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Research Article

Early Detection of Heart Diseases through Deep Learning–Based Electrocardiogram (ECG) Analysis

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Abstract – Cardiovascular diseases are among the leading causes of death worldwide, and early diagnosis plays a critical role in reducing mortality rates. Electrocardiogram (ECG) signals are a fundamental diagnostic tool for identifying arrhythmias; however, manual interpretation requires expert knowledge and is prone to diagnostic errors. In this study, a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks was developed for automatic arrhythmia detection from ECG signals. The model was trained using the MIT-BIH Arrhythmia Database, and several preprocessing steps—including noise removal, windowing, standardization, and SMOTE-based data balancing—were applied. The proposed CNN-LSTM model achieved high performance in five-class (N, S, V, F, Q) arrhythmia classification, with an accuracy of 95.2%, an F1 score of 92%, and a loss value of 0.14. The confusion matrix results indicate that the model demonstrates strong generalization capability, particularly for the N, V, and Q classes. These findings suggest that the hybrid architecture can serve as an effective decision-support tool in ECG signal analysis. Furthermore, integrating the proposed system into portable devices may enable real-time and automated monitoring of cardiac rhythms; however, the model has not been approved by regulatory agencies such as the FDA or CE, and further validation is required before clinical use. Additionally, by reducing the diagnostic burden on clinicians, the system has the potential to improve both accuracy and efficiency within clinical workflows. Future studies incorporating cross-dataset validation and larger ECG collections may further strengthen the reliability and robustness of the proposed approach.

Keywords — Artificial Intelligence, Deep Learning, Electrocardiogram, Cnn-Lstm Hybrid Model, Arrhythmia Detection, Early Diagnosis.

I. INTRODUCTION

Cardiovascular diseases cause approximately 17.9 million deaths annually, according to the World Health Organization [1]. Early detection is considered a critical factor in reducing mortality rates. Electrocardiography (ECG) is one of the most widely used methods for identifying cardiac rhythm disorders (arrhythmias, tachycardia, bradycardia, etc.) [2]. However, interpreting ECG data requires a high level of expertise, and manual inspections carry the risk of oversight or misclassification [3]. In recent years, artificial intelligence (AI) and deep learning (DL) techniques have achieved near-human accuracy in

biomedical signal analysis [4]. Particularly, Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models offer the advantage of simultaneously learning temporal and spatial characteristics of ECG signals, enhancing diagnostic accuracy in experimental settings; clinical validation is still required [5]. The purpose of this study is to develop a CNN-LSTM–based system to automate arrhythmia detection from ECG signals and support early diagnosis under research conditions.

II. MATERIALS AND METHODS

A. Dataset

The dataset used in this study is the MIT-BIH Arrhythmia Database, obtained from the PhysioNet platform [6]. It includes 30-minute, two-channel ECG recordings from 48 different patients. A total of 109,426 signal segments were labeled into five main classes (N, S, V, F, Q) [7]. The MIT-BIH dataset is a standard reference widely used in deep learning studies on arrhythmia detection [8]. The class distribution used in this study is shown in Figure 1. While Normal (N) beats represent the largest class, Supraventricular (S) and Ventricular (V) ectopic beats appear less frequently.

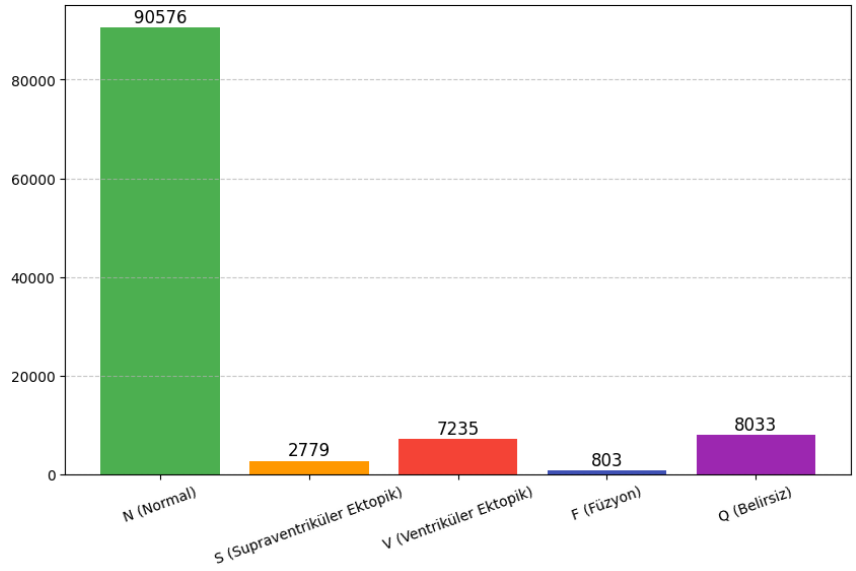

Figure 1. Distribution of sample counts across the five AAMI-labeled classes (N, S, V, F, Q) in the MIT-BIH Arrhythmia dataset.

