

## DEEP LEARNING AND ENSEMBLE MODELS FOR AUTOMATED ECG ARRHYTHMIA CLASSIFICATION

Khaliq Ahmed<sup>\*1</sup>, Muhammad Ghazanfar Ullah Khan<sup>2</sup>, Kisa e Zehra<sup>3</sup>, Syeda Bushra Shabeeh<sup>4</sup>, Abdul Khaliq<sup>5</sup>

<sup>\*1</sup>Department of Computer Science, Nazeer Hussain University, Karachi, Pakistan

<sup>2</sup>Department of Computer Systems Engineering, UIT University, Karachi, Pakistan

<sup>3,4</sup>Department of Computer Science, Iqra University

<sup>5</sup>Department of Computer Science, Institute of Business Management (IoBM), Karachi, Pakistan

<sup>1</sup>drkhaliq.ahmed@nhu.edu.pk, <sup>2</sup>ghanzafar.ullah@gmail.com, <sup>3</sup>kisa.zehra@iqra.edu.pk, <sup>4</sup>bushra.shabeeh01@iqra.edu.pk, <sup>5</sup>khaliq@iobm.edu.pk

DOI: <https://doi.org/10.5281/zenodo.19064345>

### Keywords

ECG classification, deep learning, convolutional neural networks, BiLSTM, attention mechanism, residual networks, arrhythmia detection.

### Article History

Received: 17 January 2026

Accepted: 02 March 2026

Published: 17 March 2026

Copyright @Author

Corresponding Author: \*

Khaliq Ahmed

### Abstract

Electrocardiography (ECG) serves as the primary diagnostic method which medical professionals utilize to identify heart problems and track cardiac function. The process of reading ECG signals requires extended time from doctors because it involves extensive data analysis which increases the probability of mistakes. The progress of artificial intelligence and deep learning technology has led to the creation of automated systems which can identify cardiac arrhythmias with exceptional precision. This research develops an automated ECG beat classification system which uses deep learning to process ECG signals through hybrid systems that employ convolutional neural networks (CNNs) and bidirectional long short-term memory networks (BiLSTM) and attention mechanisms and residual learning methods. The ECG dataset which the system uses includes four different heartbeat types: Normal (N) and Supraventricular Ectopic Beat (SVEB) and Ventricular Ectopic Beat (VEB) and Fusion Beat. Each heartbeat segment contains 160 normalized signal samples which represent the complete ECG waveform. The dataset creates training and validation and testing sets by using stratified sampling method which ensures equal class distribution across all groups. The research team tested three different deep learning models which they designed to compare with three different systems: ECG-ResNet and CNN-BiLSTM and CNN-BiLSTM with Attention. The research findings prove that hybrid systems achieve superior performance because they successfully capture both the spatial and temporal patterns present in ECG data. The CNN-BiLSTM-Attention model achieved the highest accuracy of approximately 97%, followed by CNN-BiLSTM with about 96%, while ECG-ResNet achieved around 92% accuracy. The assessment of performance used three main metrics which included accuracy and precision and recall.

## 1. Introduction

The heart functions as a crucial organ in the human body because it maintains blood circulation through its extensive network of blood vessels. The heart functions as a biological pump because it continuously provides oxygen and vital nutrients to body tissues while it removes waste products that result from metabolism. The human heart maintains an average daily heartbeat rate of 100,000 beats which produces electrical signals that control how heart muscles move and rest. The electrocardiogram (ECG) serves as a common non-invasive diagnostic tool which medical professionals use to track heart functions through its ability to detect electrical signals. Medical professionals capture ECG signals through electrodes which they attach to the skin to display the heart's electrical activity through three distinct wave patterns which include the P wave the QRS complex and the T wave. The analysis of heart rate variability (HRV) together with the waveform assessment provides essential insights into the heart's physiological state and its operational patterns.

Doctors use ECG signal analysis to detect cardiac arrhythmias which cause abnormal heart rhythms. Arrhythmias occur when the electrical conduction system of the heart fails to maintain a regular rhythm, resulting in irregular, excessively fast, or abnormally slow heartbeats. The medical condition leads to different clinical complications which range from minor symptoms to dangerous conditions such as ventricular fibrillation or ventricular tachycardia. Sudden cardiac death develops from these arrhythmias which lead to sudden cardiac death that establishes a major cause of cardiovascular disease deaths worldwide. The detection process for arrhythmias requires early identification together with precise classification because these factors enable doctors to make correct diagnoses while providing timely treatment.

The sinoatrial node functions as the heart's natural pacemaker which generates cardiac rhythm during normal body functions. The SA node produces electrical signals which travel through the atrial chambers before reaching the ventricular chambers through the atrioventricular

node and His-Purkinje conduction pathway. Normal sinus rhythm can experience disturbances when irregular electrical signals begin to disrupt the regular timing of heartbeats. The heart experiences abnormal contractions that medical professionals identify as premature contractions which they also call ectopic beats or extrasystoles. Premature beats begin from ectopic foci in different heart regions while normal sinus beats start from the SA node [1].

