

Automated ECG Signal Analysis for Cardiac Arrhythmia Detection

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Abstract— Cardiovascular disease continues to be the largest cause of death worldwide, quick and precise cardiac rhythm (ECG) analysis is essential. We created an automatic diagnostic solution after realizing that manual interpretation is slow and prone to mistakes when dealing with large amounts of monitoring data. First, we used baseline correction and filtering to assure signal purity using the MIT-BIH Arrhythmia Database as our benchmark. Importantly, we next used data augmentation (segmentation of records) to enhance our dataset in order to increase the number and diversity of training samples. Our main contribution is a 1D Convolutional Neural Network (CNN) frame-work that eliminates the need for manual feature engineering by automatically identifying minute patterns in these segmented pulse signals. With an overall accuracy of 0.98 on the test set, the model's results show remarkable reliability. Importantly, with detection rates (Recall) above 0.97, the system demonstrated its capacity to safely “catch” high-risk events such as Ventricular (“V”) and Questionable (“Q”) beats. This work validates a strong, computationally efficient, and highly accurate AI solution, despite the model's slight tendency to confuse the common Normal beat (“N”) with a few complex arrhythmias. This work is a major step toward developing a smart, reliable, and scalable diagnostic tool for real-time patient care in place of manual ECG interpretation.

Index Terms—ECG, Automation, Signal Processing, Machine Learning.

I. INTRODUCTION

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, making early diagnosis and continuous monitoring a public health priority [1], [2]. Since it offers vital information regarding electrical conduction and irregularities in rhythm, electrocardiography (ECG) is one of the most used non-invasive diagnostic methods for evaluating heart function [3], [4]. However, manual interpretation of ECGs is susceptible to variability, necessitates a high level of clinical knowledge, and becomes more difficult when dealing with huge amounts of monitoring data [5], [6]. This has spurred the creation of automated ECG analysis tools to help doctors make precise and quick diagnosis. Classical machine learning models and manually constructed feature extraction were the mainstays of traditional ECG analysis techniques. To capture cardiac patterns, methods including wavelet transformations, QRS detection as illustrated in Fig.1. and morphological descriptors have been widely used [7], [8]. However, these approaches struggle to manage inter-patient variability, noisy data and the scalability needed for real-time healthcare deployment [9], [10].

Improvements in heartbeat detection and arrhythmia classification were shown in early machine learning-based classification studies [11], [12] but problems with generalizability and interpretability remained [13], [14]. Thorough evaluations of machine learning applications to ECG have revealed advancements as well as enduring constraints in clinical adoption and robustness [15]. By allowing for automatic feature learning and the capture of spatiotemporal relationships, deep learning (DL) has greatly improved the classification of ECG signals [17], [18]. High performance in arrhythmia detection has been attained by CNNs, RNNs and hybrid networks, while feature representation has been enhanced by creative preprocessing techniques such as kurtosis based filtering, wavelet transform and spectrogram production [19], [20]. Accuracy across various arrhythmia types has been further improved by CNN-based models [21], encoder-decoder frameworks such as U-Net [22] and recurrence plot-based learning [23]. Although systematic evaluations highlight issues including data imbalance, noise sensitivity and explainability, they also indicate that deep learning performs better than traditional approaches [24]. ECG signals are being investigated for applications outside categorization, such as biometric authentication and predictive modeling, which would increase their usefulness beyond diagnostics [25]. The transition of ECG analysis from a rule-based to an intelligent, data-driven framework is indicative of a larger movement in healthcare toward AI-assisted diagnostics and precision medicine [9], [12]. Despite these advancements, problems still exist. There is still ongoing research into data imbalance, inter-patient variability and the requirement for real-time deployment [11], [24]. Models that are not only accurate but also interpretable, scalable and ethically deployable are key to the future of ECG analysis as research continues to close the gap between algorithmic innovation and clinical applicability [13], [14]. Building on the combined knowledge of earlier research, this study suggests a framework for classifying ECG signals with the goal of improving diagnostic accuracy while preserving computing efficiency.

II. LITERATURE REVIEW

Most studies rely on the MIT-BIH Arrhythmia Database, making it the primary benchmark for ECG classification and arrhythmia detection [3], [4], [6], [8], [12], [18], [20]. Other datasets, such as Physikalisch - Technische Bundesanstalt Diagnostic ECG [14], Beth Israel Deaconess Medical Center, Congestive Heart Failure (CHF) and those with Normal Sinus Rhythm (NSR). [3], INCART and SRP [11], and the ECG ID database for subject recognition [25] were also used. Several works emphasized cross-patient and multi-database validation for generalizability [4], [11], [19], [23].

