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ECG-Based Characterization of Heart Diseases by leveraging AI techniques

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Index

INTRODUCTION

This research analyses three distinct approaches to improve the diagnosis and classification of cardiovascular conditions through the utilisation of machine learning techniques applied to electrocardiographic (ECG) data. The first study proposes a predictive model based on a two-dimensional convolutional neural network (CNN-2D) and Gradient-weighted Class Activation Mapping (Grad-CAM) to analyse ECG images, offering an interpretable solution for detecting myocardial infarctions and arrhythmias. The second study develops a CNN to distinguish between arrhythmias and other types of disturbances, utilising data from 1,052 patients and achieving an overall accuracy of 90%, with promising results but challenges related to signal noise and device variability. Finally, the third study explores three distinct approaches, integrating CNN, heart rate variability (HRV) feature extraction, and classification models such as Random Forest; this last approach proves to be the most effective, reaching an accuracy of 92.01%, demonstrating potential for supporting clinical decision-making.

Key words: Explainable Artificial Intelligence; Electrocardiogram; ECG; Heart Disease; Convolutional Neural Networks; CNN; Grad-CAM; Predictive Analytics; Arrhythmia Detection; Machine Learning; Heart Rate Variability; Diagnostic Accuracy.

Step 1 – An Explainable Approach for Heart Disease Classification Using ECG Image Band Analysis

ABSTRACT

Cardiovascular diseases are among the leading causes of mortality worldwide, with early detection being crucial for effective prevention and treatment, as these conditions often progress asymptomatically in their initial stages. Electrocardiography (ECG) is a widely utilised diagnostic tool to assess cardiac electrical activity, providing critical information on heart function and supporting the diagnosis of various cardiovascular conditions. This study aimed to develop a predictive approach for heart disease through the analysis of ECG images, incorporating explainability through Gradient-weighted Class Activation Mapping (Grad-CAM) applied to a customised two-dimensional convolutional neural network (CNN-2D). Validation was conducted on a public dataset of ECG images from cardiac patients at the Ch. Pervaiz Elahi Institute of Cardiology, Multan (Pakistan). The results demonstrated satisfactory performance and high interpretability, suggesting this method's potential as a valuable tool for clinicians in diagnosing myocardial infarctions and arrhythmia. This research contributes to the field of explainable artificial intelligence in healthcare, offering a promising approach to enhance cardiovascular disease diagnosis and optimise risk stratification.

Key words: Explainable Artificial Intelligence; Electrocardiogram; ECG; Heart Disease; CNN-2D, Grad-CAM; Convolutional Neural Networks; Gradient-weighted Class Activation Mapping; Predictive Analytics; Cardiovascular Risk Stratification.

Key takeaways:

1. The study developed an explainable approach for heart disease prediction using ECG images and a two-dimensional convolutional neural network (CNN-2D) with Gradient-weighted Class Activation Mapping (Grad-CAM).
2. The research focused on detecting myocardial infarction and arrhythmias using a public dataset of ECG images from cardiac patients.
3. The CNN-2D model achieved high performance in classifying various cardiac conditions, with Band I (leads I, aVR, V1, V4) showing the best overall accuracy of 0.938.
4. Grad-CAM was used to enhance interpretability by visualizing the specific ECG regions influencing the model's predictions.
5. The model demonstrated robust performance in detecting Myocardial Infarction (MI), with perfect recall (1.00) and high precision (0.98) in Band III.
6. Different ECG bands showed varying effectiveness for specific cardiac conditions, suggesting the value of tailored lead combinations in diagnosis.
7. The integration of Grad-CAM improved the model's explainability, potentially increasing clinical confidence in AI-driven diagnostics.
8. Future research directions include optimizing performance for Band II, expanding to diverse ECG datasets, and incorporating advanced explainable AI techniques.
9. The study contributes to the field of explainable artificial intelligence in healthcare, offering a promising approach to enhance cardiovascular disease diagnosis and risk stratification.

I. INTRODUCTION

Cardiovascular disease, a significant global health issue, primarily affects the arterial system through processes that lead to progressive narrowing and potential obstruction of arteries due to the formation of atherosclerotic plaques. This condition is one of the leading causes of morbidity, disability, and mortality worldwide, presenting various clinical manifestations depending on the affected arterial district. Among the available diagnostic tools, electrocardiograms (ECG) play a crucial role in identifying and managing cardiovascular diseases. ECGs are non-invasive, painless, and without risks, providing essential information about heart rhythm, electrical conduction, heart rate, and various cardiac abnormalities, including arrhythmia, myocardial ischemia, infarction, and ventricular hypertrophy. Early diagnosis of heart disease via ECG analysis facilitates timely intervention, improving patient outcomes and potentially preventing serious complications. Automating heart disease detection through ECG analysis algorithms offers numerous advantages over traditional, subjective manual evaluation. Automated systems can process vast amounts of ECG data rapidly, enabling continuous patient monitoring, early anomaly detection, and the identification of specific patient subgroups, facilitating more personalised and targeted disease management. This study aims to support clinicians in the detection and management of cardiac diseases through an explainable predictive approach based on ECG image analysis. Specifically, it proposes a novel method that analyses 12-lead ECG images segmented into three signal bands to determine the most effective band for classifying various cardiac conditions. The methodology employs a two-dimensional convolutional neural network (CNN-2D), a model well-suited for examining ECGs due to its layered structure that highlights distinct cognitive features and its capacity to recognise meaningful patterns in input images [2]–[5]. To enhance interpretability, the Gradient-weighted Class Activation Mapping (Grad-CAM) approach is utilised to visualise the specific ECG signal portions that most influence the model's predictive decisions. By focusing on bands of electrodes and incorporating explainability through Grad-CAM, this research aims to develop a trustworthy support tool for physicians, enhancing both disease recognition capabilities and transparency in the model's decision-making process.