The classification system for premature contractions depends on the specific location where the unusual electrical signal begins. If the ectopic impulse originates above the ventricles, typically in the atria or the atrioventricular node, it is referred to as a Premature Atrial Contraction (PAC) or atrial premature beat. The term Premature Ventricular Contraction (PVC) describes the condition when electrical impulses start at the ventricular area. The two types of premature beats can be identified through examination of the ECG waveform's morphological features.

Premature atrial contractions show abnormal P-wave morphology but maintain a QRS complex which resembles a normal sinus beat. The PAC occurs when the interval between two sinus beats becomes shorter than the time needed for two normal RR intervals. The next sinus beat cannot occur because a PVC is present in the patient. The SA node maintains its usual discharge rate but the electrical signal cannot move to the ventricles because the premature ventricular beat has created a refractory period. The patient experiences a compensatory pause which interrupts the sequence between PVC and the next sinus beat.

Another distinguishing characteristic of PVCs is that they may originate from various locations within the ventricles after the conduction pathway divides into the left and right bundle branches. The ventricular ectopic focus generates its impulse which travels through the heart different from how the normal conduction system operates resulting in a QRS complex that shows both prolonged duration and irregular shape which differs from the pattern of a normal sinus beat. The QRS complex shows two distinct

characteristics because it becomes wider and develops an irregular shape.

Premature atrial contractions demonstrate their detection through two distinct features which include their early occurrence and their creation of an atypical P wave pattern that shows electrical activity started from a distant atrial area rather than the sinus node [1]. The occurrence of PACs during the early stages of the cardiac cycle results in abnormal conduction patterns that show right bundle branch block to happen more often than left bundle branch block. The atrioventricular node will completely block a PAC that occurs at its most extreme early point in time. Doctors can mistakenly identify patients who show these symptoms as having sinoatrial block.

A PAC that occurs during the atrial repolarization vulnerable phase which medics identify as "P on Ta" will create an increased risk for more dangerous heart rhythms which include atrial fibrillation. Atrial bigeminy remains an uncommon condition but it can develop when PACs create multiple episodes of heart rhythm disturbances which make doctors struggle to reach a diagnosis. Patients experience premature atrial contractions with lower frequency than they experience premature ventricular contractions although they encounter these two conditions more often than they encounter supraventricular premature beats that start in the AV junction. Physicians typically find PACs present in most patients who have heart disease but patients who experience frequent PACs show early signs of heart failure which later develops into atrial fibrillation [3].

Studies have shown that more than 80% of deaths among patients with heart failure are associated with cardiovascular diseases [4]. Researchers have discovered that healthy young people show premature atrial contractions in 64% of cases during ambulatory electrocardiographic monitoring using Holter ECG recordings which they conduct without showing any visible symptoms [2].

Medical professionals frequently identify bundle branch block as another conduction abnormality that occurs in electrocardiograms. The condition occurs when electrical signals fail to travel properly

through one of the bundle branches which causes the ventricles to take longer time to complete their depolarization process. Bundle branch block occurs together with multiple heart muscle disorders yet it may also develop in people who have no major heart disease. Large electrocardiographic surveys have shown that many apparently healthy individuals may exhibit bundle branch block without experiencing noticeable symptoms [5].

The detection of arrhythmias through ECG analysis functions as an essential method for diagnosing cardiovascular complications. The process of manually interpreting ECG signals presents difficulties because it requires extensive time to complete especially when working with 24-hour Holter ECG signals. The process of identifying abnormal patterns in waveform data requires cardiologists or trained specialists to examine large volumes of data from these recordings. The classification of arrhythmias becomes difficult for even skilled clinicians because multiple arrhythmias share similar waveform features.

The development of computer-aided diagnosis (CAD) systems helps medical professionals to analyze ECG signals and identify heart problems with greater efficiency which serves as a solution for these challenges. The biomedical research community has focused on automated ECG interpretation systems because these systems enable doctors to detect cardiac arrhythmias during their initial stages. Multiple machine learning methods exist for this task which includes decision trees, random forests, k-nearest neighbors (KNN), hidden Markov models, hyper-box classifiers, optimum-path forest classifiers, and conditional random fields, as well as various other machine learning methods.

Previous studies produced promising outcomes but most existing research uses an intra-patient evaluation approach which enables ECG recordings from one patient to appear in both training and testing datasets. The method produces inaccurate performance results because the classifier detects exclusive patient characteristics instead of common attributes. The reported classification accuracy shows an

excessively positive assessment of performance results.

