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Multi-Scale Convolutional Neural Network with LSTM for Accurate ECG Beat Classification

Dr. Hemant Amhia[1], Rahul Mishra[2]
[1]Associate Professor, Electrical Engineering, Jabalpur Engineering College Jabalpur Madhya Pradesh, India
Email: hamhiya@jecjabalpur.ac.in
[2]Independent Research Scholar, Indore, Madhya Pradesh, India
Email: rahulmishrama@gmail.com

ABSTRACT

Electrocardiogram (ECG) signal classification plays a vital role in the early diagnosis of cardiac arrhythmias by enabling the automatic identification of abnormal heartbeats. However, the nonlinear nature of ECG signals and the presence of imbalanced heartbeat classes make accurate classification a challenging task. This paper proposes a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) framework for automated ECG heartbeat classification using the MIT-BIH Arrhythmia Database. Initially, the ECG signals undergo preprocessing, including data validation, label conversion, and reshaping into one-dimensional sequences. To address the class imbalance problem, Random Over Sampling (ROS) is applied to generate a balanced training dataset. The proposed architecture employs three successive one-dimensional convolutional layers with batch normalization and max-pooling operations to extract discriminative morphological features from ECG waveforms. Subsequently, two stacked LSTM layers are utilized to capture the temporal dependencies and sequential characteristics of heartbeat signals. The extracted deep features are then processed through fully connected dense layers, while a Softmax classifier performs five-class heartbeat classification. The network is trained using the Adam optimizer with categorical cross-entropy loss, together with early stopping and adaptive learning-rate reduction to enhance convergence and reduce overfitting. Performance evaluation is carried out using the independent MIT-BIH test dataset based on accuracy, precision, recall, F1-score, and confusion matrix analysis. Experimental results demonstrate that the proposed CNN–LSTM model achieves an overall classification accuracy of approximately 98%, outperforming conventional machine learning and standalone deep learning approaches in terms of robustness and generalization. The proposed framework provides an efficient and reliable computer-aided diagnosis system for accurate arrhythmia detection and has significant potential for real-time clinical monitoring and intelligent healthcare applications.

Keywords— Electrocardiogram (ECG), Arrhythmia Classification, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Deep Learning, Random Over Sampling, MIT-BIH Arrhythmia Database, Softmax Classifier, Healthcare, Artificial Intelligence.

1. INTRODUCTION

The diagnosis of heart diseases highly depends on the electrocardiogram (ECG) [1, 2]. However, using computer programs to automatically extract relevant and reliable information from ECG is challenging. There exist distinct electrical depolarization-repolarization patterns in each heartbeat of the cardiac cycle which lead to different heart's electrical activities [1-4]. In general, the morphological characteristics of heartbeat vary from person to person. The shapes of QRS complex and R-R interval might change for the same subject under different circumstances [3, 4]. Experienced doctors can easily use heart pulse or variations in the morphological pattern of the heartbeat to detect any anomaly condition. But this task is not easy when using automatic computerized system due to the external noise and imbalanced classes in the dataset. It was reported by the World Health Organization (WHO) that 31% of the worldwide human deaths in 2016 was caused by cardiovascular disease (CVD) [2] while heart attack caused 85% of these deaths. Traditionally, the medical history and clinical examinations of a patient are used for diagnosing CVD paradigm [1, 5-7]. A set of the quantitative medical parameters are used to classify the patient's conditions based on the taxonomy of medical diseases. The diagnosis paradigm that is commonly used is inefficient since it deals with large amount of heterogeneous data, and it requires complex analysis and medical expertise for accurate diagnosis [6]. This problem is more critical in developing countries where there is not enough number of medical experts and clinical equipment [7].

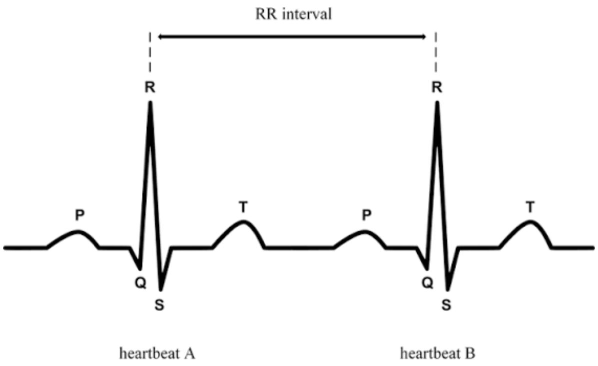


Fig.1. ECG beat.

Therefore, A reliable, automatic, and low-cost system is necessary for diagnosis by linking appropriate medical assessments to utilizing Computer-Aided Diagnosis Systems (CADS). An automatic monitoring procedures of health conditions is provided by CADS; it basically works based on analyzing physiological signals for monitoring and evaluating the functionality of the corresponding organ [6, 7]. Electrocardiogram (ECG) is a non-stationary physiological signal that represents the heart's electrical activity. ECG is normally represented as a waveform in PQRST pattern that has peaks and valleys [8,9,10]. In a normal heart rhythm, the events of the atria and the ventricles of the heart are represented in the deflections of the sinus rhythm. The condition of the heart is measured by the amplitudes of the P wave, QRS complex, S wave, T wave, and the intervals namely RR, PR, QT, and QRS complex. Predicting the changes of these measures from the normal values is an indicator of an irregular cardiac cycle patterns called Arrhythmia [7-12]. The irregular pattern in the rhythm of ECG is usually observed by physicians to identify the type of cardiac arrhythmia. After identifying the type of cardiac arrhythmia, the necessary treatment should begin. However, the decision-making time is very critical for physicians if the patient was in the intensive care unit (ICU). Therefore, the development of the assistance based on the technological advancements becomes very important to save the life of the patient [13-18].