II. BACKGROUND

The electrocardiogram (ECG) is a widely utilised diagnostic test that records and graphically represents the heart's rhythm and electrical activity using 12 electrodes placed on the patient's skin. These electrodes detect voltage variations generated by cardiac cells during the cardiac cycle, producing graphs that illustrate heart rhythm and potential abnormalities [6]. ECGs are employed in a variety of clinical scenarios, such as routine examinations, emergency evaluations for acute cardiac symptoms (e.g., chest pain, dyspnoea, or syncope), monitoring response to treatment, and assessing cardiac function prior to surgical procedures or invasive interventions.

Several types of ECG are utilised based on the clinical situation and the specific symptoms presented [7]:

- Basal ECG (at rest): Conducted while the patient is in a supine position with electrodes positioned on their body.
- Dynamic Holter ECG: Performed with a portable electrocardiograph for 24-hour continuous monitoring, enabling detection of events not captured by a basal ECG.
- Stress ECG: Evaluates heart function under physical exertion, with real-time monitoring of both the electrocardiogram and blood pressure.

Cardiopathy, a comprehensive term encompassing all heart diseases, impairs the heart's pumping capacity. This can result from structural abnormalities, such as occluding blood vessels, or functional issues, like disruptions in the heart's electrical system, leading to conditions such as arrhythmia. This study focuses on two specific cardiac conditions:

1. Myocardial Infarction (MI): Characterised by evidence of acute myocardial ischaemia and alterations in cardiac troponin levels. Diagnostic indicators include ECG changes, pathological Q-wave formation, imaging evidence of myocardial tissue loss, regional wall motion abnormalities, and identification of coronary thrombus via angiography or autopsy [8]. The study differentiates between first-time myocardial infarction (MI) and previous myocardial infarction (PMI).
2. Abnormal Heartbeat (Arrhythmia): Defined as an atypical heart rate, where the normal adult range is typically 60 to 100 beats per minute. Arrhythmias can involve a heart rate that is too slow (bradycardia, below 60 bpm), too fast (tachycardia, above 100 bpm), or irregular, as in cases of extrasystole, where single or multiple abnormal beats occur [9].

This background underscores the relevance of ECG analysis in diagnosing myocardial infarction and abnormal heart rhythms, providing a foundation for understanding the study's focus on automated ECG interpretation for enhanced cardiac care.

III. RELATED WORK

Artificial Intelligence (AI) has significantly advanced medical diagnostics, offering promising solutions for early disease detection, including rare pathologies [10]–[14]. In particular, ECG signal analysis has been a focal point in the literature for diagnosing heart diseases, with numerous studies utilising convolutional neural networks (CNNs) for analysing ECG data [15]–[17]. Common approaches include one-dimensional CNNs (CNN-1D), two-dimensional CNNs (CNN-2D), and hybrid models, often combined with other network types to enhance diagnostic accuracy [3]–[5].

Recent studies have also incorporated Gradient-weighted Class Activation Mapping (Grad-CAM) to improve interpretability in AI models for ECG analysis. For instance, in [18], DenseNets and CNN-1D models combined with Grad-CAM were employed to detect myocardial infarction, focusing solely on ECG signals. Similarly, in [19], ResNet50 with Grad-CAM was applied for myocardial infarction analysis based on electrical signals rather than ECG images. While some studies have explored non-cardiac conditions, such as ADHD detection using CNN-1D and Grad-CAM [20], other works have targeted cardiac arrhythmia detection through CNN-1D, and LSTM networks paired with Grad-CAM [21].

Image-based approaches to ECG analysis have also gained prominence. For example, [22] utilised Grad-CAM and CNN-2D on ECG images to detect aortic valvular stenosis in both 12 and 4 lead cases, while [23] implemented a VGG network with Grad-CAM for binary classification of various cardiac diseases on ECG images. Despite similar methodologies, [16] applied a lightweight CNN-2D architecture on the same dataset as this study but focused on entire ECG images without signal band partitioning, potentially limiting explainability. Additionally, the authors did not analyse model complexity or lead significance, raising questions about the purported lightweight nature of their solution.

This study builds upon the foundation laid by [15] and extends the analysis by introducing cross-validation and Grad-CAM modules to improve explainability. Unlike [16], which employed a 22-layer architecture, the proposed CNN-2D model here utilises only 11 layers (excluding the final layer), yielding superior recall rates in myocardial infarction detection, a crucial metric in medical contexts that often-achieved values up to 100%. Moreover, this study uniquely partitions ECG data into bands and investigates the importance of individual leads in classification outcomes, enhancing result transparency. Grad-CAM is further employed to identify the most discriminant pixels, and these findings are verified for consistency with the original ECG signal images, supporting a more interpretable and reliable classification process for various heart diseases in a multiclassification context.

This related work section situates the present study within existing literature, emphasising its novel contributions, including band-based ECG analysis, cross-validation, lead significance, and enhanced interpretability in AI-driven cardiac diagnostics.