Survey studies [7], [16], [17], [24] highlighted recurring issues like class im-balance, narrow arrhythmia focus and lack of standardized evaluation protocols. Overall, while MIT-BIH remains the real-world validation is essential for clinically robust ECG analysis. Across the reviewed studies, signal preprocessing and feature extraction emerged as critical steps for enhancing ECG interpretation and ensuring robust classification. Preprocessing and feature extraction are central to reliable ECG classification. Classical filtering methods were used for noise reduction [12], while advanced approaches like CWT [3], scalograms [1], Hilbert/wavelets [15] and tunable Q-wavelets [20] provided richer signal representations. Hybrid and minimal-preprocessing pipelines improved P-QRS-T detection [11], [19] and novel representations such as SCM [18] and recurrence plots [23] enhanced arrhythmia discrimination. Deep models automated feature learning-CNNs for spatial pat-terns, RNNs for temporal dynamics supported by interpretability techniques like CAM and LRP [13], [22], [24]. Handcrafted methods such as P-Q-R-S-T based feature vectors also proved effective [25]. Studies across machine and deep learning models have progressed from traditional classifiers like SVM, Random Forest and Naive Bayes [4], [8], [12], [20] to advanced deep learning models, with CNNs, ResNets and hybrid networks delivering high accuracy [1], [6], [21]. Transfer learning with AlexNet, VGG16 and SqueezeNet [3] and lightweight custom CNNs [21] supported mobile and real-time use.

Autoencoders [5] and U-Net variants [22] enhanced interpretability through activation maps. Reviews stressed CNN's spatial strengths and RNN's temporal modeling but highlighted gaps in scalability, regularity readiness and wearable deployment. overall, research trends point to accurate, efficient and interpretable models, yet clinical validation remains a key challenge. While the reviewed studies provide valuable insights into ECG signal classification, most rely heavily on benchmark datasets like MIT-BIH and lack extensive real-world validation. Signal preprocessing and feature extraction methods remain fragmented, with scalability and wearable integration still unresolved.

Existing ML/DL models achieve high accuracy but often struggle with generalization, interpretability, and deployment readiness. Surveys consistently highlight gaps in standardization and clinical applicability. To address these shortcomings, this project implements improved methodologies aimed at enhancing accuracy, scalability and robustness in ECG signal classification.

III. METHODOLOGY

The proposed methodology for ECG signal classification follows a structured pipeline, as illustrated in Fig.1. The process begins with dataset acquisition and progresses through preprocessing, feature extraction, analysis and model training/testing, ultimately leading to classification results. Each stage is detailed below.

A. Dataset Acquisition

The main dataset is the MIT-BIH Arrhythmia Database, which is well known for being a standard for classifying ECG signals. It offers ECG recordings with annotations for a variety of arrhythmia types, guaranteeing a strong assessment of classification models. Signal Pre-processing Raw ECG readings frequently have baseline drift, noise and artifacts from electrodes or muscle contractions. Preprocessing methods including baseline correction, denoising and band-pass filtering are used to guarantee accurate feature extraction. A normal heartbeat signal and its component waves are shown in Fig.1, which serves as the foundation for additional denoising and feature extraction.

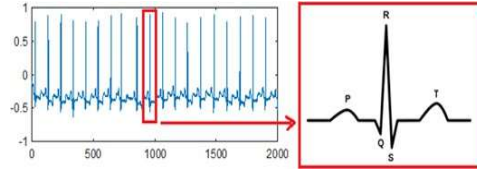


Fig. 1. A normal heartbeat signal with its constituent waves [1]

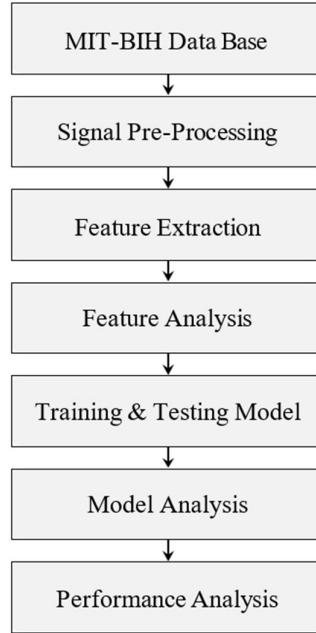


Fig. 2. Structured pipeline illustrating the methodology for automated ECG

B. Feature Extraction

At this point, both automated and manual techniques are used to extract significant features. While deep learning-driven techniques use time-frequency representations (scalograms, spectrograms) to capture morphological and temporal variations in ECG data, classical methods include wavelet transforms, Fourier transforms and frequency-domain analysis.