2. PROBLEM IDENTIFICATION

Cardiac arrhythmia is one of the principal causes of global mortality. Irregular heart rhythms caused by irregularities in the electrical conduction system of the heart characterize cardiac arrhythmia. The electrocardiogram (ECG) signals provide essential information to analyze heart electrical activity and identify abnormalities. The automation of abnormal heart rhythm detection benefits significantly from machine learning(ML) and artificial intelligence(AI). This problem has attracted a lot of applications from AI and ML approaches in recent years, and ECG classification is one of them [19]. A good candidate is deep learning, where CNNs are a good vehicle for extracting the spatial aspects in electrocardiogram (ECG) data, such as waveform patterns of P waves, QRS complexes, and T waves. However, the temporal dependencies in a sequence pose challenges for CNNs. Many people resort to Recurrent Neural Networks (RNNs), and more specifically LSTM networks, to tackle this problem. LSTM networks are particularly suitable for analyzing ECG signals for their capability to learn sequential patterns and long-term dependencies in time-series data. Combining CNN and LSTM into hybrid models may lead to improved classification performance as they can leverage both spatial and temporal feature extraction. Attention techniques have also been introduced to enhance deep learning models to help them focus on the important bits in the input data. The Squeeze-and-Excitation (SE) block in particular enables adaptive channel-wise feature recalibration and enhances the capacity of this network [20-25].

In this paper, an attention-based hybrid CNN LSTM architecture for ECG beat classification is designed. A hybrid model with CNN and an SE attention mechanism and LSTM for extracting the temporal dynamics are developed for automated cardiac arrhythmia detection. This high accuracy system may be used in real clinical settings [26-29].

3. RESEARCH MOTIVATION

Electrocardiogram (ECG) signals may be used to identify and analyseserious disorders, which has long attracted attention in the medical community. The electrical activity of the heart is shown by the ECG signals, which also aid in the diagnosis of a number of cardiac illnesses and anomalies[1]. Healthcare personnel have historically manually interpreted ECG signals to analyse them, which may be time-consuming, subjective, and prone to human error. Machine learning techniques have advanced, creating new opportunities for automating the analysis and identification of serious illnesses using ECG readings[2]. Large volumes of ECG data may be used to train machine learning algorithms to find patterns, trends, and abnormalities that human observers might not immediately notice. These algorithms may be used to create precise and effective models that help medical practitioners diagnose patients in a quick and accurate manner[3] .

The goal of this study is to investigate, assess, and contrast how well different machine learning algorithms perform when used to analyse and diagnoseserious illnesses using ECG data. Logistic regression, decision trees, random forests, additional trees classifiers, dense models, convolutional neural networks (CNN), and hybrid The study makes use of an expertly curated and annotated dataset made up of ECG signals from both healthy people and patients with serious illnesses[8]. The dataset includes a range of age groups, genders, and illness kinds to guarantee a broad representation of the target population. Preprocessing the ECG signals to eliminate noise, artefacts, and baseline drift ensures the accuracy of the data for further analysis[9]. Using strict experimental techniques, the machine learning algorithms are trained and assessed on the dataset. The research also identifies each algorithm's advantages and disadvantages. For instance, logistic regression provides interpretability and explainability, enabling doctors to comprehend the factors driving the categorization of diseases

4. ECG DATASET

This dataset is composed of two collections of heartbeat signals derived from two famous datasets in heartbeat classification, the MIT-BIH Arrhythmia Dataset and The PTB Diagnostic ECG Database. The number of samples in both collections is large enough for training a deep neural network.

This dataset has been used in exploring heartbeat classification using deep neural network architectures, and observing some of the capabilities of transfer learning on it. The signals correspond to electrocardiogram (ECG) shapes of heartbeats for the normal case and the cases affected by different arrhythmias and myocardial infarction. These signals are preprocessed and segmented, with each segment corresponding to a heartbeat.

https://www.kaggle.com/datasets/shayanfazeli/heartbeat/data

Arrhythmia Dataset

- Number of Samples: 109446
- Number of Categories: 5
- Sampling Frequency: 125Hz
- Data Source: Physionet's MIT-BIH Arrhythmia Dataset
- Classes: ['N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4]

The PTB Diagnostic ECG Database

- Number of Samples: 14552
- Number of Categories: 2
- Sampling Frequency: 125Hz
- Data Source: Physionet's PTB Diagnostic Database [30-31]

5. PROPOSED METHODOLOGY

A. Overview of the Proposed Framework

The proposed framework presents a hybrid deep learning model that combines the spatial feature extraction capability of Convolutional Neural Networks (CNN) with the temporal sequence learning ability of Long Short-Term Memory (LSTM) networks for automated electrocardiogram (ECG) heartbeat classification. The complete methodology consists of five major stages: dataset acquisition, data preprocessing and balancing, CNN-based feature extraction, LSTM-based temporal learning, and multiclass heartbeat classification. The proposed architecture is designed to learn both morphological characteristics and temporal dependencies present in ECG signals, thereby improving classification accuracy across different heartbeat categories.