IV. APPROACH AND SETTINGS

This section delineates the neural network architecture and explainability methodology employed in this study, as well as the details of the dataset and preprocessing steps.

A. Neural Network Architecture

The study utilises a two-dimensional Convolutional Neural Network (CNN) with 12 layers, selected for its capacity to analyse ECG images effectively. Key components include:

- *Convolutional layers:* Extract features from input images.
- *Pooling layers:* Summarise extracted information, reducing computational costs.
- *Activation function:* Rectified Linear Unit (ReLU) introduces nonlinearity, identifying significant features for classification.
- *Fully Connected layers*: Serve as the decision-making component, generating predictions.

Additional parameters include the Adam optimiser for efficient training, a dropout rate of 0.15 to prevent overfitting, a batch size of 32, and 100 training epochs. Table I provides a detailed layer configuration of the CNN architecture.

B. Explainability Methodology

Given that CNNs operate as black-box models, interpretability is essential to ensure clinical reliability. To achieve this, the Gradient-weighted Class Activation Mapping (Grad-CAM) method is employed, focusing on the last convolutional layer to create activation maps based on gradient values. This probability map highlights regions most influential in the CNN's predictions, thereby providing insight into the model's decision-making process [25][26].

C. Implementation

The architecture was developed using Python, with TensorFlow 2 and Keras libraries. Figure 1 illustrates the overall model design, encompassing both classification and explainability modules.

D. Dataset

The study utilises a public dataset of ECG images from 928 cardiac patients at the Ch. Pervaiz Elahi Institute of Cardiology, Multan, Pakistan [27]. Each ECG image (in .jpg format) is based on a 12-lead system and was manually reviewed and labelled by experienced medical professionals using the TeleHealth ECG diagnostic system.

E. Data Preprocessing

The preprocessing phase comprises two steps:

1. Segmentation: Each ECG image is divided into three bands, each representing specific sets of electrodes:
    - i. BAND I: Electrodes I, aVR, V1, V4
    - ii. BAND II: Electrodes II, aVL, V2, V5
    - iii. BAND III: Electrodes III, aVF, V3, V6
2. Image Resizing: Each band image was resized to 227 × 227 pixels to optimise analysis time without compromising feature quality.

This approach combines CNN-based ECG classification with Grad-CAM for enhanced interpretability, utilising a preprocessed dataset of segmented and resized ECG images to support effective and reliable heart disease diagnosis.

V. RESULTS AND DISCUSSION

This section presents the outcomes of the CNN-2D model in terms of performance and interpretability.

Classification Performance

Table II summarises the classification performance of the proposed CNN-2D model for each ECG image band across key metrics, utilising a 5-fold cross-validation process. Band I, comprising leads I, aVR, V1, and V4, demonstrated the highest overall accuracy (0.938), precision (0.947), recall (0.926), and F1-score (0.933). This robust performance, with high precision indicating a low false-positive rate, reflects the model's efficacy in identifying ECG patterns within these leads. Band III (leads III, aVF, V3, V6) achieved the second-best performance with accuracy of 0.901 and balanced metrics, while Band II (leads II, aVL, V2, V5) exhibited slightly lower, yet consistent, metrics with a marginal bias towards recall (0.888). The variation in performance across bands highlights the potential diagnostic value of different lead combinations, with Band I's superior results potentially attributable to the complementary information provided by its combination of limb and chest leads.

Disease-Specific Analysis

Table III provides detailed metrics per disease category across bands. Myocardial Infarction (MI) demonstrated consistently high performance across all bands, particularly in Band III, which achieved perfect recall (1.00) and high precision (0.98), underscoring the model's robust capability in detecting MI. For Heart Block (HB), Band I had the highest precision (0.98), while Band III provided a balanced recall and F1-score (0.93 for both), rendering it optimal for reliable HB detection. Previous Myocardial Infarction (PMI) exhibited variability, with Band I achieve the highest recall (0.97) but lower precision (0.76), indicating a slight tendency towards false positives, whereas Band III had the highest precision (0.96) with more conservative recall (0.81).

Explainability via Grad-CAM

Figure 2 illustrates the Grad-CAM analysis results, demonstrating the most significant pixels utilised by the CNN-2D model for classification in each ECG band. This pixel-based interpretability enables clinicians to identify the regions contributing to the model's decisions, thereby enhancing trust and transparency in AI-driven diagnostics. The capacity of the Grad-CAM approach to highlight key areas specific to each cardiac condition provides a valuable layer of interpretability, facilitating expeditious and targeted disease identification.

Summary of Findings

1. High Classification Performance: The CNN-2D model achieved robust performance across all bands, with Bands I and III demonstrating efficacy for various cardiac conditions, especially MI.
2. Interpretability with Grad-CAM: The explainable Grad-CAM approach facilitated the visualisation of discriminative ECG regions, enhancing the model's interpretability for clinical applications.
3. Disease-Specific Band Effectiveness: Band I proved highly effective for PMI detection, whilst Band III was optimal for MI, demonstrating the value of tailored lead combinations in ECG-based diagnosis.

VI. CONCLUSIONS

This investigation evaluated an explainable CNN-2D architecture with Grad-CAM to identify the most efficacious ECG image bands and components for classifying three specific cardiac conditions and healthy patients. The findings indicate that Bands I and III are particularly effective in distinguishing between cardiac conditions, especially for detecting acute myocardial infarction. The integration of Grad-CAM enhanced the model's explainability by enabling clinicians to precisely identify the ECG regions influencing the model's predictions, thus improving interpretability and clinical confidence.

