INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD)
© 2026 IJNRD | Volume 11, Issue 6, June 2026 | ISSN: 2456-4184 | IJNRD.ORG

ARRHYTHMIA DETECTION USING ADVANCED DEEP LEARNING

Gundla Shirisha (M.Tech)
Student of Computer Science and Engineering
MGIT Autonomous, TG
Hyderabad, India
gshirisha_pg24csea905@mgit.ac.in

Dr. A. Ratna Raju
Assistant Professor of Computer Science and Engineering
MGIT Autonomous, TG
Hyderabad, India
aratnaraju_cse@mgit.ac.in

Dr. Kadupukotla Satish Kumar
Associate Professor of Computer Science and Engineering
MGIT Autonomous, TG
Hyderabad, India
ksatishkumar_cse@mgit.ac.in

Abstract— **In smart healthcare systems, cardiac arrhythmia monitoring plays a crucial role because undetected irregular heart rates can lead to severe heart issues. Local morphological features, e.g., in ECG signals, or sequential (temporal) relationships can be important. In cases where data is not uniformly distributed among classes, however, common machine learning techniques may not be able to learn these. The article discusses a new method to prompt and instantaneously detect arrhythmias. To classify ECG signals into several classes, we are planning to use ResNet1D and BiLSTM network. The dataset used to create the pipeline had five different types of heartbeats: Normal Beat (N), Ventricular Ectopic Beat (VEB), Supraventricular Ectopic Beat (SVEB), Fusion Beat (F), and Unknown Beat (Q). Preparing the data includes removing records, dealing with missing values using the median, clipping values within the IQR, feature standardization, label encoding, class weighting, and tensor rewriting for sequence learning. To get hierarchical representations of features, the ResNet1D part does the work, and the BiLSTM part takes care of two-way temporal links. Based on the test results, it was seen that the classification is very good with F1 score being 95.49%, AUC-ROC 99.33%, precision 96.84%, recall 94.79% and F1 score 94.79%. That is, it was a successful technology that could detect the arrhythmias.**

“Keywords— Arrhythmia Detection, Electrocardiogram (ECG), Deep Learning, ResNet1D, Bidirectional LSTM, Multiclass Classification, Cardiovascular Diagnosis, Signal Classification.”

I. INTRODUCTION

Cardiovascular diseases are more likely to occur and are the cause of death in people with heart rhythm problems. This is a worldwide health problem. One of these diseases is called arrhythmia. Irregular electrical activity of the heart can affect the speed, timing and pathway of the heart's electrical impulses. If left undiagnosed, arrhythmias may result in sudden events of the heart, heart failure and strokes. ECG: This is a safe, non-invasive test that can reveal heart issues, monitor electrical activity of the heart and is useful to screen the circulatory system.

As more physiological data and standardized ECG records are obtained into computer-aided cardiac diagnostic devices get better. The public ECG databases such as PhysioNet database and the MIT-BIH Arrhythmia Database have facilitated the development of smart systems that can read ECGs [2, 3]. The standard for automated ECG analysis is these databases. The new technologies make it possible to study computer tools that can be used to help find heart patterns that aren't working right.

The most common methods of detecting arrhythmias are the custom signal processing, structural analysis, the reading of the R-R intervals and the feature extraction. In a structured setting, it's easier to identify the QRS complex and to perform statistical ECG analysis. However, they are less effective when patient is changing/recovering from the change, signals are complicated, readings are noisy, or heartbeat distribution is irregular [4, 5, 7]. ML makes classification better by using a decision-making process based on data. But a lot of these methods rest on features and training methods that are unique to the task and domain and are hard to use in other domains and tasks [6, 8].

In many applications such as cardiac analysis, DL has been proven to be effective, and hierarchical representations have been learned from ECG patterns. Nearly as accurately as an expert, modern DNN [9, 10] can classify arrhythmias. Local properties of signals are important, and designs that are based on convolution look good. Smart tools could be key to improving the reliability and efficacy of arrhythmia screening.

So, based on this change, we want to build a different system that will be able to correctly classify the heartbeat pattern from an ECG reading and classify the various patterns. Objectives: Enable automatic detection of other types of arrhythmia and enhance the confidence in the clinical data environment. The main way this is done is by creating and testing a DL classification system that makes automated ECG reading and early detection of heart disease better.