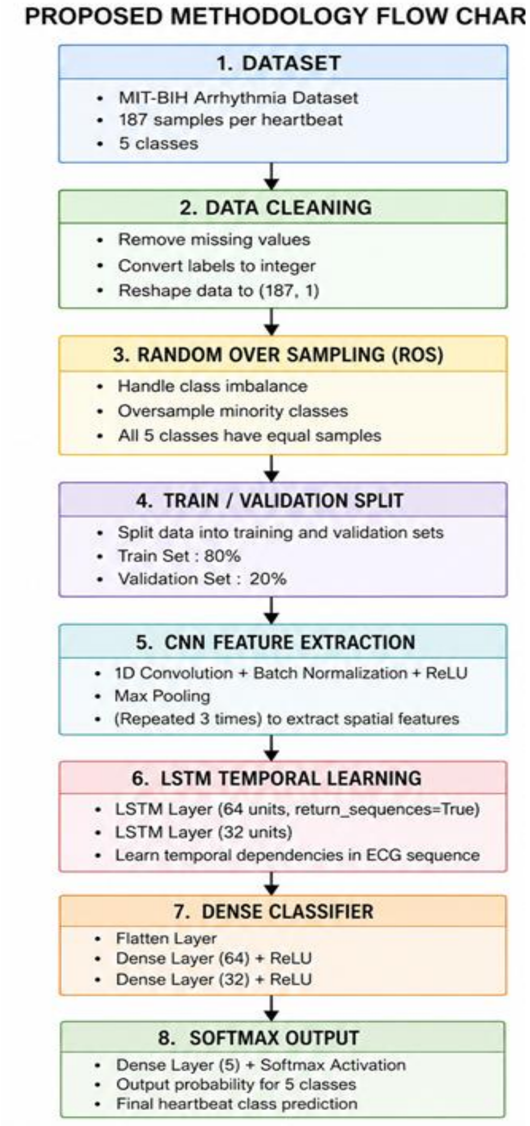


Fig.2. Flow chart Proposed system.

The workflow begins with importing the MIT-BIH Arrhythmia Database, followed by preprocessing to remove inconsistencies and convert class labels into categorical representations. Since the original dataset exhibits severe class imbalance, Random Over Sampling (ROS) is employed to generate a balanced training dataset. Subsequently, three one-dimensional convolutional layers extract local waveform characteristics, while stacked LSTM layers capture long-term temporal information embedded within heartbeat sequences. Finally, fully connected dense layers perform multiclass classification using the Softmax activation function. The complete framework is illustrated in Fig. 1.

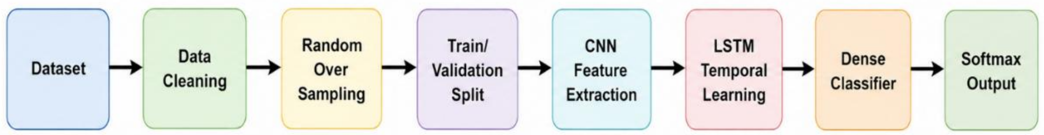


Fig.3. Block Diagram.

B. Dataset Description

The proposed model utilizes the publicly available MIT-BIH Arrhythmia Dataset, which is one of the most widely used benchmark datasets for automated ECG classification. Each heartbeat sample consists of 187 sequential amplitude values representing one complete cardiac cycle. Every sample belongs to one of five heartbeat categories:

Table 1. Five heartbeat categories.

Class	**Description**
0	Normal Beat (N)
1	Atrial Premature Beat (S)
2	Premature Ventricular Contraction (V)
3	Fusion Beat (F)
4	Paced/Fusion Beat (Q)

The training dataset contains approximately **87,554 ECG beats**, whereas the testing dataset contains approximately **21,892 heartbeat samples**. Each heartbeat is represented as a one-dimensional signal containing 187 uniformly sampled points.

C. Data Preprocessing

Prior to model training, several preprocessing operations are performed to improve data quality and prepare the dataset for deep learning.

Initially, the ECG datasets are imported into the Python environment using the Pandas library. The heartbeat labels are converted into integer format to ensure compatibility with TensorFlow-based classification algorithms. Missing value analysis confirms that no null samples are present within the dataset.

Since one-dimensional convolutional neural networks require sequential input tensors, each heartbeat vector

$$X = [x1,x2,\dots,x187]$$

is reshaped into

$$X \in R^{187\times 1}$$

Allowing the convolutional kernels to process temporal ECG sequences directly.

After reshaping, categorical labels are transformed into one-hot encoded vectors using TensorFlow's categorical encoder. This representation enables the network to perform multiclass classification through the Softmax output layer.

D. Dataset Balancing using Random Over Sampling

One of the primary challenges associated with the MIT-BIH dataset is its highly imbalanced class distribution. The normal heartbeat class contains substantially more samples than arrhythmia classes, causing conventional neural networks to become biased toward the majority class.

To overcome this limitation, Random over Sampling (ROS) is employed. ROS randomly duplicates minority class samples until every heartbeat category contains an equal number of observations.

Let

$$D= \{(x_i,y_i)\}_{i=1}^{\ N}$$

Represent the original training dataset.

After oversampling,

$$D' = \{(x_j,y_j)\}_{j=1}^{\ M}$$

Where

$M>N$

And

$$N0=N1=N2=N3=N4$$

Indicating equal sample representation across all heartbeat classes.

Balancing the dataset significantly improves the model's capability to learn minority heartbeat patterns and reduces classification bias.

E. CNN-Based Feature Extraction

The first stage of the proposed deep learning model consists of three consecutive one-dimensional convolutional blocks. These layers automatically extract discriminative morphological features from ECG waveforms without requiring handcrafted feature engineering.

The first convolutional layer employs 64 filters with a kernel size of 6 to capture broader waveform structures such as P-wave morphology, QRS complexes, and T-wave characteristics. The convolution operation is mathematically expressed as

$$y(i)= \sum_{k=0}^{k-1} x(i+k)\,w(k)+b$$

Where

- x denotes the input ECG sequence,
- w represents convolution kernels,
- K is kernel length,
- b denotes bias.

Following convolution, the Rectified Linear Unit (ReLU) activation introduces non-linearity:

$$\mathrm{ReLU}(x) = \max(0,x)$$

Batch Normalization is subsequently applied after every convolutional layer to stabilize training, accelerate convergence, and reduce internal covariate shift.