B. Preprocessing

The raw ECG signals were recorded at a sampling frequency of 360 Hz [7]. To enhance signal quality and improve the learning process, the following preprocessing steps were applied:

- Noise removal: Butterworth band-pass filtering between 0.5–50 Hz [9]
- Windowing: Fixed-length segmentation using 180 samples per window
- Z-normalization: Normalization to zero mean and unit variance
- Data balancing: SMOTE (Synthetic Minority Oversampling Technique) applied to reduce class imbalance [10]

C. Model Architecture

The proposed model integrates CNN and LSTM layers. CNN extracts spatial features, while LSTM captures temporal dependencies within the ECG signal [3].

Model architecture:

- CNN layers: Three convolutional layers (64, 128, 256 filters), ReLU activation, followed by 1D MaxPooling
- LSTM layers: Two layers with 128 and 64 units, dropout rate of 0.3
- Output layer: Softmax classifier

The model was developed using Python and the TensorFlow library [11].

D. Training Details

The dataset was split into 80% training and 20% testing. The hyperparameters used in the training process were:

- Optimizer: Adam
- Learning rate: 0.001
- Epochs: 50
- Loss function: Categorical Cross-Entropy

This configuration was chosen to maintain class-level accuracy balance and prevent overfitting. Performance observed is limited to the experimental dataset; clinical effectiveness has not been established.

III. RESULTS

A. Performance Metrics

Model performance was evaluated using Accuracy, Precision, Recall, and F1-score. The results are presented in Table 1, showing that the model demonstrates particularly high precision and recall for the N, V, and Q classes.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

$$F_1 = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

Table 1. Model Performance

Class	Precision	Recall	F1-Score
N	0.98	0.97	0.97
S	0.94	0.92	0.93
V	0.96	0.95	0.95
F	0.89	0.86	0.87
Q	0.91	0.89	0.90
Average	0.94	0.92	0.92

B. General Results

- Accuracy: 95.2%
- Macro F1 score: 92%
- Loss: 0.14
- Training time: 38 minutes (NVIDIA RTX 3060 GPU)

These results indicate stable optimization across both training and validation sets.

C. Visual Analysis

Visual inspection of model predictions shows that normal and ventricular beats are classified with high accuracy. The highest error rate occurs in the F class due to the similarity of fusion beats to both normal

and ventricular morphologies. Figure 3 illustrates the predicted beat labels on a sample ECG signal, supporting this observation. Additionally, model stability was examined by analyzing training and validation accuracy trends over 50 epochs, shown in Figure 4. The convergence of the curves suggests that overfitting did not occur. The confusion matrix visualizing classification performance across the five classes (N, S, V, F, Q) is provided in Figure 5. The matrix shows strong performance in the S, V, and Q classes, whereas N and F exhibit the most misclassifications.