C. Feature Analysis

Features that have been extracted are examined and refined to improve discriminative capability. Dimensionality reduction techniques and interpretability tools are applied to refine feature sets, ensuring that the classifier focuses on clinically relevant ECG characteristics.

D. Training and Testing Model

To categorize arrhythmias, processed features are used to train machine learning and deep learning models. Deep architecture like CNN is contrasted with conventional classifiers like SVM. To reduce overfitting and enhance generalization, cross-validation and supplemented datasets are used during training.

E. Model Analysis

Understanding how the trained models learn and make judgments is the main goal of this step. To shed light on the decision-making process, feature importance analysis and attention visualization are used. Their viability for practical clinical deployment is further highlighted by a comparative analysis of model robustness, training, efficiency and complexity.

F. Performance Analysis

The trained model's prediction abilities are compared and evaluated in the last step. Reports include standard performance indicators such as F1-score and accuracy. For a more thorough evaluation, precision, recall and confusion matrices are also employed. The suggested framework's effectiveness, scalability and clinical application are shown by comparative findings across several models and datasets.

IV. IMPLEMENTATION

This section outlines the practical implementation of the proposed 1D Convolutional Neural Network (1D CNN) for the classification task, covering data handling, model architecture, training process, and evaluation methodologies.

A. Data Preprocessing and Preparation

To give the model the best chance of learning, we started by preparing the raw data. Using a method similar to data augmentation, we divided the records into many short time-series samples in order to optimize the diversity and number of training examples. Missing Value Handling: For analysis, a CSV dataset with particular record segments was imported. We started by cleaning the dataset. Any heart segments without a classification label were thrown out. As a practical solution to the gaps, we simply filled in the remaining data holes (missing sensor readings) with the average value from that column.

Feature and Label Separation: X (features) and y (labels). Drop non-feature columns (record-id, segment-id, unnamed: 7203). Neural networks require arithmetic, thus we have to convert text labels (N, V, etc) to numbers (0, 1, 2, etc). Because it guaranties that the network perceives the classes as separate, non-ordered categories. Convert string labels(y) to integer codes (yencoded). One-hot encoding which is converting yen-coded to categorical format ycategorical (e.g., [1,0,0,0,0]) is required for the Softmax output of the last layer. Train/Test Split: X, ycategorical split into Xtrain, Xtest, ytrain, ytest. The complete dataset was divided into two primary groups: 0.20 was retained to assess the model's learning performance, while the remaining 0.80 was used for training. We ensured that this split was completely reproducible but also random. Reshaping for 1D CNN: With N being the number of samples and L being the length of the time series segment, the feature data (Xtrain and Xtest) was transformed from 2D (N, L) to 3D (N, L, 1). This format, which treats each time step as a feature with a single channel, is required for the Conv1D input.

B. 1D CNN Model Architecture

A sequential 1D CNN architecture was employed, which is well-suited for extracting local temporal features from time-series data. The model structure is defined as follows in Table I:

TABLE I: 1D CNN ARCHITECTURE

Layer Type	P Parameters (Design)	Keras Output Shape (N, L, 1)	Purpose
Input	Shape=(L,1)	(None, 7200, 1)	Entry point for time series data.
Conv1D	Filters=32, Kernel=3, ReLU	(None, 7198, 32)	Learns local temporal features (patterns).
Max Pooling1D	Pool Size=2	(None, 3599, 32)	Down-samples and reduces computational complexity.
Conv1D	Filters=64, Kernel=3, ReLU	(None, 3597, 64)	Learns higher-level temporal features.

Max Pooling1D	Pool Size=2	(None, 1798, 64)	Further down-samples the feature maps (L/4).
Flatten	-	(None, 115072)	Prepares data for the fully connected layers.
Dense	Units=128, ReLU	(None, 128)	High-level feature aggregation.
Dropout	Rate=0.5	(None, 128)	Regularization to prevent overfitting.
Dense	Units=5, Softmax	(None, 5)	Final layer for multi-class probability output.