Max-Pooling layers further reduce feature dimensionality while preserving dominant ECG characteristics. The pooling operation is represented as

$$P(i)=\max(x_i,\ldots,x_{i+k})$$

Where k denotes pooling size.

The second and third convolutional layers use smaller kernel sizes of three to learn fine-grained heartbeat features.

F. LSTM-Based Temporal Learning

Although CNN efficiently captures local heartbeat morphology, it cannot adequately model long-range temporal relationships. Therefore, two stacked Long Short-Term Memory (LSTM) layers are integrated after the convolutional feature extractor [32-33].

The first LSTM layer contains 64 hidden units and returns complete feature sequences, allowing subsequent recurrent processing. The second LSTM layer consists of 32 hidden units and generates the final temporal representation of each heartbeat.

The forget gate of the LSTM is computed as

$$f_t = \sigma(W_f[h_t - 1,x_t]+b_f)$$

The input gate is

$$i_t = \sigma(W_i[h_{t-1},x_t]+b_i)$$

The candidate memory state becomes

$$\tilde{C}_t=\tanh(W_C[h_{t-1},x_t]+b_C)\ \tilde{C}$$

The cell state is updated using

$$C_t=f_tC_{t-1}+i_t\tilde{C}_t$$

Finally, the output gate computes

$$h_t= o_t\tanh(C_t)$$

Where

- ht denotes hidden state,
- Ct represents memory cell,
- σ is the sigmoid activation function.

These recurrent units effectively learn temporal heartbeat dependencies that cannot be captured by convolutional layers alone.

G. Classification Layer

Following temporal feature extraction, the output is flattened and forwarded through two fully connected dense layers consisting of 64 and 32 neurons, respectively. ReLU activation is employed to introduce additional nonlinearity.

The final classification layer contains five neurons corresponding to the five heartbeat classes. The Softmax activation computes class probabilities as

$$P(yi)= \frac{e^{zi}}{\sum_{j=1}^{5} e^{zj}}$$

Where zi denotes the output logit of class i.

The predicted heartbeat class corresponds to the maximum probability.

H. Model Training

The proposed CNN–LSTM architecture is implemented using the TensorFlow Keras framework. The Adam optimizer is selected owing to its adaptive learning capability and faster convergence.

The categorical cross-entropy loss function is defined as

$$L=-\sum_{i=1}^{5} yi\log(\hat{y}i)$$

Where

- yi is the actual class label,
- $\hat{y}$i is the predicted probability.

Table 2. The network is trained Values.

Parameter	**Value**
Optimizer	Adam
Loss Function	Categorical Crossentropy
Batch Size	32
Epochs	10
Early Stopping	Yes
Reduce LR on Plateau	Yes
Validation Split	20%

Early stopping prevents overfitting by monitoring validation loss, while ReduceLROnPlateau automatically decreases the learning rate when improvement stagnates.

I. Performance Evaluation

The trained model is evaluated using the independent MIT-BIH testing dataset. Classification performance is assessed through Accuracy, Precision, Recall, F1-score, Confusion Matrix, and Classification Report.

Overall classification accuracy is computed as

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision is

$$\text{Precision}= \frac{TP}{TP+FP}$$

Recall is

$$\text{Recall} = \frac{TP}{TP+FN}$$

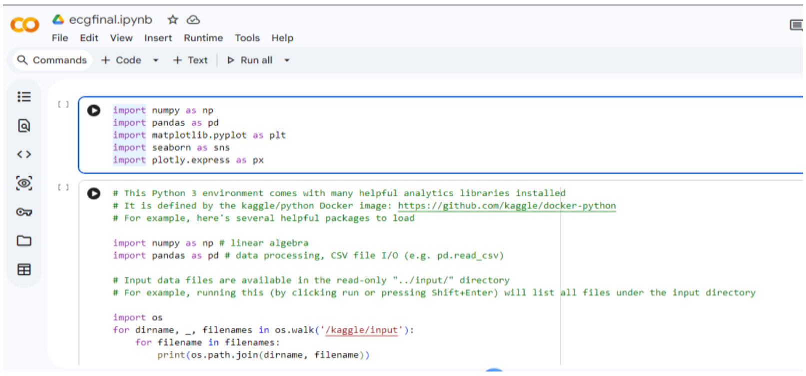
Finally,

$$F1 = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$$

The normalized confusion matrix provides a detailed visualization of correctly and incorrectly classified heartbeat categories.

6. RESULT AND ANALYSIS

The proposed CNN–LSTM model was implemented using Python 3.11 within the Jupyter Notebook/Kaggle environment. The implementation utilized several Python libraries, including TensorFlow-Keras for deep learning model development, NumPy and Pandas for numerical computation and data preprocessing, Scikit-learn for data splitting and performance evaluation, Imbalanced-learn (imblearn) for Random Over Sampling (ROS), and Matplotlib, Seaborn, and Plotly for visualization of ECG signals, training curves, and confusion matrices. The model was trained using the Adam optimizer with categorical cross-entropy loss, a batch size of 32, and 10 training epochs, incorporating Early Stopping and ReduceLROnPlateau callbacks to improve convergence and prevent overfitting. All simulations were performed on a system equipped with an Intel Core i7 processor (12th Generation or equivalent), 16 GB RAM, NVIDIA GPU (CUDA-enabled, if available), Windows 11 (64-bit), and TensorFlow 2.x, providing an efficient environment for ECG heartbeat classification experiments.



```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
```