The high-performance metrics across all bands demonstrate the robustness of this approach for automated ECG analysis in clinical settings. Future research could focus on optimising performance for Band II to align it more closely with Bands I and III, potentially through architectural refinements or ensemble methods that utilise the strengths of each band. Additionally, expanding the model's applicability with diverse ECG datasets and incorporating advanced explainable AI techniques may further enhance result interpretability for cardiologists.

Future directions

Future research could involve expanding the model to diverse ECG datasets and exploring additional explainable AI techniques to further enhance result interpretability. Additionally, optimising the model for Band II could potentially elevate its performance to a level comparable with that of Bands I and III, potentially improving diagnostic reliability.

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Table I. Architecture of the 2D Convolutional Neural Network

Layer	Type	Output Shape	Kernel Size
I	Convolutional	(222, 222, 64)	3
II	Batch Normalization	(222, 222, 64)	--
III	Drop Out	(222, 222, 64)	--
IV	Pooling	(111, 111, 64)	2
V	Convolutional	(109, 109, 32)	3
VI	Batch Normalization	(109, 109, 32)	--
VII	Drop Out	(109, 109, 32)	--
VIII	Pooling	(55, 55, 32)	2
IX	Global Average Pooling	32	--
X	Dense	64	--
XI	Drop Out	64	--
XII	SoftMax	4	--

Table I delineates the comprehensive structure of a 2D convolutional neural network, comprising twelve layers. Each row elucidates a layer's characteristics, including its type, output shape, and kernel size where applicable. The network commences with convolutional layers, followed by normalisation and regularisation techniques such as batch normalisation and dropout. Subsequently, it incorporates pooling layers for dimensionality reduction, culminating in dense and softmax layers for classification. This architecture exemplifies a typical deep learning model design for image processing tasks, balancing feature extraction, model complexity, and overfitting mitigation.

Table II. Performance Metrics Across Different ECG Image Bands

Band	Accuracy	Precision	Recall	F1-Score
I	0.938	0.947	0.926	0.933
II	0.876	0.869	0.888	0.875
III	0.901	0.900	0.901	0.888

Table II presents the key performance metrics (accuracy, precision, recall, and F1-score) for a classification model applied to three distinct ECG image bands (I, II, and III). Band I demonstrates the highest performance across all metrics, with an accuracy of 93.8% and an F1-score of 0.933. Bands II and III exhibit slightly lower but nonetheless robust performance, with accuracy of 87.6% and 90.1%, respectively. These results provide a comparative analysis of the model's efficacy in evaluating different components of the ECG signal.

Table III. Classification Performance of the Proposed CNN-2D Model for Heart Disease Based on Band Analysis

PATIENT	BAND I			BAND II			BAND III		
CLASS	PRECISION	RECALL	F1-SCORE	PRECISION	RECALL	F1-SCORE	PRECISION	RECALL	F1-SCORE
HB	0,980	0,750	0,850	0,870	0,790	0,850	0,900	0,930	0,930
MI	0,910	1,000	0,950	0,950	0,960	0,980	0,980	1,000	0,990
PMI	0,760	0,970	0,850	0,850	0,880	0,800	0,960	0,810	0,880

Table III presents the classification performance of the proposed CNN-2D model for heart disease based on band analysis. The table delineates precision, recall, and F1-score values for three patient classes (HB: Heart Block, MI: Myocardial Infarction, PMI: Previous Myocardial Infarction) across three ECG bands (I, II, III). The results indicate generally high performance of the model, with variations across classes and bands. Band III demonstrates the most consistent scores, particularly for MI and PMI classes, while Band I exhibits high precision but lower recall for the HB class.

Abbreviations: HB: Heart Block; MI: Myocardial Infarction; PMI: Previous Myocardial Infarction

Figure 1. Overview of the Proposed ECG Image Analysis Pipeline with CNN-2D and Grad-CAM