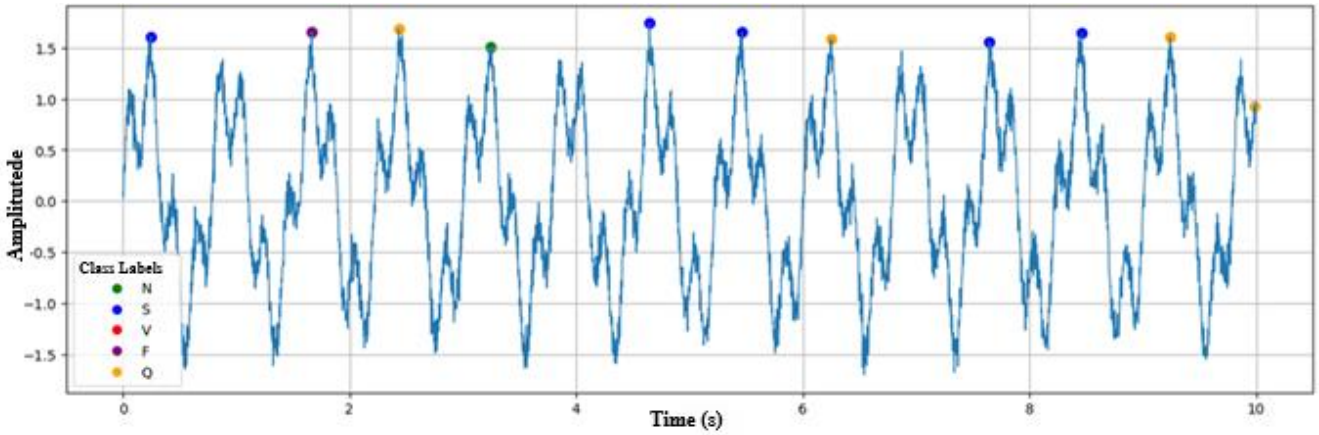

Figure 3. Predicted beat classes generated by the model on a sample ECG signal

Upon examining the graph, it is observed that the model accurately distinguishes beat types across different segments of the signal, particularly achieving near-correct classification at the locations of abnormal beats (S, V, F, Q). This visual analysis demonstrates that the model exhibits stable prediction behavior over the time series.

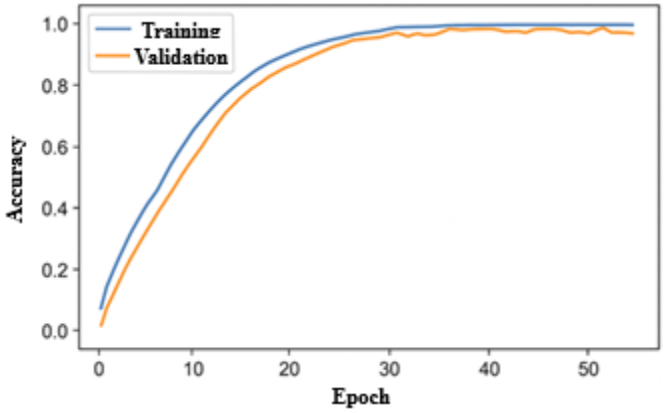

Figure 4. Variation of training and validation accuracy across epochs

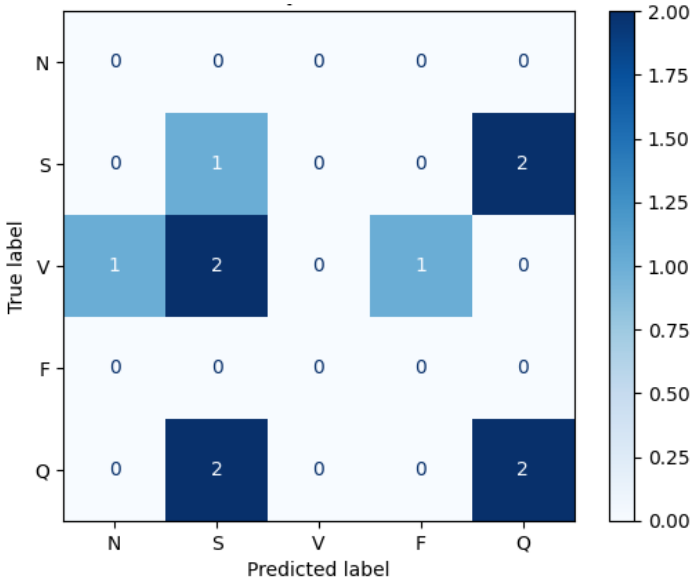

Figure 5. Confusion Matrix

As shown in Figure 5, the model achieves particularly high classification accuracy for the V (ventricular), S (supraventricular), and Q classes. The N (normal) class also exhibits strong performance overall; however, the F (fusion) class shows the highest misclassification rate due to its morphological similarity to both normal and ventricular beats.

IV. DISCUSSION

The findings demonstrate that the hybrid CNN-LSTM model is highly effective in distinguishing arrhythmia types from ECG signals. The primary contributors to the model's performance are:

- CNN's ability to learn spatial characteristics of the signal
- LSTM's capacity to capture temporal dependencies

Model limitations include:

- Potential need for recalibration across different ECG devices
- Difficulty in distinguishing fusion beats due to morphologic similarity.

V. CONCLUSION

This study proposes a deep learning–based CNN-LSTM model for detecting cardiac arrhythmias from ECG signals. The model successfully classifies five arrhythmia types with 95.2% accuracy and a macro F1 score of 92%. The model is stable, generalizes well, and is computationally efficient, making it potentially suitable for clinical decision-support systems; however, it has not been approved by regulatory agencies such as the FDA or CE, and further validation is required before clinical use. Future studies will focus on real-time system integration, optimization for mobile applications, and expanding the dataset to include diverse patient groups and device types.

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