II. RELATED WORK

Since traditional ML, automated arrhythmia identification has come a long way thanks to DL-based ECG interpretation tools. During the last several years, the advancement of signal engineering, feature representation, and the stability of the classification, has improved the multiclass heartbeat analysis. So to guess the ECG signals, DL is required as the temporal pattern and the local morphology of the ECG signals are very unique and difficult to guess by normal methods.

The first is a convolutional structure to automatically extract data for the DL arrhythmia classification. A small number of manual feature engineering allowed DCNN to identify the heartbeat in ECG records [11]. To help the categorization learn how to represent the signal straight from the sequential ECG input, a one-dimensional CNN was made for each patient [12]. This enabled the signals to be processed as they arrived in real-time. These changes demonstrated that there was potential to learn local features as a waveform, therefore not manually labeling them.

This was because more research was conducted, and sequence modeling began to be more prevalent. This enabled them to determine the evolution of the cardiac signal over time. LSTM networks help learn sequential ECG patterns better. They were able to get an average of the heartbeats over time [13]. Recurrent models were combined with the neural feature extractors, to deduce the time. When space and time learning methods were used in convolutional recurrent architectures [14], capsule networks were better at finding arrhythmia when they were used to model structural and sequence information.

In later works, the prediction and analysis of hybrid deep systems have been looked into. It has been found that learning to go forward and backward in time helps people understand ECG rhythms in CNN and BiLSTM designs [15]. This enables an Attention-enhanced BiLSTM model to differentiate between the critical parts of the sequence for attention and to emphasize features related to sorting [16]. In other approaches, automatic representation learning and unsupervised feature extraction were adopted to speed up the pre-processing process and to reduce the instability of the heartbeat [17].

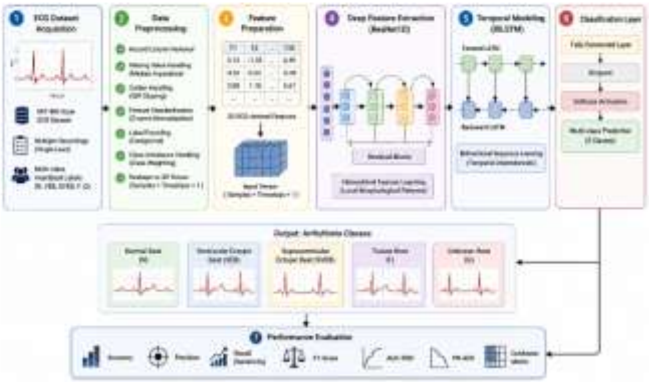
We also explored the concept of converting the ECG into a picture and applying a two dimensional CNN for the detection of arrhythmias [18]. Multi-level learning representations, very deep architectures and feature fusion methods were mixed to improve classification [19]. Multi-channel deep neural approaches were also found to be effective in providing more temporal information for hard time-series classification [20].

Even though these steps forward have been taken, there are still problems with the way things are done now. Typically, pure convolutional models only exhibit local shape and not long-range temporal connections. The "recurrent designs" are harder than the linear "behavior" when they are used to encode hierarchical properties of the signals. Attention-based models and Feature fusion models construct more complex structures, requiring more computer power. If a heartbeat is not evenly distributed it can be difficult to excel in more than one class. Since these parts are hard, a complete system that does not sacrifice accuracy in the classification task is needed, that is, data feature extraction and temporal dependency learning functions should be performed without degradation in accuracy. Hence, a DL-based arrhythmia detection system was proposed to tackle this issue.

III. METHODOLOGY

A. Overall System Workflow

An end-to-end structured workflow guides the suggested arrhythmia detection system as it automatically finds different types of heartbeats from an ECG. The first step in the whole process is to retrieve an ECG data set. After careful preprocessing, the data is made more accurate and is in accordance with the picture. The cleaned data then are put in a file for DL analysis and fed into the recommended classification scheme. The combined use of feature extraction and sequential pattern learning is employed to record the activity of heartbeats as well as the factors that make them occur at different times. The learnt models were then applied to a multi-class forecast so as to discover various types of arrhythmia. Finally, outputs are categorised by means of standard performance measures to check their effectiveness and reliability. The whole system for measuring arrhythmia is depicted in Figure 1.