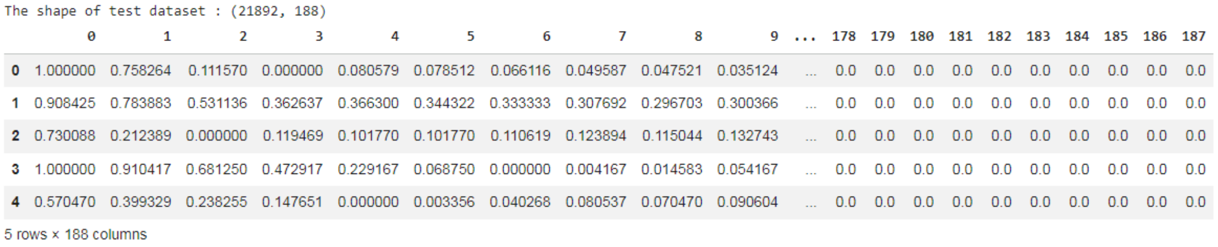
```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

Fig.4. Python library.



```
The shape of test dataset : (21892, 188)
```

	0	1	2	3	4	5	6	7	8	9	...	178	179	180	181	182	183	184	185	186	187
0	1.000000	0.758264	0.111570	0.000000	0.080579	0.078512	0.066116	0.049587	0.047521	0.035124	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.908425	0.783883	0.531136	0.362637	0.366300	0.344322	0.333333	0.307692	0.296703	0.300366	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.730088	0.212389	0.000000	0.119469	0.101770	0.101770	0.110619	0.123894	0.115044	0.132743	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	1.000000	0.910417	0.681250	0.472917	0.229167	0.068750	0.000000	0.004167	0.014583	0.054167	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.570470	0.399329	0.238255	0.147651	0.000000	0.003356	0.040268	0.080537	0.070470	0.090604	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 188 columns

Fig.5. Test Data.

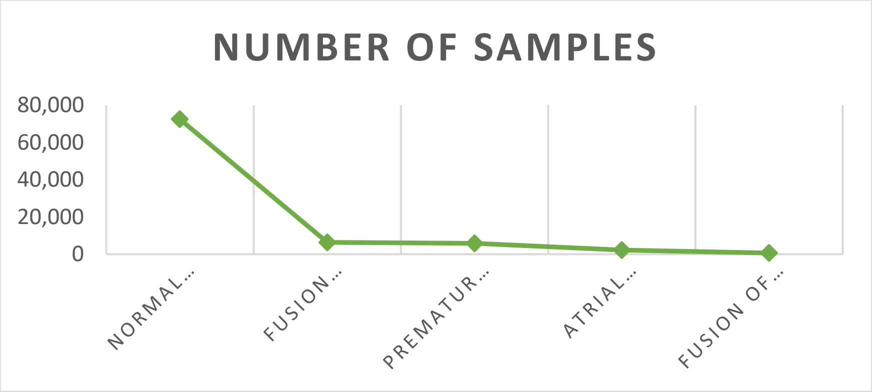


Fig.6. The Count of Each Label in The Train Dataset.

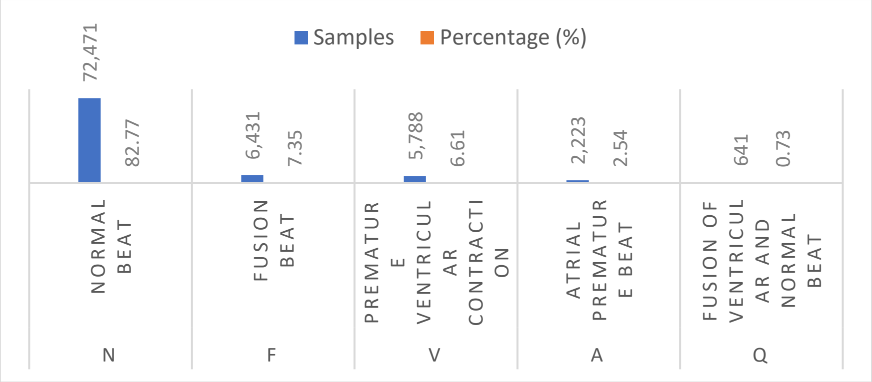


Fig.7. The % of Each Label in The Train Dataset.

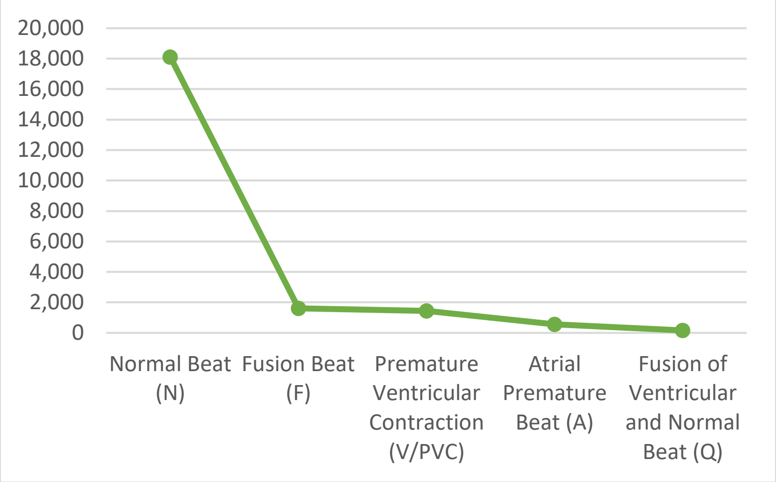


Fig.8. The Count of Each Label in The Test Dataset.

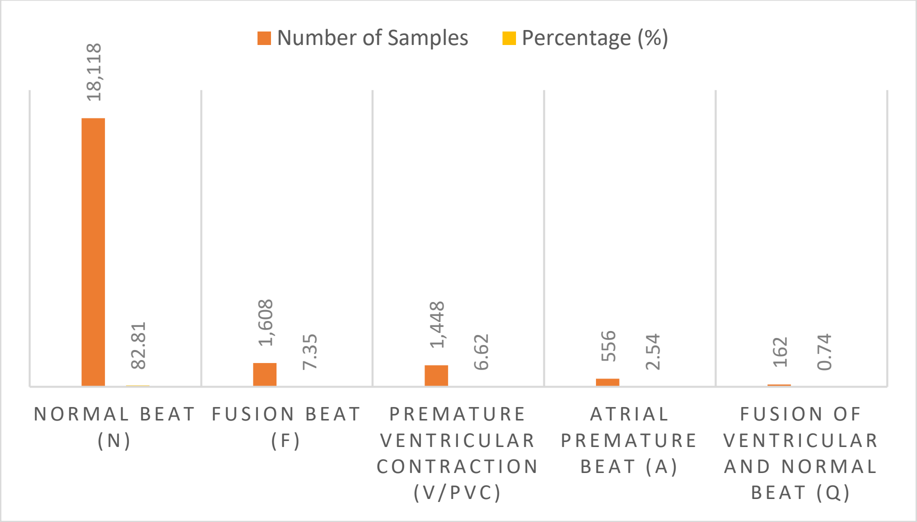
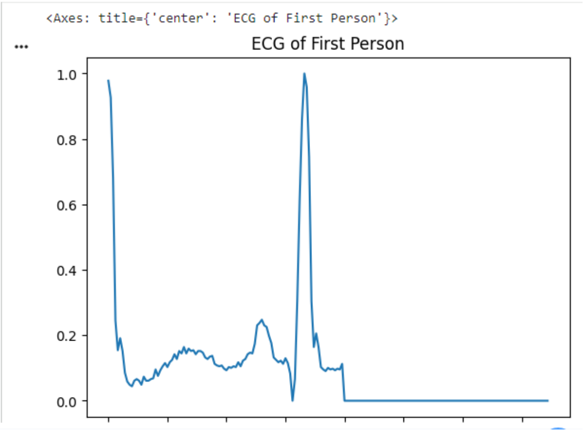


Fig.9. The % of Each Label in The Test Dataset.