The inter-patient paradigm was developed by researchers to address this challenge. The method divides ECG data from different patients into separate sets for training and testing purposes. The approach gives better results because it shows actual medical procedures and tests the accuracy of classification systems. The previous research developed an inter-patient separation method which divides patients into two groups based on the AAMI classification standards for training and testing purposes.

Multiple research studies have successfully implemented this inter-patient evaluation approach which generated positive results for ECG classification studies according to references 24 to 27. The inter-patient framework has been used by researchers to investigate AAMI-based classes and non-AAMI classes which include Normal Beat (NOR) and Left Bundle Branch Block Beat (LBBB) and Right Bundle Branch Block Beat (RBBB) as well as Premature Atrial Contraction (PAC) and Premature Ventricular Contraction (PVC) according to references 22 and 28.

The study introduced a classification method that used three different classifiers to produce results through majority voting which successfully classified three different heartbeat patterns which were Normal and LBBB and RBBB. The system used a weighted Linear Discriminant Analysis (LDA) classifier to separate NOR from RBBB and a weighted Support Vector Machine (SVM) classifier to separate LBBB from NOR and a Minimum Distance Classifier (MDC) for LBBB and NOR classification. The method showed good results when testing individual classes but failed to perform well in tests that required simultaneous classification of all classes.

Researchers have tested different machine learning models to classify ECG signals through their investigations. Some studies developed feature extraction methods that utilize empirical mode decomposition and variational mode decomposition together with decision tree algorithms [29]. The researchers used time-domain and frequency-domain features to develop ECG

classification models that employed random forest classifiers [8]. The methods show useful results but they require substantial computational resources to operate.

The research study demonstrates better results for minority arrhythmia types which include SVEB and VEB when compared to standard classifiers through the use of weighted conditional random fields for arrhythmia classification. The researchers conducted their investigation using k-nearest neighbor classifiers which analyzed different heartbeat feature representations between two different studies. The researchers developed support vector machine classifiers which used generalized discrimination analysis-based feature selection to process heart rate variability features extracted from RR intervals in ECG signals according to their study.

The traditional machine learning methods which have shown positive results require expert knowledge because they depend on manually created features. Biomedical signal processing has seen a rise in deep learning techniques because these methods can automatically extract multiple levels of features from unprocessed data. The methods require no manual feature extraction because they have shown better results than traditional ECG classification methods. In this research, we develop a comprehensive deep learning framework for ECG arrhythmia classification using multiple architectures, including:

- Residual CNN (ECG-ResNet)
- CNN-BiLSTM hybrid network
- CNN-BiLSTM with Attention mechanism

These models are trained and evaluated on a balanced ECG dataset containing four heartbeat categories. The objective of this study is to analyze the effectiveness of hybrid deep learning architectures for ECG classification and identify the most accurate model for automated arrhythmia detection.

**The main contributions of this work include:**

1. Implementation of multiple deep learning architectures for ECG classification.
2. Development of a hybrid CNN-BiLSTM-Attention model for improved feature learning.

3. Comparative evaluation of residual networks and hybrid sequence models.
4. Comprehensive performance analysis using multiple evaluation metrics.

The remainder of this paper is organized as follows. Section 2 reviews related work in ECG classification. Section 3 describes the dataset and preprocessing methods. Section 4 explains the proposed methodology and deep learning architectures. Section 5 presents experimental results and analysis. Section 6 discusses the findings and implications. Finally, Section 7 concludes the study and outlines future research directions.

## 2. Literature Review

Automated classification of ECG data is an active area of research within biomedical signal processing. Most researchers collected data for these studies using conventional machine learning methodologies, whereby researchers specify the features they will extract (i.e., shape features) based upon initial data analysis (i.e., extracting HRV, QRS durations, and wave amplitude). Heartbeat classification was accomplished using these extracted features along with support vector machines (SVMs), k-nearest neighbors (KNNs), and decision tree algorithms. The overall accuracies of these methods were relatively low as they were highly dependent upon how well researchers combined different types of feature data generated by manual processes. The increasing development of deep learning technology and the fact that researchers began to utilize neural networks for heartbeat classification, particularly with the introduction of convolutional neural networks (CNNs) for automated feature extraction of frequency based or "raw" signals, has placed CNNs as a preferred methodology for automated (arrhythmic) heartbeat classification as they have demonstrated the ability to "learn" from the waveform patterns of the ECG signal directly.

Recent studies have explored the use of hybrid models consisting of CNNs and RNNs to develop new architectures. The LSTM and BiLSTM are powerful constructs for analyzing ECG signals and offer a unique way to accomplish this. While the

CNN component extracts spatial features from the data, the LSTM portion studies the temporal relationships between heartbeats through an analysis of each individual ECG signal.