“Fig. 1 System Architecture”

This is evident from Figure 1. Suggested structure of the steps to be taken: Collect the data set, Pre-process the data, Prepare the features, Deep feature extraction, Learning from time sequences, Multi-class classification. Incorporating a hierarchical representation learning and a sequential dependency modeling made it possible for ECG reading to be done automatically and for arrhythmias to be reliably found in a wide range of heartbeats.

B. Dataset Collection

That you utilize the proposed system to identify the rhythms and an ECG signal set that resembles the MIT-BIH data set. This data set contains structured heartbeat data displayed as a set of numerical characteristics derived from the ECG. This collection has already been partitioned into train and test sets and one heartbeat may have more than one category. There are 100,689 samples in total. Of these, 25,173 are for tests and 75,516 are for work. There are 32 traits obtained from the ECG that describe the shape and length of the heartbeats for each sample. There are 5 types of heartbeats: Normal Beat (N), Ventricular Ectopic Beat (VEB), Supraventricular Ectopic Beat (SVEB), Fusion Beat (F), Unknown Beat (Q). A list of all the features in the whole data set is provided with a breakdown of the distribution of the groups in Table 1.

“Table.1 Dataset Description and Class Distribution”

Parameter	Value
Dataset Type	MIT-BIH Style ECG Dataset
Total Samples	100,689
Training Samples	75,516
Testing Samples	25,173
Number of Features	32 ECG-derived Features
Number of Classes	5
Class Labels	N, VEB, SVEB, F, Q
Normal Beat (N)	67,550
Ventricular Ectopic Beat (VEB)	5,284
Supraventricular Ectopic Beat (SVEB)	2,074
Fusion Beat (F)	596
Unknown Beat (Q)	12

C. Data Preprocessing

We addressed a variety of issues, such as cleaning the data, making it more consistent and removing noise. Next, we were able to prepare the ECG-derived feature space for DL-based well-performing classification. The data was preprocessed by cleaning, handling outliers, normalization of features, re-labeling of the data, creation of tensors, and balancing the classes.

Data Cleaning: First, useless data was discarded to work with incomplete data. The RecordID has been removed from the dataset as it does not assist in grouping the heartbeats, and may cause more difficulties in learning. It was used median imputation to fill in numerical characteristics with values that were missing. The middle value of the feature was used to fill in the blanks for each item that was missing. It was decided that median replacement would be used to ensure the distribution was stable and not too greatly influenced by extreme values.

Outlier Handling: The IQR cutting method was used to get rid of the features that were too far out of the range and make them more stable. This was to prevent the strange facts from having a strong impact. First quartile (Q1) and third quartile (Q3) were used to determine the lower and upper limits. Values that weren't in the right range were rounded up to the next level.

$$IQR = Q_3 - Q_1 \qquad (1)$$

$$Lower = Q_1 - 3(IQR) \qquad (2)$$

$$Upper = Q_3 + 3(IQR) \qquad (3)$$

This approach will preserve some useful variation and reduce the effect of traits having a very high or very low value.

Feature Standardization: The range of traits extracted from the ECG numbers was standardized to make them more uniform and to allow keeping the gradient optimized during training. The range was standardized for each trait to be 1 and the mean was calculated to be 0 in a standard distribution. This is accomplished by the StandardScaler change.

$$Z = \frac{X - \mu}{\sigma} \qquad (4)$$

The original number of the feature is X, the mean is μ and the standard deviation is π. Standardization ensures that all the features are equally weighted, and convergence is improved.

Label Encoding and Tensor Formation: Heartbeat categories were presented as categorical data and needed to be encoded and transformed into categories to be read by computers. The prepared feature matrix was changed into a three-dimensional tensor structure so that it could be used by the DL design after it was encoded. Sequential learning changes the way the samples are laid out, as well as the timesteps and feature channels.