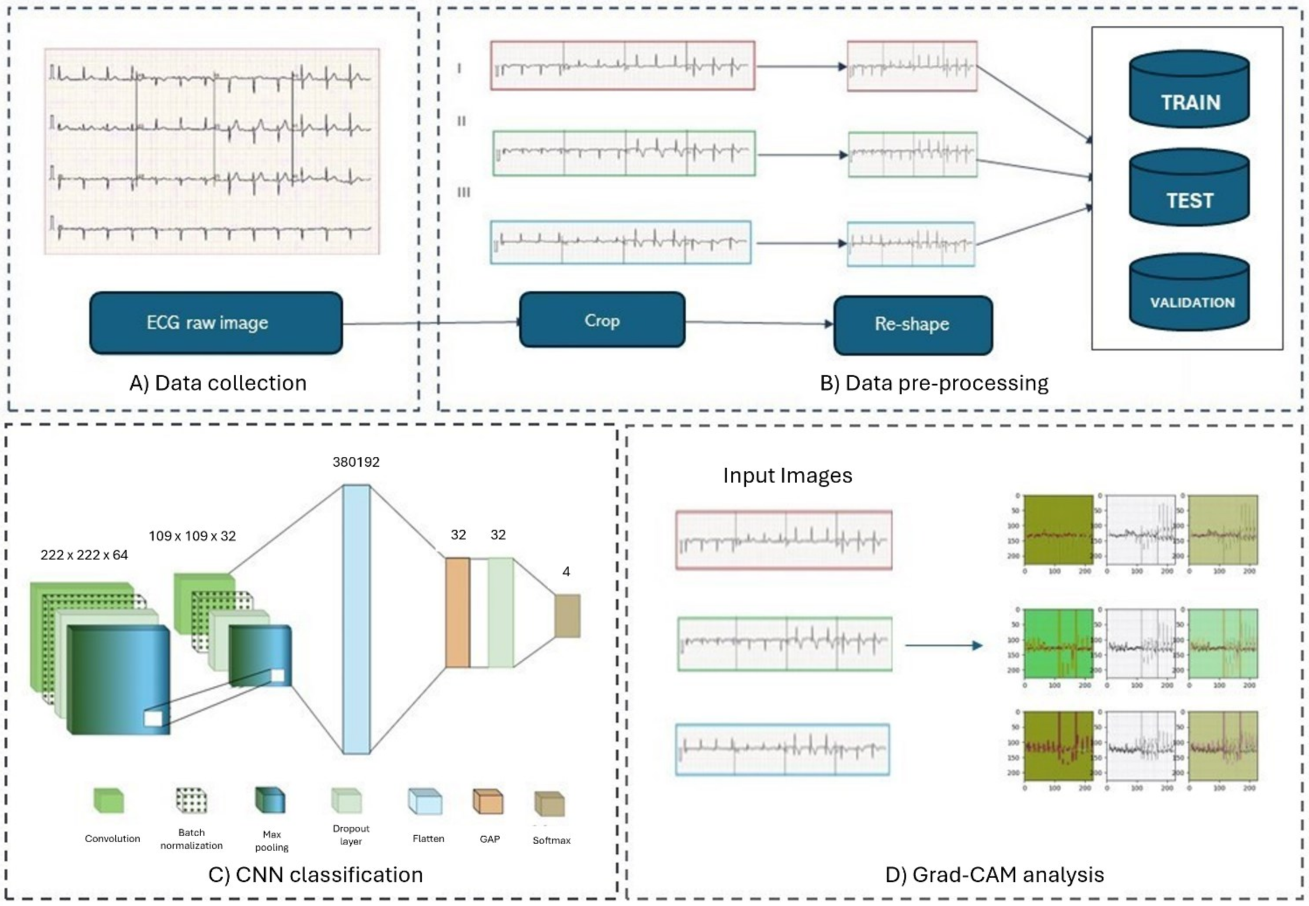

Figure 1. Proposed methodology encompassing: A) acquisition of raw electrocardiograms (ECGs), B) segmentation of the original ECG image into three distinct images, one per band, C) training and evaluation of the two-dimensional convolutional neural network (CNN-2D), and D) analysis utilising Gradient-weighted Class Activation Mapping (Grad-CAM).

Abbreviations: HB: Heart Block; MI: Myocardial Infarction; PMI: Previous Myocardial Infarction

Figure 2. Comparative ECG Signal Analysis Across Bands for Different Cardiac Conditions