Attention mechanisms are an important part of any deep learning system's ability to produce the best classification output. By allowing a network to focus on those segments of input data that contain critical information about the desired result, attention mechanisms are helping to improve the classification capabilities of ECG signal-classification networks. ECG signal-classification networks are also utilizing attention mechanisms to determine the important waveform components of an ECG signal, such as QRS complexes, and to highlight any abnormality in the ECG waveform.

Researchers are also utilizing residual networks as the basis of their research on biomedical signal processing. Skip connections in a residual network allow developers to create deep networks while still being able to achieve training stability throughout training.

## 3. Dataset Description

The research utilized a dataset which includes processed ECG heartbeat segments that are saved in CSV format. The ECG record consists of a heartbeat waveform that contains 160 signal samples which measure the heart's electrical activity throughout one complete cardiac cycle.

The dataset contains four heartbeat classes:

1. Normal Beat (N)
2. Supraventricular Ectopic Beat (SVEB)
3. Ventricular Ectopic Beat (VEB)
4. Fusion Beat

The dataset contains one ECG heartbeat record for each row which contains:

- The first 160 columns represent normalized ECG signal values
- The final column represents the class label

The dataset required augmentation because its existing sample distribution needed to match equal class sample sizes in order to achieve balanced learning. This prevents bias toward dominant classes during model training.

The dataset was divided into three subsets:

- Training set (70%) – used to train the models
- Validation set (15%) – used to tune hyperparameters
- Test set (15%) – used to evaluate final model performance

Stratified sampling was used to maintain equal class distribution across all subsets.

#### 4. Proposed Methodology

The framework consists of multiple stages and processes, which have been established to ensure that the deep learning models used for classifying ECG signals are accurate and reliable. The stages consist of the loading and pre-processing of the data, the splitting of the dataset, the design of the model architecture, the training and optimisation of the model, and the evaluation of the performance. Because these stages create a trustworthy automated classification system, they are essential in ensuring that the system performs efficiently.

The two first steps of this process are to load and process the data; during this step the ECG dataset will be imported from a stored file format and will be prepared to undergo analysis. The measured signals are numerical representations of how electrical impulses pass through the heart (how the

heart contracts) at each heartbeat. Prior to training the deep learning model with the ECG signals, the signals have to be evaluated to ensure their quality and reliability. The ECG signal values have to be normalised to produce the same number scale as each other, as all of the input features have to fit within the same range. The purpose of normalising the ECG signal data is to improve the stability of training as well as to reduce any one feature from having a greater influence on the training process than any other. Once the ECG signals have been normalised, they will be converted to tensor format for importation into the deep learning framework.

Dataset splitting is the second stage of the approach, whereby the entire dataset is divided into training, validation, and testing subsets. The purpose of this step is to assess how well the models generalize. The training dataset is used for learning model parameters and the validation dataset is used to evaluate the model's performance throughout the training process in order to fine-tune hyperparameters. Once training has been completed, the testing dataset will be used to determine how well the model performs on new data. An overview of the methodology is illustrated in figure

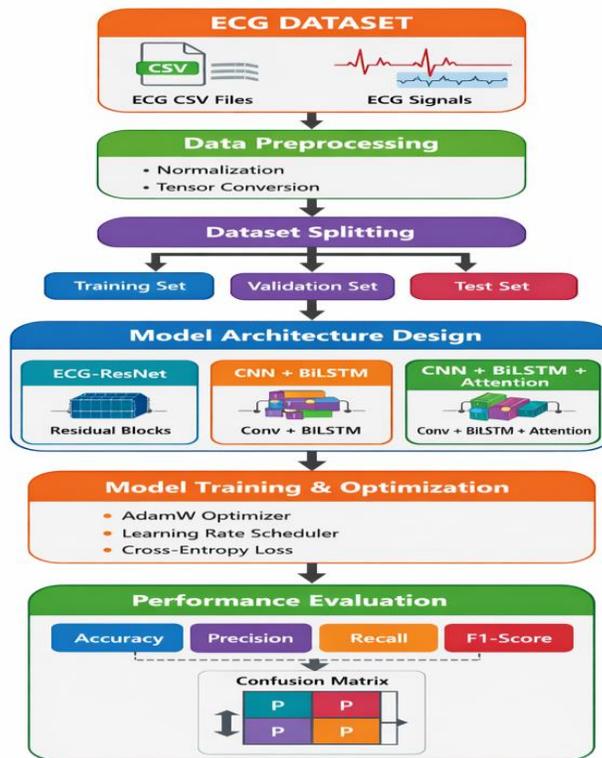


Figure 1: overall methodology

The third stage focuses on model architecture design. The research develops multiple deep learning architectures which include residual convolutional networks and hybrid CNN-BiLSTM models. The ECG signals function as one-dimensional time series data which requires 1D convolutional layers to extract automatic waveform features that include peaks and intervals and signal patterns. The fourth stage involves model training and optimization, where the networks learn patterns from the ECG data using optimization algorithms. The performance evaluation stage uses accuracy and precision together with recall and F1-score metrics to measure model effectiveness in order to determine which architecture performs best.