Class Imbalance Handling: Since heartbeats were not spread out evenly across classes, training with classes that were not balanced was thought about. A class ranking method was employed to divert the focus away from heartbeat classes towards classes that do not occur as frequently. The method of assigning weights reduces learning bias and ensures that the optimal answer is delivered for a multi-class prediction task, while leaving the manner of assembling the original data unchanged.

At the end of the preprocessing pipeline, a better and more consistent representation of the input was made. In the proposed heartbeats taxonomy and the extraction of features in a hierarchical manner, this would be applied.

D. Proposed Deep Learning Architecture

We suggest a mixed ResNet1D–BiLSTM architecture that sorts ECG data into different groups to find heart arrhythmias. sequence learning and convolution-based feature extraction are used in the design to figure out the heartbeat pattern's shape and time. Holding a group of unused convolutional blocks to obtain local feature representations again. Finally, two-way temporal models and multiclass prediction are done.

ResNet1D Feature Extraction: To get hierarchical models from ECG feature patterns, ResNet1D is used with one-dimensional convolutional layers. Local heartbeat features are captured by Conv1D and residual links facilitate information and DL movement.

It is written like this to explain the convolution operation:

$$y(t) = \sum x(t - i)\, w(i) + b \qquad (5)$$

This is the term for learning that lasts:

$$H(x) = F(x) + x \qquad (6)$$

with F(x) being the learned map and (x) being information regarding quick routes to things.

BiLSTM Temporal Modeling: The extracted features are passed to a BiLSTM layer which learns the relationship of features on the basis of sequence. The BiLSTM allows for information to be processed in both forward and reverse directions, enabling a better understanding of the heartbeat context.

This is what the LSTM change looks like:

$$h_t = o_t \odot tanh(c_t) \qquad (7)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \qquad (8)$$

where (h_t) refers to "hidden" and (c_t) refers to "cell states.

Classification Head: Lastly, a classification layer with dense layers that are all linked, dropout regularization, and a Softmax activation function for predicting between multiple classes. Dense layers – used to create class-level models, and dropout – for better generalization.

This is the code for softmax classification:

$$P(y_i) = \frac{e^{z_i}}{\sum e^{Z_j}}$$

P(y_i) is the probability of class i. The category for arrhythmia that is forecast is based on how likely it is to happen.

E. Model Training Configuration

The suggested DL model was trained by a technique known as supervised learning in order to discriminate various types of arrhythmia as best as possible. A method called adaptive optimization was used to get stable convergence and make quick changes to the training settings. A fixed split was used in the training process to see how well generalization was working, and callbacks were used to make training more stable and stop training rounds that weren't needed. All the training environment and the hyperparameters that were selected for training the model are pieced together into

“Table.2 Hyperparameter Configuration”

Parameter	Value

Optimizer	Adam
Learning Rate	0.001
Number of Epochs	50
Batch Size	64
Validation Split	15%
Loss Function	Categorical Crossentropy
Early Stopping	Enabled
Reduce Learning Rate	Enabled
Model Checkpoint	Enabled

Selected setup will provide a balanced optimization, better generalization during training, and control of convergence.

F. Performance Evaluation Metrics

A classification and ranking based test was conducted to evaluate the effectiveness of the proposed system for detecting arrhythmias. Several tests were employed to determine the accuracy of the results, the degree of reliability at the class level and the general level of discrimination ability.

Accuracy: The number of correct classifications of heartbeat samples over all guesses is called the accuracy. It indicates the overall accuracy of the model.

$$Accuracy = \frac{\mathrm{TP + TN}}{\mathrm{TP + FP + TN + FN}} \tag{9}$$

“True positive (TP), true negative (TN), false positive (FP) and false negative (FN) are displayed.”

Precision: The aim of precision is to learn what the accuracy of good guesses is and how effective the model is at not making too many mistakes.

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP\ + FP}} \tag{10}$$

Here we demonstrate that the model is capable of learning real good instances and how sensitive the classification is.

Recall: Recall is better; it's easy to pick out abnormal heartbeats.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP\ +\ FN}} \tag{11}$$

Recall is higher and hence abnormal heartbeat groups can be easily identified.