Compilation: The Adam optimizer was used to construct the model, with accuracy serving as the main performance indicator and Categorical Cross-entropy as the loss function (fit for multi-class classification with one-hot encoding).

C. Training and Evaluation

The model was trained for 40 epochs with a batch size of 64. The test set (X_{test} , y_{test}) was used as validation data during training, allowing real-time monitoring of generalization performance and detection of potential overfitting. After training, the model's performance was evaluated by the following: Prediction: Generation of probability predictions (y_{pred}) on the X_{test} data. Filtering: The evaluation was focused specifically on five key classes: 'F', 'N', 'Q', 'S', 'V'. The true and predicted labels were filtered to include only samples belonging to these five categories to provide a targeted analysis of the model's performance on the classes of interest. Metrics Generation: Classification Report: The precision, recall, and F1-score were computed for the filtered classes to provide a comprehensive view of the model's predictive ability per class. Training History Plot: Plots of training accuracy versus validation accuracy and Training Loss vs. Validation loss were generated over 40 epochs to visualize the learning process and diagnose overfitting or underfitting.

V. RESULT

The five clinically significant arrhythmia classes – “F”, “N”, “Q”, “S”, and “V” were the primary focus of a thorough evaluation of the suggested 1D CNN model's performance on the test set.

A. Training Dynamics and Generalization

In order to evaluate the stability and generalizability of the model, this section evaluates the learning curves from the training history. The network effectively extracted features from the time series data, as shown by the obvious decline in both the training and validation loss in Fig.4, which shows that the model learned effectively across 40 epochs. Indicating that the model was not becoming stuck during optimization, we saw a healthy convergence. After about epoch 5, the training accuracy continuously exceeded the validation accuracy, creating a little but steady gap as illustrated in Fig.3. This gap suggests that the 0.5 dropout rate successfully reduced extreme overfitting and guaranteed strong generalization to new data.

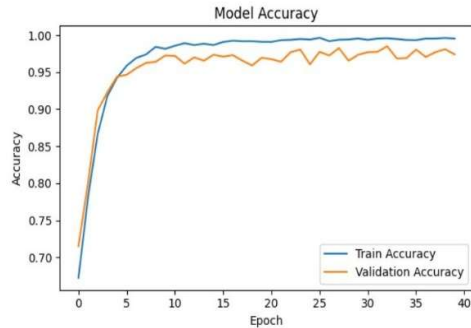


Fig. 3. Model Accuracy

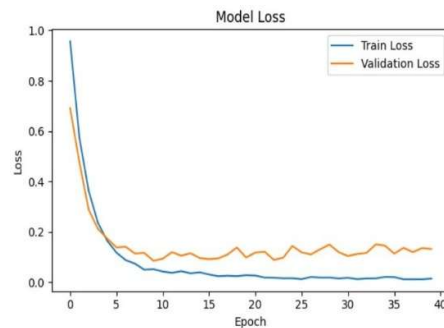


Fig. 4. Model Loss

B. Comprehensive Classification Performance

Using the classification report, this segment shows the model's quantitative performance on the filtered subset as shown in TABLE II. On the filtered test set, the model's overall accuracy of 0.98 showed remarkable dependability. With an F1-score of 1.00, it performed nearly flawlessly on the 'F' (Fusion) class; however, it's

crucial to remember that this class had very little support (only 4 samples). With an F1-score of 0.98, the model demonstrated great dependability for the most common 'N' (Normal) beats. Crucially, the system demonstrated effective-ness in detecting these clinically relevant circumstances by demonstrating a great ability to “catch” the harmful Ventricular beats ('V') and Questionable beats ('Q'), as evidenced by remarkable Recall scores of 0.97 and 0.98, respectively. Even while the 'S' (Supraventricular) class sometimes misidentifies other types as 'S' its high Recall of 0.98 indicates the model is highly good at detecting these beats, despite its slightly lower Precision of 0.89. expected given physiological similarities in specific heartbeat morphologies, but it also demonstrates the model's sensitivity and generalization.

C. Error Analysis via Confusion Matrix

The model performed well, as evidenced by the Normalized Confusion Matrix as shown in Fig.5, which had high success rates overall. High Confidence: Recall scores for all major classes ('N', 'Q', 'S', and 'V') reached 0.97 or above, demonstrating that the model correctly 'caught' practically every beat type as it happened. Minor Confusion: The primary difficulty was a mild back-and-forth misunderstanding between some of the other classes and the Normal ('N') beats. The model performs remarkably well generally, as evidenced by the high diagonal dominance of the normalized confusion matrix, even though there is some slight misunderstanding between some arrhythmic and regular beats. Across all main heartbeat classes, the model regularly receives recall ratings of 0.97 and higher, demonstrating its resilience in accurately identifying a variety of cardiac rhythms.