#### 4.1 ECG-ResNet Architecture

The ECG-ResNet model used in this research is based on the concept of residual learning which

was originally introduced to address the challenges that researchers encounter when they try to train very deep neural networks. Traditional deep convolutional networks experience performance degradation and slow convergence and vanishing gradients when their layer count increases. The introduction of skip connections in residual networks enables information to bypass particular network layers and reach the deeper sections of the network. The system preserves vital features while it enables efficient gradient transfer during backpropagation through its operational mechanism.

The ECG-ResNet architecture functions as a dedicated system for processing one-dimensional ECG signals. The model uses 1D convolutional layers because ECG recordings represent time-series signals instead of image data which would require 2D convolutional layers. The layers can identify local signal patterns which include peaks

and slopes and intervals that match crucial ECG elements like the P wave and QRS complex and T wave.

The architecture begins with an initial convolutional layer that processes the input ECG signal and extracts basic waveform features. The network structure includes several residual blocks that follow this initial layer. The structure of each residual block includes multiple convolutional layers together with batch normalization layers and activation functions. The network uses skip connections to combine the output from these layers with the original input, which enables the network to learn residual mappings instead of direct feature transformations.

The learning process achieves greater stability through the implementation of batch normalization. The system normalizes convolutional layer outputs to decrease internal covariate shift, which results in faster training times. The model uses ReLU activation functions to create non-linear boundaries, which helps it understand complex ECG signal patterns.

The architecture of the ECG-ResNet model includes the following main components:

- Four residual convolutional blocks for hierarchical feature extraction
- Batch normalization layers for training stability and faster convergence
- Adaptive average pooling layers to reduce feature dimensionality
- A fully connected classification layer for final prediction

The adaptive average pooling layer reduces the spatial dimension of feature maps while preserving the most important learned representations. The model receives this step because it needs to manage different input sizes and extract features which will be used in the final classification process. The last fully connected layer transforms the learned features into target classes which represent different heartbeat categories.

The ECG-ResNet architecture functions as a powerful system which enables deep hierarchical learning of ECG signal representations. The residual connections guarantee dependable training results for deep network architectures while the convolutional layers successfully detect

nearby signal features. The model identifies complex ECG waveform characteristics which represent various arrhythmia types through its advanced capabilities.

#### 4.2 CNN-BiLSTM Model

The CNN-BiLSTM model functions as a deep learning framework which integrates two distinct elements to analyze ECG signals through their spatial and temporal properties. The ECG recordings contain both essential waveform patterns and the ability to follow their progression throughout time. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) together provide a full perspective of the ECG signal due to their respective capabilities. With respect to the combined system, the CNN system is used to extract spatial features from ECG signals via the capabilities of its operational functions. The convolutional layers of the CNN are applied using multiple convolutional filters across the ECG signal to find local patterns that are of interest such as the QRS complex, amplitude variation, and waveform form. The extracted spatial features are then used to uniformly identify normal heart beats and identify abnormal arrhythmias.

The BiLSTM network takes feature maps from the convolutional layers to analyse key features of the input. LSTM networks are a class of recurrent neural networks, used to work with sequential data by utilizing their unique ability to address appropriately the vanishing gradient issue and different limitations that accompany RNNs. Utilization of memory cells within LSTM units in combination with gating mechanisms allows the system to maintain relevant information over longer periods of time.

Utilizing bidirectional LSTMs increases the model's potential to capture temporal relationships because the BiLSTMs process input signals (examples) in both forward and backward timelines, while standard LSTMs only process data in one direction (forwards). This action allows the model to obtain samples from both past and future time periods in the ECG signal stream, which improves the model's understanding of the overall signal.

Within the Convolutional Neural Network Bidirectional Long Short Term Memory (CNN-BiLSTM) architecture, the CNN layers serve as feature extractor layers while the BiLSTM layers act as sequence analyzing layers. The collaboration between these two phases of the model provides an opportunity for the model to manage and capture the relationship between waveform characteristics to the corresponding temporal characteristics of the ECG signal. The BiLSTM layers extract temporal features which then proceed to the fully connected layers that perform classification. The output layer generates probability scores which represent each heartbeat class. The hybrid architecture establishes a powerful ECG classification system through its combination of spatial pattern recognition and temporal sequence modeling capabilities.