F1-Score: I believe the F1 score will be useful as it takes into account both recall and accuracy.

$$F1\ Score = 2 * \frac{Precision \ \mathrm{X}\ Recall}{Precision\ \ + Recall} \tag{12}$$

This may be helpful if there are different amounts of students in each class.

AUC–ROC: AUC–ROC indicates the performance of the model to distinguish between groups at various decision thresholds.

$$AUC - ROC = \int TPR(FPR)\, d(FPR) \tag{13}$$

As the value increases the difference between the classes is greater.

PR–AUC: The pros/cons of accuracy/memory curve is measured by Area Under the accuracy–memory Curve (PR–AUC).

$$PR - AUC = \int Precision(Recall)\, d(Recall) \tag{14}$$

This measure provides an insight into the non-fair multiclass classification.

These review techniques provide a comprehensive picture of the accuracy, reliability and effectiveness of the device at detecting multiple arrhythmias.

G. Prediction Framework

After training the prediction framework can utilize the parameters it learned from the proposed design to make decisions based upon ECG samples which it has never encountered before. The following steps are exactly the same as what the raw data would undergo prior to being fed into the learned ResNet1D–BiLSTM model. Each type of heartbeat is assigned a chance score using the model by inference. The final output is selected as one that has the highest anticipated probability to be the best. It is possible to classify the data into several groups and easily distinguish Normal Beat (N), VEB, Supraventricular Ectopic Beat (SVEB), Fusion Beat (F), and Unknown Beat (Q) within the framework.

IV. RESULTS AND DISCUSSION

A. Experimental Setup

The suggested arrhythmia detection system was tested in real-life situations by applying a set training and testing portion of the ECG data to verify its ability to classify the data into different groups. A different validation split was adopted to monitor the learning process and ensure that the model is better generalizing in the process of being optimized. Supervised learning was used to train the model. Following the training, tests were administered on samples not seen during the training. The actual labels were contrasted to the expected labels. To obtain a complete understanding of the performance of the classification and reliability of the results, we have used the following measures: Accuracy, Precision, Recall, F1-Score, AUC – ROC, and PR – AUC.

B. Training Performance Analysis

The model suggested is trained in the training history as presented in the picture Fig. The number of epochs were plotted against the error in the model and 3 curves were plotted to show the accuracy and error after the end of each epoch. The quality of training data and test data continued to improve. This demonstrated stability of learning and good generalization. Meanwhile, the training loss gradually decreased and approached unity during the training. The behaviours of learning and evaluating were very similar, and there was no significant difference in the effectiveness of the model. Also, there wasn't a big difference between the learning curves. This means that the optimization wasn't too strong, and the training process was fair.

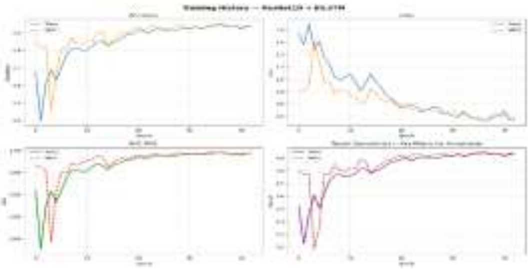


Fig.3 Training History

C. Classification Performance Evaluation

Standard multiclass performance measures were used to verify the performance of the proposed framework of locating arrhythmias in different classes. The accuracy, precision, recall and f1 measures were very good when trying to guess the outcome, at 94.79%, 96.84%, 94.79% and 95.49% respectively. Not only that but the model achieved good results on both the AUC–ROC (99.33%) and the PR–AUC (99.23%). This demonstrates that it did a good job and was not influenced by having an irregularly distributed heartbeats. Based on these results, it looks like the suggested framework learned the typical ECGs and correctly predicted multiclass arrhythmia. The whole numeric review is summed up in Table III.

Table.3 Final Performance Summary

Metric	Value (%)
Accuracy	94.79
Precision	96.84
Recall	94.79
F1-Score	95.49
AUC–ROC	99.33
PR–AUC	99.23

D. Confusion Matrix Analysis

If more than one class forecast is made, there are a larger number of misunderstandings, as illustrated in the grid in Fig. 4, which is a complement to the description above of the suggested arrhythmia detection framework. The model did a good job of classifying by correctly finding most of the heartbeats that fell into each group. There was a lot of agreement between the actual classes and what classes were expected, with the majority of the estimates being made along the main diagonal. Class heartbeats that were close together and didn't have many students didn't seem to cause much uncertainty. The overall distribution of the estimates indicates the reliability of the multiclass learning and the balance in recognition performance. The proposed arrhythmia classification framework by automation has proven to be effective.