TABLE II: PERFORMANCE ANALYSIS

Class	Precision	Recall	F1-Score	Support
F	1.00	1.00	1.00	4
N	0.99	0.98	0.98	1357
Q	0.96	0.98	0.97	227
S	0.89	0.98	0.93	139
V	0.96	0.97	0.97	271
Accuracy			0.98	1998
Macro Avg	0.96	0.98	0.97	1998
Weighted Avg	0.98	0.98	0.98	1998

TABLE III: SUMMARY OF KEY RESEARCH STUDIES ON ECG CLASSIFICATION

Reference	Dataset/ Data Samples	Method Used	Accuracy/ Performance
1.	PhysioNet ECG signals converted into scalograms (~162 samples)	ResNet-34 with scalogram-based feature extraction	~97.9% accuracy
2.	12-lead ECG (6877 recordings)	Lead Feature Guide Network (LFG-Net)	F1-score ~0.93
3.	2-D ECG spectrograms (dataset not specified)	CNN-based deep learning	High accuracy (not stated)
5.	Real & synthetic 12-lead ECG data	Convolutional Autoencoder (CAE)	Acc ~99.75%
6.	ECG signals	Hybrid ML/DL framework	Accuracy not replaced
8.	12-lead ECG dataset	Comparative ML algorithms with advanced feature extraction	~97% accuracy
9.	Review of AI applications in ECG	Literature review (No dataset)	-
This work	MIT-BIH Dataset (10004 samples)	CNN-1D Architecture	Acc-0.98 F1-score & Recall -0.97

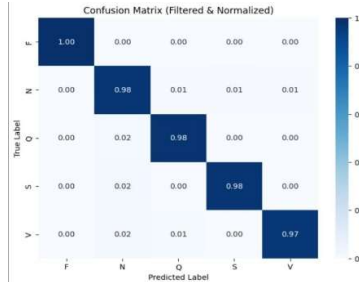


Fig. 5. Confusion Matrix (Filtered)

Even in the face of difficult real-world changes, this high consistency shows that the model has successfully learned the important patterns in the ECG data. Not only is the slight degree of overlap between classes like “N”, “Q”, “S”, and “V”. All things considered, the results show that the suggested model is quite dependable for real-time monitoring or clinical applications, providing precise identification with little mis-classification. Strong classification across a variety of ECG beat patterns is made possible by the model’s structural design and the preprocessing and filtering pipeline, both of which are further validated by the impressive performance.

VI. CONCLUSION

Through the successful construction of a reliable Automated ECG signal analysis for cardiac arrhythmia detection, this research advanced the ECG analysis from human interpretation prone to errors to intelligent automated diagnosis. In order to overcome previous issues with consistency and generalization, we trained the network using a large number of segmented heartbeat samples, enabling the model to automatically discover subtle patterns. The outcomes were outstanding: with an overall accuracy of 0.98, the system demonstrated exceptional dependability. Most importantly, it demonstrated a great ability to “catch” complicated or dangerous beats, such as Ventricular (“V”) and Questionable (“Q”) arrhythmias. Its high detection rates validate its strong potential for use in life-critical patient monitoring. Although our examination was successful, it revealed a little, controllable tendency for confusion when distinguishing the extremely common Normal (“N”) beat from some of the more complicated or uncommon arrhythmias (“Q” and “S”). The subtle overlapping characteristics of the raw ECG data are probably the cause of this small classification inaccuracy. In the end, our study shown in TABLE III produces a diagnostic tool that is extremely accurate and efficient. However, future work will concentrate on improving the model’s capacity to resolve these subtle distinctions, opening the door for its dependable implementation in actual clinical settings and AI-assisted healthcare.

DISCUSSION

The experimental findings demonstrate that the suggested 1D-CNN architecture successfully and highly accurately classifies ECG heartbeats. Compared to conventional manually engineered methods, automatic feature extraction streamlines the workflow and boosts performance. When combined with live ECG capture hardware such as the AD8232, the model is reliable, scalable, and appropriate for real-time arrhythmia identification. Expanding the dataset, refining segmentation methods, and implementing the model on embedded systems for portable cardiac monitoring are some potential future enhancements.

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