#### 4.3 CNN-BiLSTM with Attention

The hybrid model gains improved performance through the implementation of an attention mechanism within the CNN-BiLSTM framework. Attention mechanisms have become an important component in modern deep learning models because they allow networks to selectively focus on the most relevant parts of the input data. All parts of the ECG signal which researchers use for analysis lead to different results in their classification work. The accurate diagnosis of a medical condition requires doctors to analyze particular waveform elements which include QRS complexes that show abnormal patterns and intervals that display irregularity. The attention mechanism enables the model to automatically identify and emphasize these important segments during the learning process. The proposed architecture starts with CNN layers which extract spatial features from the ECG signal. The BiLSTM layers process these features to establish temporal dependencies throughout the entire signal sequence. The system uses an attention layer after BiLSTM to calculate attention weights for every time step within the sequence.

The attention layer gives more importance to specific time periods which hold critical data needed for making classification decisions. The system uses weighted features to create a context

vector which shows the most important aspects of the ECG signal. The system uses this context vector to send data to the final classification layers which will create the prediction output.

The attention mechanism helps the model better identify tiny arrhythmia patterns by directing its attention toward essential signal parts. The attention mechanism shows which parts of the ECG signal had the greatest influence on the model Decision making process. The CNN-BiLSTM with Attention model uses three advanced deep learning methods which include convolutional feature extraction and bidirectional sequence learning and attention-based feature weighting. The model can create complex spatial and temporal patterns which it uses to detect important ECG waveform elements that lead to better classification results.

#### 5. Experimental Setup

The models were implemented using the **PyTorch deep learning framework**.

Training configuration:

Optimizer: AdamW

Loss Function: Cross-Entropy Loss

Batch Size: 256

Learning Rate: 0.001

Epochs: 30

A learning rate scheduler (ReduceLROnPlateau) was used to adjust the learning rate when validation performance plateaued.

Training was performed using GPU acceleration when available.

#### 6. Results and Analysis

The research used multiple performance evaluation metrics which are commonly used in the field to evaluate the effectiveness of the developed deep learning models that classify ECG beats. The assessment metrics include accuracy precision recall F1-score and confusion matrix analysis. The method of accuracy determines what percentage of ECG beats the system classified correctly while precision shows what percentage of actual positive cases the system predicted as positive. The model's ability to identify actual positive samples gets evaluated through recall which shows the number of true instances it

successfully detected. The F1 score combines precision and recall into a single metric which shows how well the model performs. The study used confusion matrices to display how classification results appeared at the same time they helped researchers find out which heartbeat categories were wrongly classified.

We investigated three deep learning architectures including a CNN+A BiLSTM network (convolutional neural network with Bidirectional Long Short-Term Memory), a CNN+A BiLSTM+A network (convolutional neural network with Bidirectional Long Short-Term Memory + Attention), and an ECG ResNet (residual network with traditional deep convolutional layers) for classifying electrocardiogram (ECG) signals. We found that hybrid models (which utilized both convolutional feature extraction and sequential learning) yielded better classification performance than pure convolutional model architectures. Among the architectures, a CNN+A BiLSTM+A model

consistently provided the most robust classification results. This is primarily due to the fact that in addition to convolutional feature extraction, this model employed BiLSTM layers and an attention mechanism to capture both spatial features from the ECG signal waveforms while maintaining time-dependencies of the ECG signal. The attention mechanism has been demonstrated to improve the classification results of the CNN+A BiLSTM+A model by isolating the most salient portions of the ECG signal waveform. The CNN+A BiLSTM model exhibited strong classification performance because of the successful combination of convolutional layers and sequence learning networks. However, even though the ECG ResNet model utilized residual learning and made use of traditional convolutional layers to extract features, it demonstrated inferior classification performance when compared to the hybrid models previously stated.

The quantitative comparison of the three models is presented in Table 1.

Table 1: Performance Comparison of Deep Learning Models

Model	Accuracy	Precision	Recall	F1-Score
CNN-BiLSTM-Attention	97.21%	0.9723	0.9721	0.9720
CNN-BiLSTM	96.74%	0.9672	0.9674	0.9672
ECG-ResNet	92.84%	0.9346	0.9284	0.9246

The proposed models receive validation through the analysis of the confusion matrix results. The system accurately classified most ECG beats into their correct categories while only making small errors between similar arrhythmia classes. The study demonstrates that hybrid deep learning systems which learn spatial and temporal features of ECG signals achieve better classification accuracy than traditional convolutional networks. The results demonstrate that advanced deep learning methods enable dependable automated ECG arrhythmia detection.

## 7. Discussion

The experimental results show that deep learning models achieve accurate classification of ECG signals. The model uses convolutional layers

together with recurrent networks to learn both local waveform characteristics and their time-based relationships. The system uses an attention mechanism to boost performance by identifying critical parts of the ECG signal. The study shows that residual networks deliver effective feature extraction but hybrid architectures perform better in terms of accuracy.