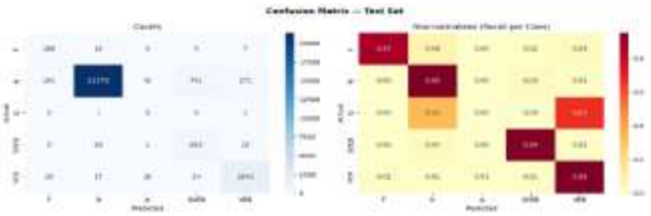


Fig.4 Confusion Matrix

E. ROC and Multiclass Performance Discussion

A receiver operating characteristic (ROC) analysis and a per-class performance evaluation give us more information about how well the suggested framework for arrhythmia detection can tell the difference between the different types of arrhythmia. This is shown in Figure 1. 5. The ROC curves clearly show that the heartbeat groups differ greatly in nature. This implies that separation of the groups can be accomplished at a number of choice levels. The model should be able to continue to make few mistakes and continue to classify things correctly as long as the AUC values are high. Furthermore, the results by class presented in Fig. 6 are consistent and exhibit only minor variations in their performance for different types of heartbeats, leading to only slight differences in their goodness in each class. The data shown here show that the suggested method for finding multiclass arrhythmias works well and can be used in other situations.

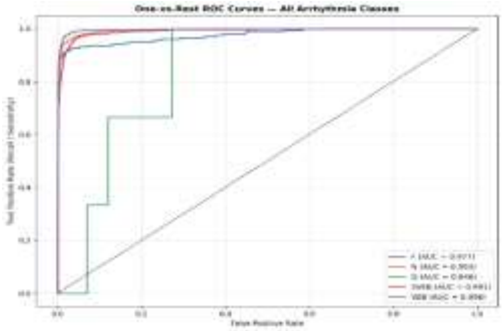


Fig.5 ROC Curves

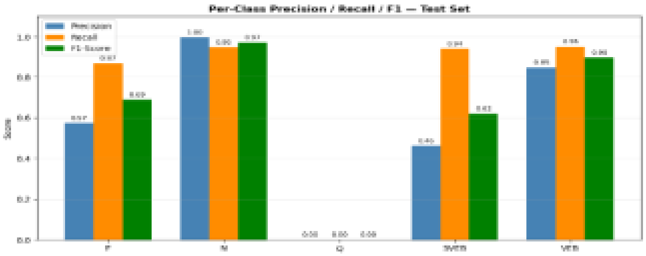


Fig.6 Per-Class Performance Comparison

V. CONCLUSION

With a hybrid DL-based ECG classification into a number of groups, this study suggested an automated way to find arrhythmias. The proposed approach to detect unique features of the heartbeat was feature extraction by ResNet1D. It also used BiLSTM sequence modeling to find the temporal relationships in the ECG data. A well-thought-out preparation pipeline has been established to enhance the data and maintain the learning process. This process made the data clean, removed outliers, standardized, changed labels, and ensured equal length of all the classes. It has been proven to function with various types of heartbeats in an experiment. It was accurate 94.79% of the time, precise 96.84% of the time, remember 94.79% of the time, had an F1-score of 95.49%, an AUC–ROC of 99.33%, and a PR–AUC of 99.23%. We can conclude from these results that it can sort into classes and distinguish between different classes. Another balanced recognition was observed for good generalization performance both from the confusion matrix and from the ROC tests. Furthermore, the outcomes show that the suggested model can help make it possible for computers to automatically find rhythms in ECGs.

The system can be further improved in the future if the system is tested on large ECG databases comprising a large population of patients. This would be more useful in more circumstances. Predictions would be even more helpful and accurate if they studied lightweight architectures, attention-based processes, and real-time deployment methods. Last but not least, combining the arrhythmia screening systems with environments that have continuous ECG monitoring can make them flexible and scalable.

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