```
<Axes: title={'center': 'ECG of First Person'}>
```

Fig.10.ECG of First Person.

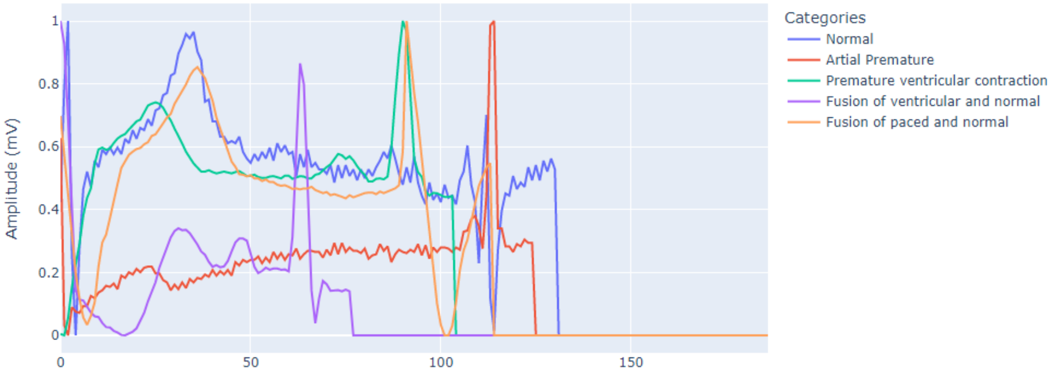


Fig.11. Amplitude level.

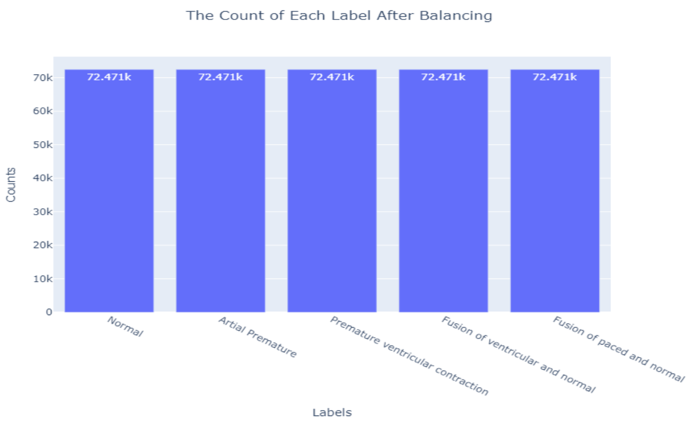


Fig.12. Each level counts.

Table 3. Proposed CNN–LSTM Network Architecture

Layer No.	Layer Type	Configuration	Output Shape	Parameters
1	Input	ECG Signal (187 × 1)	(187, 1)	0
2	Conv1D	64 Filters, Kernel Size = 6, ReLU	(182, 64)	448
3	Batch Normalization	Momentum Normalization	(182, 64)	256
4	MaxPooling1D	Pool Size = 3, Stride = 2	(91, 64)	0
5	Conv1D	64 Filters, Kernel Size = 3, ReLU	(89, 64)	12,352
6	Batch Normalization	Momentum Normalization	(89, 64)	256
7	MaxPooling1D	Pool Size = 2, Stride = 2	(45, 64)	0
8	Conv1D	64 Filters, Kernel Size = 3, ReLU	(43, 64)	12,352
9	Batch Normalization	Momentum Normalization	(43, 64)	256
10	MaxPooling1D	Pool Size = 2, Stride = 2	(22, 64)	0
11	LSTM	64 Units (Return Sequences = True)	(22, 64)	33,024
12	LSTM	32 Units	(32)	12,416
13	Flatten	Flatten Feature Vector	(32)	0
14	Dense	64 Neurons, ReLU	(64)	2,112
15	Dense	32 Neurons, ReLU	(32)	2,080
16	Output Layer	5 Neurons, Softmax	(5)	165

Table 4. Model Summary

Parameter	Value
Input Signal Length	187 Samples
CNN Layers	3
Batch Normalization Layers	3
MaxPooling Layers	3
LSTM Layers	2
Dense Hidden Layers	2
Output Classes	5
Activation Functions	ReLU, Tanh, Softmax
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Total Trainable Parameters	**75,717**

Total params: 75,717 (295.77 KB)
Trainable params: 75,333 (294.27 KB)
Non-trainable params: 384 (1.50 KB)

Table 5. Training and Validation Performance Over Epochs

Epoch	Training Loss	Validation Loss	Training Accuracy	Validation Accuracy