## 8. Conclusion

The research developed a deep learning system that uses hybrid models to automatically identify ECG arrhythmia patterns through its integrated deep learning framework. The researchers tested three different models which include ECG-ResNet and CNN-BiLSTM and CNN-BiLSTM-Attention. The experimental results showed that CNN-

BiLSTM-Attention model reached the highest classification accuracy with a result of approximately 97%. The results demonstrate that ECG classification results significantly improve when researchers combine convolutional feature extraction with sequence learning and attention mechanisms. The proposed approach provides automated ECG analysis support to clinicians which decreases their need for manual ECG interpretation work.

### Future Work

Future research may focus on:

- Applying transformer-based architectures for ECG classification
- Using larger multi-lead ECG datasets
- Developing real-time ECG monitoring systems
- Improving model interpretability for clinical applications

### REFERENCES

- Sörnmo, L.; Laguna, P. Chapter 6—The Electrocardiogram—A Brief Background. In *Bioelectrical Signal Processing in Cardiac and Neurological Applications*; Sörnmo, L., Laguna, P., Eds.; Academic Press: Burlington, MA, USA, 2005; pp. 411–452. [CrossRef]
- Atrial Premature Beats. *The ECG Manual: An Evidence-Based Approach*; Springer London: London, UK, 2009; pp. 197–200. [CrossRef]
- Rajoub, B. Machine learning in biomedical signal processing with ECG applications. In *Biomedical Signal Processing and Artificial Intelligence in Healthcare*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 91–112.
- Masarone, D.; Limongelli, G.; Ammendola, E.; Verrengia, M.; Gravino, R.; Pacileo, G. Risk Stratification of Sudden Cardiac Death in Patients with Heart Failure: An update. *J. Clin. Med.* 2018, 7, 436. [CrossRef] [PubMed]
- Khan, M.G. Bundle Branch Block. In *Encyclopedia of Heart Diseases*; KHAN, M.G., Ed.; Academic Press: Burlington, MA, USA, 2006; pp. 185–187. [CrossRef]
- Latif, G.; Al Anezi, F.Y.; Zikria, M.; Alghazo, J. EEG-ECG Signals Classification for Arrhythmia Detection using Decision Trees. In *Proceedings of the 2020 Fourth International Conference on Inventive Systems and Control (ICISC)*, Coimbatore, India, 8–10 January 2020; pp. 192–196.
- Kung, B.H.; Hu, P.Y.; Huang, C.C.; Lee, C.C.; Yao, C.Y.; Kuan, C.H. An Efficient ECG Classification System using Resource-Saving Architecture and Random Forest. *IEEE J. Biomed. Health Inform.* 2020, 25, pp. 1904–1914. [CrossRef]
- Kropf, M.; Hayn, D.; Schreier, G. ECG classification based on time and frequency domain features using random forests. In *Proceedings of the 2017 Computing in Cardiology (CinC)*, Rennes, France, 24–27 September 2017; pp. 1–4. *J. Clin. Med.* 2021, 10, 5450 21 of 22
- Khatibi, T.; Rabinezhadsadatmahaleh, N. Proposing feature engineering method based on deep learning and K-NNs for ECG beat classification and arrhythmia detection. *Phys. Eng. Sci. Med.* 2020, 43, 49–68. [CrossRef] [PubMed]
- Ali, K.M.N. A new arrhythmia clustering technique based on Ant Colony Optimization. *J. Biomed. Inform.* 2008, 41, 874–881.
- Coast, D.A.; Stern, R.M.; Cano, G.G.; Briller, S.A. An approach to cardiac arrhythmia analysis using hidden Markov models. *IEEE Trans. Biomed. Eng.* 1990, 37, 826–836. [CrossRef]
- Gomes, P.R.; Soares, F.O.; Correia, J.H.; Lima, C.S. ECG Data-Acquisition and classification system by using wavelet-domain Hidden Markov Models. In *Proceedings of the 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, Buenos Aires, Argentina, 31 August–4 September 2010; pp. 4670–4673. [CrossRef]