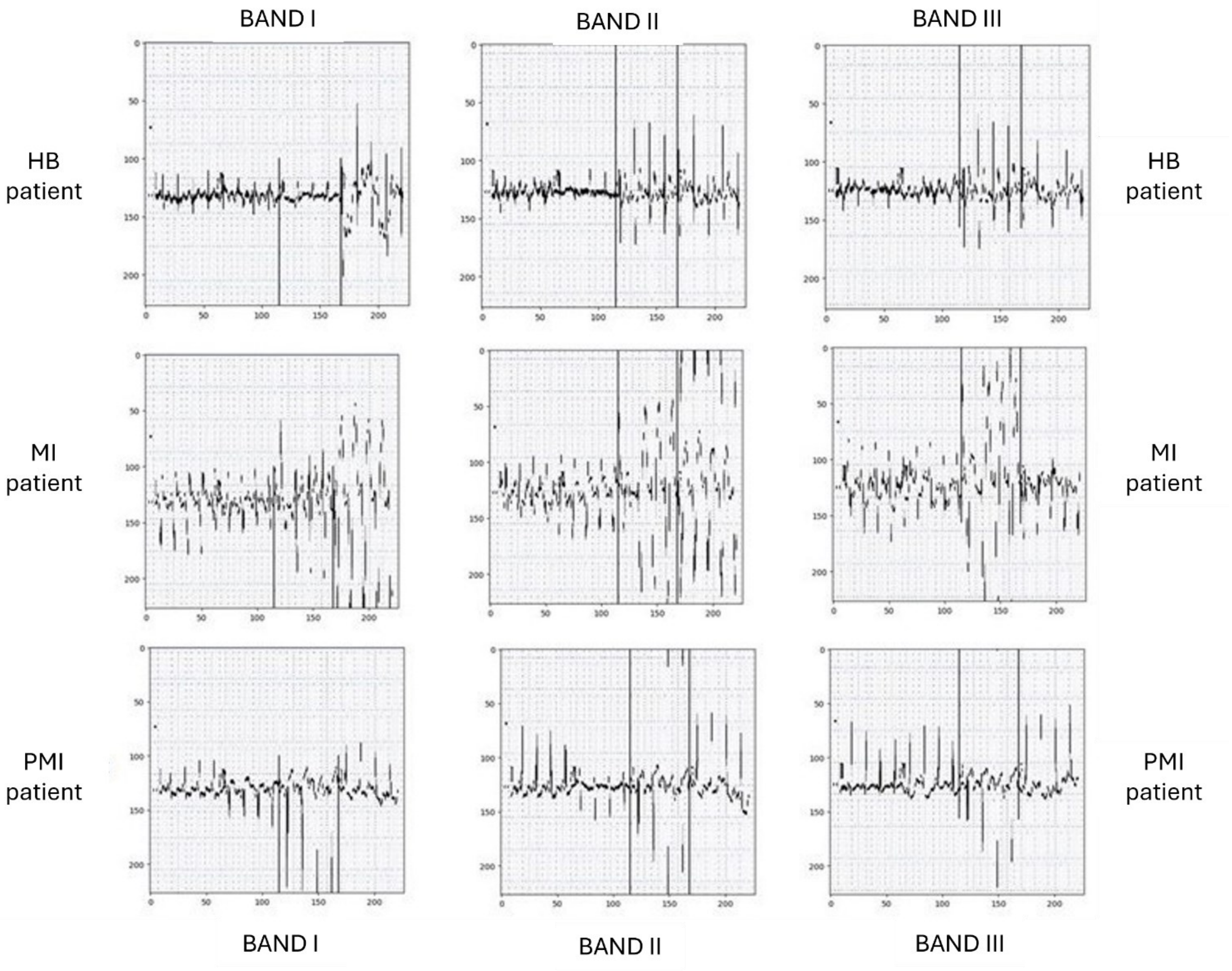

Figure 2. This figure presents a comparative analysis of electrocardiogram (ECG) signals categorised by bands (BAND I, BAND II, and BAND III) for three classes of patients with distinct cardiac conditions: Heart Block (HB), Myocardial Infarction (MI), and Previous Myocardial Infarction (PMI). Each row represents a patient type and demonstrates the variations in the ECG signal for each band, elucidating the characteristic ECG patterns associated with each condition.

Step 1 – Detection of Arrhythmias in ECG: A CNN Approach for Classifying Cardiac Anomalies.

Preliminary results.

ABSTRACT

This study investigates the application of machine learning for automated classification of electrocardiogram (ECG) traces to distinguish arrhythmias from other disturbances and interference. A convolutional neural network (CNN) model was developed and evaluated utilising ECG data from 1,052 patients. The model achieved an overall accuracy of 90% in classifying ECG traces, with 92% accuracy for arrhythmias and 88% for other disturbances. The findings demonstrate the potential of machine learning in enhancing diagnostic accuracy and efficiency in cardiology. However, challenges related to signal noise, device variability, and complex cardiac anomalies were identified, highlighting areas for future research and improvement.

Key words: Electrocardiography; Arrhythmia detection; Machine learning; Convolutional neural networks; ECG classification; Cardiac diagnostics.

Key Takeaways:

1. A CNN model achieved 90% accuracy in classifying ECG traces, demonstrating its potential as a diagnostic support tool in cardiology.
2. The model exhibited high precision in distinguishing arrhythmia (92% accuracy) from other disturbances (88% accuracy).
3. Challenges in ECG classification encompass managing signal interference, device variability, and complex cardiac anomalies.
4. Further research is required to refine preprocessing techniques and enhance model adaptability to various ECG devices.
5. While promising, the study emphasises the importance of clinical oversight and the necessity for continued optimisation of machine learning models in medical diagnostics.

I. INTRODUCTION

Electrocardiography (ECG) is a crucial diagnostic tool in cardiology for the early detection of cardiac rhythm abnormalities. Arrhythmia detection is essential for timely diagnosis and treatment of heart conditions, as undiagnosed arrhythmias may lead to severe health outcomes, including stroke, heart failure, or sudden cardiac arrest. The interpretation of ECG signals presents challenges due to the complexity and variability of cardiac signals, which frequently contain noise and interference. This study investigates a machine learning approach to automate the classification of ECG traces, distinguishing arrhythmias from other types of disturbances and interference, with the potential to enhance diagnostic accuracy and optimise clinical workflow [1–3].

Cardiac arrhythmias are alterations in normal heart rhythm that can significantly affect patient health and quality of life. These irregularities can range from benign to life-threatening conditions, necessitating prompt and accurate identification for effective clinical management. Conventional manual interpretation of ECGs is time-consuming, requires specialised expertise, and may be subject to inter-practitioner variability. Machine learning (ML), and in particular deep learning, has emerged as a powerful tool for the automatic analysis of complex physiological signals, with convolutional neural networks (CNNs) demonstrating high performance in image and signal classification tasks [4–6]. Automating the identification of arrhythmias with ML can enhance diagnostic efficiency and support healthcare providers by highlighting potential abnormalities for further review.

II. AIM

The primary aim of this investigation is to develop and evaluate a machine learning model capable of accurately classifying ECG traces, differentiating between patients with arrhythmias and those presenting with other types of disturbances or interference. This approach seeks to utilise deep learning techniques to enhance diagnostic accuracy and mitigate the workload of healthcare professionals.