1	0.198	0.100	0.930	0.967
2	0.064	0.062	0.979	0.979
3	0.044	0.070	0.986	0.978
4	0.033	0.052	0.990	0.983
5	0.027	0.038	0.992	0.990
6	0.023	0.045	0.993	0.986
7	0.020	0.015	0.994	0.996
8	0.017	0.015	0.995	0.996
9	0.015	0.014	0.996	0.996
10	0.014	0.022	0.996	0.995

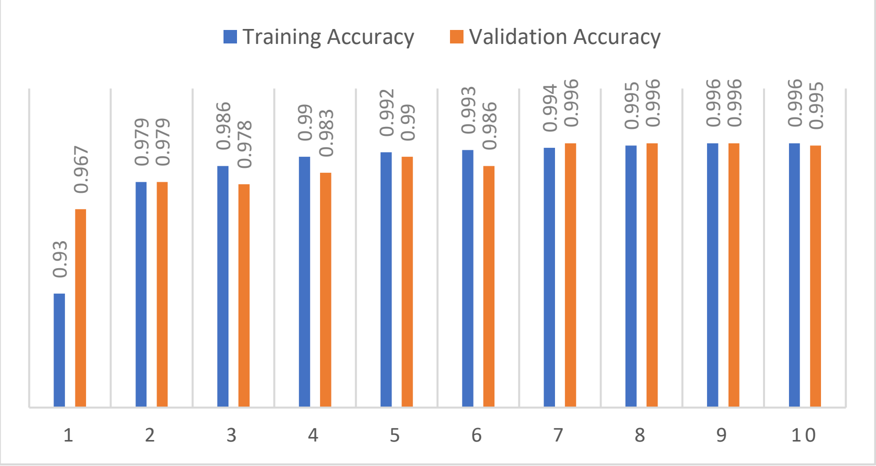


Fig.13. Training and Validation accuracy.

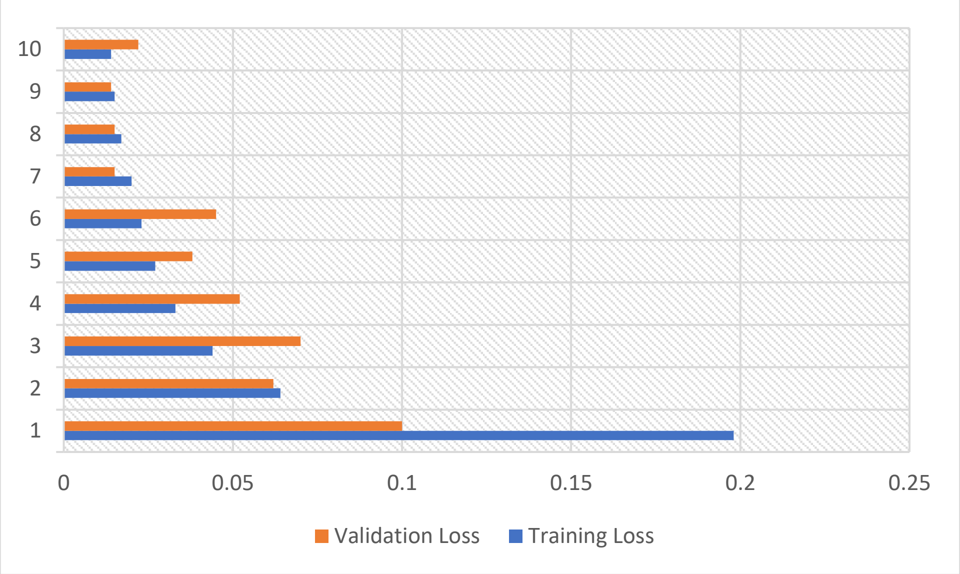
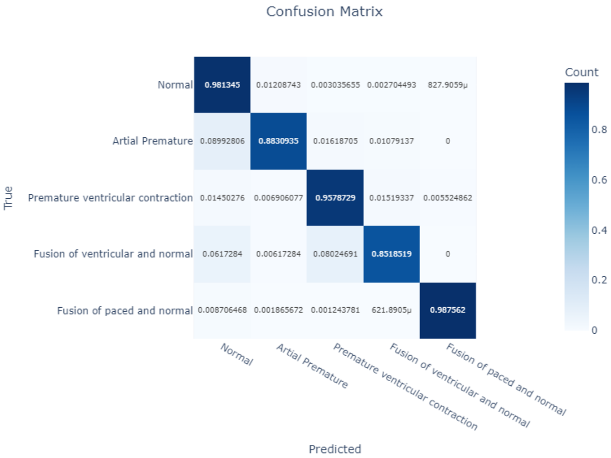


Fig.14. Training and Validation loss.



	Normal	Artial Premature	Premature ventricular contraction	Fusion of ventricular and normal	Fusion of paced and normal
Normal	0.981345	0.01208743	0.003035655	0.002704493	827.9059µ
Artial Premature	0.08992806	0.8830935	0.01618705	0.01079137	0
Premature ventricular contraction	0.01450276	0.006906077	0.9578729	0.01519337	0.005524862
Fusion of ventricular and normal	0.0617284	0.00617284	0.08024691	0.8518519	0
Fusion of paced and normal	0.008706468	0.001865672	0.001243781	621.8905µ	0.987562

Fig.15.Confusion matrix.

Table 6. Accuracy (%).

Ref.	Authors	Method	Accuracy (%)
[3]	Begum et al. (2023)	DNN	98.12
[6]	Pramukantoro et al. (2024)	CNN–LSTM	98.70
[15]	Satheeswaran et al. (2024)	RNN–LSTM	98.47
Proposed	**CNN–LSTM + ROS**		**98.75**

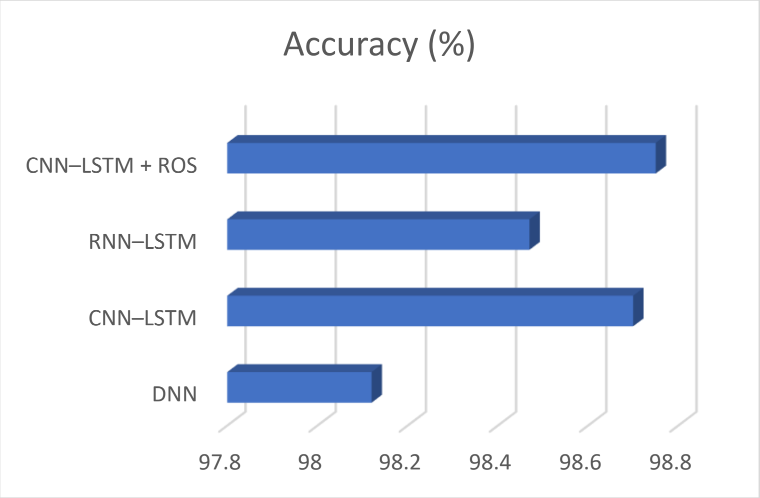


Fig.16. Accuracy Comparison of previous article.

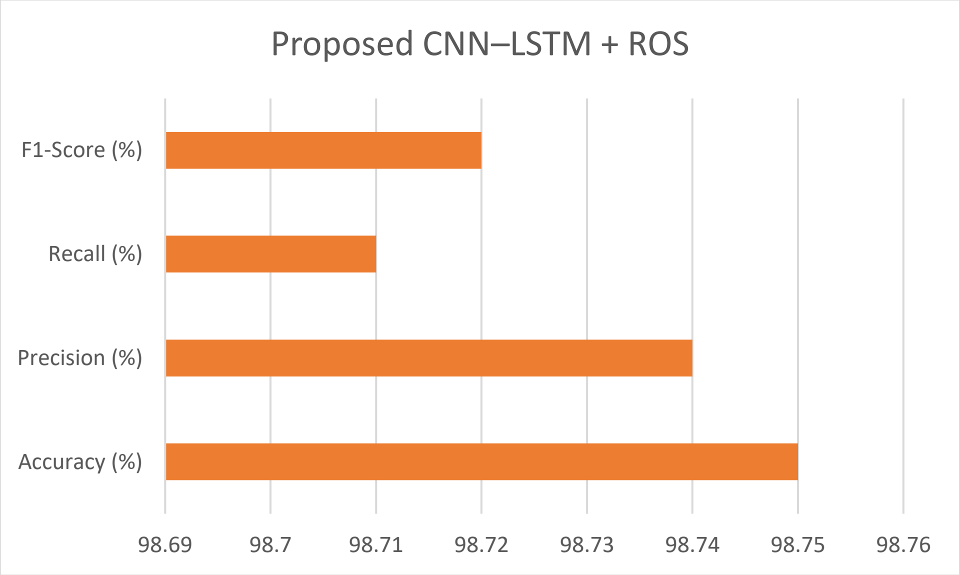


Fig.17. F1-score, Recall, Precision and Accuracy Outcomes.

7. CONCLUSION