- Bortolan, G.; Christov, I.I.; Pedrycz, W. Hyperbox classifiers for ECG beat analysis. In Proceedings of the 2007 Computers in Cardiology, Durham, NC, USA, 30 September–3 October 2007; pp. 145–148. [CrossRef]
- da S. Luz, E.J.; Nunes, T.M.; De Albuquerque, V.H.C.; Papa, J.P.; Menotti, D. ECG arrhythmia classification based on optimum-path forest. *Expert Syst. Appl.* 2013, 40, 3561–3573. [CrossRef]
- Lannoy, G.d.; Francois, D.; Delbeke, J.; Verleysen, M. Weighted Conditional Random Fields for Supervised Interpatient Heartbeat Classification. *IEEE Trans. Biomed. Eng.* 2012, 59, 241–247. [CrossRef]
- De Chazal, P.; Reilly, R.B. A patient-adapting heartbeat classifier using ECG morphology and heartbeat interval features. *IEEE Trans. Biomed. Eng.* 2006, 53, 2535–2543. [CrossRef]
- Escalona-Morán, M.A.; Soriano, M.C.; Fischer, I.; Mirasso, C.R. Electrocardiogram classification using reservoir computing with logistic regression. *IEEE J. Biomed. Health Inform.* 2014, 19, 892–898. [CrossRef]
- Lorenzoni, G.; Sabato, S.S.; Lanera, C.; Bottigliengo, D.; Minto, C.; Ocagli, H.; De Paolis, P.; Gregori, D.; Iliceto, S.; Pisanò, F. Comparison of machine learning techniques for prediction of hospitalization in heart failure patients. *J. Clin. Med.* 2019, 8, 1298. [CrossRef]
- Pérez-Valero, J.; Caballero Pintado, M.V.; Melgarejo, F.; García-Sánchez, A.J.; García-Haro, J.; García Córdoba, F.; García Córdoba, J.A.; Pinar, E.; García Alberola, A.; Matilla-García, M.; et al. Symbolic Recurrence Analysis of RR Interval to Detect Atrial Fibrillation. *J. Clin. Med.* 2019, 8, 1840. [CrossRef] [PubMed]
- Padmanabhan, M.; Yuan, P.; Chada, G.; Nguyen, H.V. Physician-Friendly Machine Learning: A Case Study with Cardiovascular Disease Risk Prediction. *J. Clin. Med.* 2019, 8, 1050. [CrossRef]
- Hasegawa, D.; Yamakawa, K.; Nishida, K.; Okada, N.; Murao, S.; Nishida, O. Comparative Analysis of Three Machine-Learning Techniques and Conventional Techniques for Predicting Sepsis-Induced Coagulopathy Progression. *J. Clin. Med.* 2020, 9, 2113. [CrossRef] [PubMed]
- Shi, H.; Wang, H.; Zhang, F.; Huang, Y.; Zhao, L.; Liu, C. Inter-patient heartbeat classification based on region feature extraction and ensemble classifier. *Biomed. Signal Process. Control* 2019, 51, 97–105. [CrossRef]
- De Chazal, P.; O'Dwyer, M.; Reilly, R.B. Automatic classification of heartbeats using ECG morphology and heartbeat interval features. *IEEE Trans. Biomed. Eng.* 2004, 51, 1196–1206. [CrossRef]
- Wang, T.; Lu, C.; Sun, Y.; Yang, M.; Liu, C.; Ou, C. Automatic ECG Classification Using Continuous Wavelet Transform and Convolutional Neural Network. *Entropy* 2021, 23, 119. [CrossRef]
- Saenz-Cogollo, J.F.; Agelli, M. Investigating feature selection and random forests for inter-patient heartbeat classification. *Algorithms* 2020, 13, 75. [CrossRef]
- Alfaras, M.; Soriano, M.C.; Ortín, S. A fast machine learning model for ECG-based heartbeat classification and arrhythmia detection. *Front. Phys.* 2019, 7, 103. [CrossRef]
- Chen, J.; Peng, H.; Razi, A. Remote ECG monitoring kit to predict patient-specific heart abnormalities. *J. Syst. Cybern. Inform.* 2017, 15, 82–89.
- Huang, H.; Liu, J.; Zhu, Q.; Wang, R.; Hu, G. Detection of inter-patient left and right bundle branch block heartbeats in ECG using ensemble classifiers. *Biomed. Eng. Online* 2014, 13, 72. [CrossRef] [PubMed]

- Sahoo, S.; Subudhi, A.; Dash, M.; Sabut, S. Automatic classification of cardiac arrhythmias based on hybrid features and decision tree algorithm. *Int. J. Autom. Comput.* 2020, 17, 551-561. [CrossRef]
- Mishra, A.K.; Raghav, S. Local fractal dimension based ECG arrhythmia classification. *Biomed. Signal Process. Control* 2010, 5, 114-123. [CrossRef]
- Christov, I.; Jekova, I.; Bortolan, G. Premature ventricular contraction classification by the Kth nearest-neighbours rule. *Physiol. Meas.* 2005, 26, 123. [CrossRef] [PubMed]
- Asl, B.M.; Setarehdan, S.K.; Mohebbi, M. Support vector machine-based arrhythmia classification using reduced features of heart rate variability signal. *Artif. Intell. Med.* 2008, 44, 51-64. [CrossRef]
- Pandey, S.K.; Janghel, R.R.; Vani, V. Patient Specific Machine Learning Models for ECG Signal Classification. *Procedia Comput. Sci.* 2020, 167, 2181-2190. [CrossRef]