III. METHODS

- Data Collection: ECG data were collected from 1,052 patients, divided into two groups: 589 patients exhibiting arrhythmias (classified as "Normal") and 463 with other types of anomalies (classified as "Abnormal"). Each ECG trace was recorded in CSV format, containing time-stamped measurements and corresponding values. The data was meticulously organised to ensure a balanced distribution across both groups [7].
- Data Preparation: The ECG traces were aggregated into two distinct datasets, output_norm.csv and output_abn.csv, each containing 750 measurements per patient. Arrhythmia patients were assigned a target label of 0, while patients with other disturbances were assigned a label of 1. Preprocessing included data normalisation and removal of artefacts to enhance model robustness [8].
- Model Architecture: A convolutional neural network (CNN) was implemented utilising the Keras framework. The CNN architecture comprises Conv1D layers for feature extraction, BatchNormalization for enhanced learning stability, MaxPooling1D to reduce dimensionality, and Dense layers for classification.

Specifically:

  - Conv1D layers: Employed with 64 filters and a kernel size of 6, utilising ReLU as the activation function.
  - Batch Normalisation: Applied to normalise outputs from previous layers.
  - MaxPooling1D: With a pool size of 3 and stride of 2 to downsample feature maps.

    - Dense Layers: Fully connected layers with 128 and 64 units, and ReLU activation.
    - Output Layer: A single unit with sigmoid activation for binary classification. The model was compiled with the Binary Cross-Entropy loss function and optimised using the Adam optimiser, with accuracy as the primary evaluation metric [9–10].
- Training and Evaluation: The dataset was partitioned into a training set (50%), test set (30%), and validation set (20%). The model was trained over 20 epochs, with the accuracy and loss metrics monitored throughout training and testing [11].

IV. RESULTS

The model demonstrated an overall accuracy of approximately 90% in classifying ECG traces. Specific findings include (Fig. 1):

- True Positives (correctly identified arrhythmias): ~92%
- True Negatives (correctly identified disturbances/interference): ~88%

A confusion matrix analysis on the test set revealed (Fig. 2):

- Arrhythmias: 166 out of 181 traces correctly classified.
- Disturbances: 118 out of 134 traces correctly classified.

These results indicate the model's efficacy in distinguishing arrhythmias from other disturbances with high precision. Visual examination of misclassified traces suggests that further refinement in the handling of signal noise and artefacts may enhance performance [12].

V. DISCUSSION

This study demonstrates the feasibility and potential benefits of utilising a CNN model for the automatic classification of ECG traces, achieving a consistent accuracy of approximately 90%. This level of accuracy indicates the model's potential to support clinicians in diagnosing cardiac anomalies, particularly in resource-limited settings. However, several limitations were observed:

1. Interference and Noise: Elevated levels of signal interference or noise resembling arrhythmia may result in misclassifications, emphasising the necessity for refined data preprocessing techniques [13].
2. Obsolete Devices: Data acquired from outdated ECG devices may contain artefacts that impede the model's interpretative capability [14].
3. Pacemaker Interference: Patients with pacemakers frequently exhibit additional peaks in their ECG traces, which may confound the model [15].
4. Overlapping Anomalies: Instances where disturbances coincide with arrhythmias present a challenge for accurate classification [16].

VI. CONCLUSIONS

This investigation demonstrates the potential of machine learning in automating ECG trace classification for arrhythmia detection. The developed CNN model attained a promising accuracy of 90%, highlighting its viability as a diagnostic support tool. The findings also underscore the significance of clinical oversight and the necessity for further optimisation, particularly regarding interference management and device standardisation. Subsequent research could focus on model enhancements to better address noise and improve adaptability to varying ECG devices, in conjunction with the integration of additional clinical data to augment diagnostic accuracy [17].

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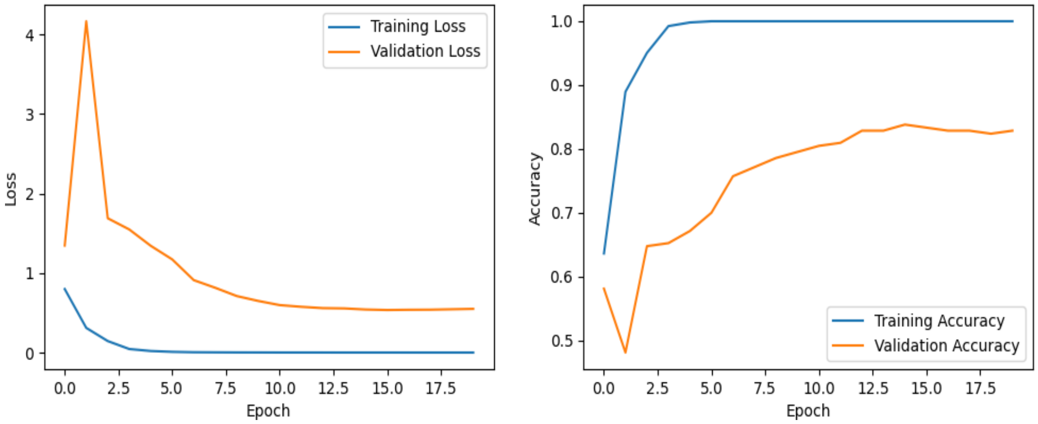
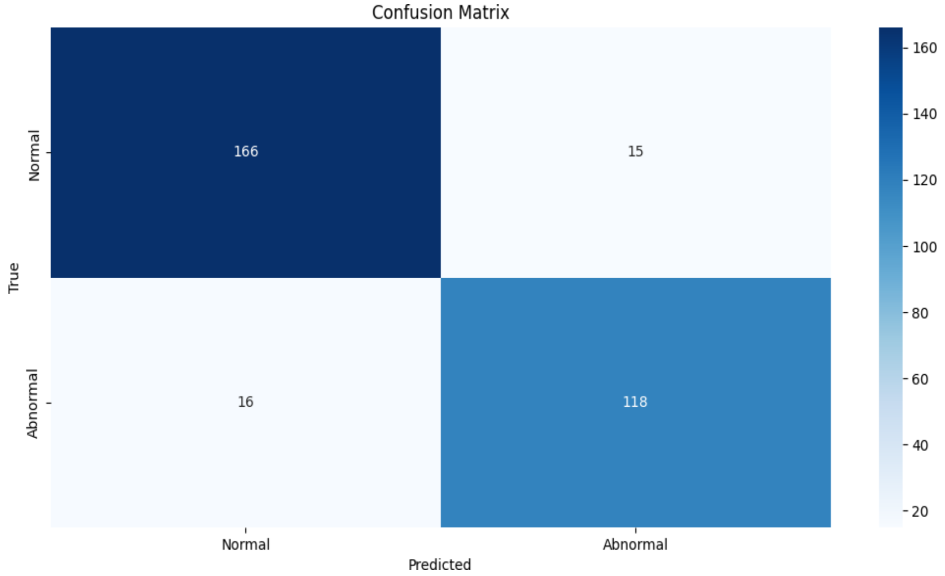
Figure 1. Training and Validation Loss and Accuracy Over Epochs for Arrhythmia Detection Model