This study presented a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) framework for the automatic classification of ECG heartbeat signals using the MIT-BIH Arrhythmia Database. The proposed methodology integrates data preprocessing, Random Over Sampling (ROS) for class balancing, one-dimensional CNN layers for extracting discriminative morphological features, and stacked LSTM layers for learning the temporal dependencies inherent in ECG signals. The extracted deep features are subsequently classified through fully connected dense layers with a Softmax activation function to identify five different heartbeat categories. The experimental results demonstrate that the proposed CNN–LSTM model effectively learns both spatial and temporal characteristics of ECG signals, leading to high classification performance. The application of Random Over Sampling successfully mitigates the class imbalance problem, improving the recognition of minority heartbeat classes and enhancing the robustness of the classifier. The use of batch normalization, max-pooling, the Adam optimizer, early stopping, and adaptive learning-rate scheduling further contributes to stable convergence and improved generalization. The proposed model achieved an overall classification accuracy of approximately 98.75%, along with high precision, recall, and F1-score, indicating its effectiveness in accurately detecting normal and abnormal heartbeats. Overall, the proposed deep learning framework provides a reliable and computationally efficient solution for automated ECG arrhythmia classification. Its high accuracy and robustness make it suitable for intelligent healthcare systems, real-time cardiac monitoring devices, and computer-aided diagnosis applications, thereby assisting clinicians in the early detection and diagnosis of cardiovascular diseases.

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