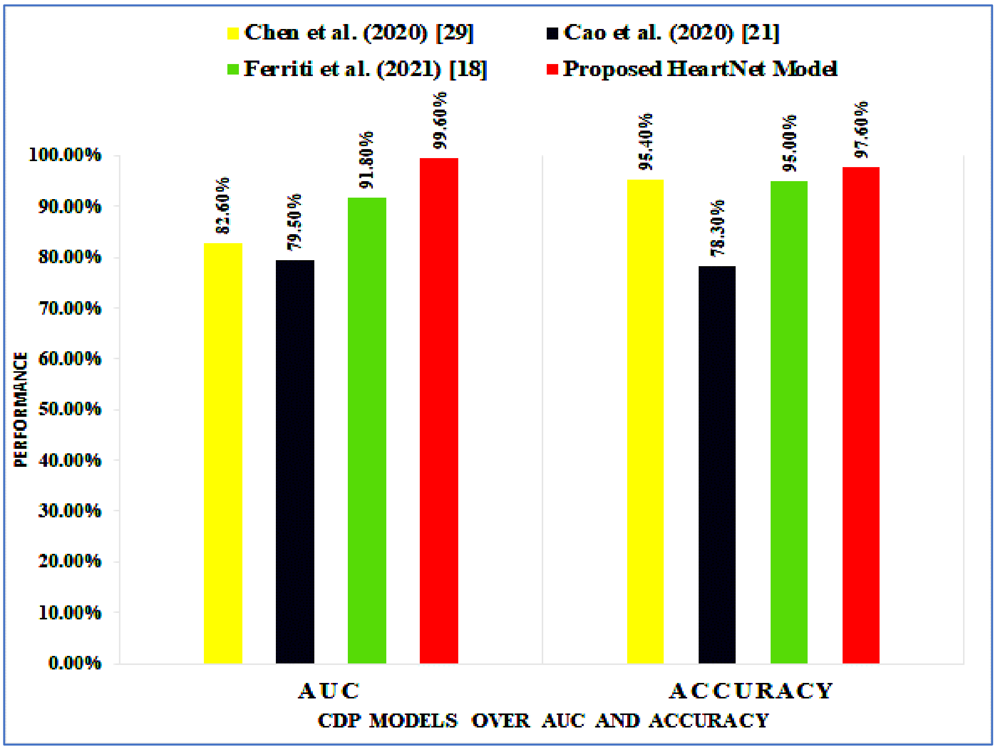

Figure 10. Proposed HeartNet Model Vs Baseline Models

#3. Statistical proof for the work conducted- ***Finding Answer to RQ3***

It is to investigate for the statistical proof for the answer reported for RQ2. To find the statistical proof, Friedman's test is conducted [32]. The result of test reflects upon whether the statistical proof for the RQ2 exists or not. The test is conducted with significance level of 5%. The results show that the value of p-statistic is less than 0.05 (see Figure 11). Hence, it can be statistically validated that proposed HeartNet model is better than selected baseline models.

Friedman's ANOVA Table

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	18.5	3	6.16667	11.1	0.0112
Error	1.5	9	0.16667		
Total	20	15			

Test for column effects after row effects are removed

Figure 11. p-statistic for Friedman Test

Answer to RQ3- *"Yes, the proposed model (HeartNet) is statistically better than the selected baseline models for arrythmia prediction."*

5. Conclusions

This work is dedicated to accurately predict cardiovascular disease. Cardiovascular disease is one of the biggest causes of human death in the entire world. If it is detected well in advance and the patient is fore alarmed, then millions of lives can be saved. It is observed that the classification learning algorithms are prominently being used for detecting Arrhythmia. Arrythmia is unusual and abnormal heart beatings which is alarming condition to predict the heart related issues. ECG signals are analyzed by physicians to diagnose arrythmia. The authors of this work contributed an automated model for arrythmia detection from ECGs. In this paper, a novel CNN based HeartNet model has been proposed and implemented. This model utilizes resampling and batch processing for pre-processing of the dataset. A combination of CNN model and LSTM model has been demonstrated in this enhanced HeartNet model. Further, a comparison is made among the performance of the proposed method and the selected baseline models from the literature. The authors conclude that the proposed HeartNet model performs best for Arrhythmia Disease detection in Humans with the value of 97.6% for Accuracy measure and exhibits the highest AUC score of 99.6%. In future, the authors propose to replicate the work with latest datasets to contribute more accurate Heart Disease Detection.

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Data Availability Statement:

Enquiries about data availability should be directed to the authors.

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