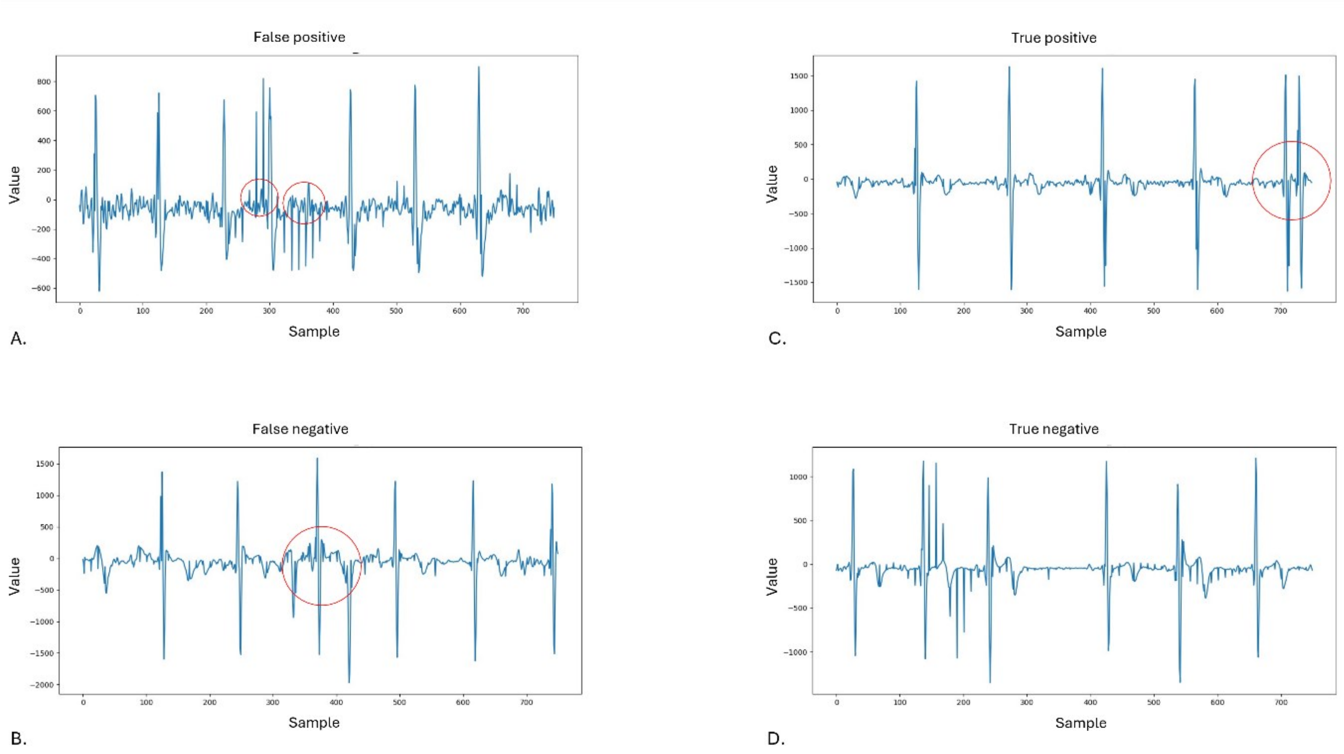
The graphs depict the training and validation loss (left) and accuracy (right) across 20 epochs for a convolutional neural network model applied to ECG data for arrhythmia detection. The graph on the left demonstrates a substantial decrease in both training and validation loss, which stabilises after the initial epoch. The right graph indicates a rapid increase in training accuracy, which plateaus above 90%, whilst validation accuracy exhibits gradual improvement, attaining approximately 80% by the conclusion of training. These results suggest effective model learning, with potential for further optimisation of validation performance.

Figure 2. Confusion Matrix for CNN Model in ECG Classification.



The confusion matrix illustrates the performance of a convolutional neural network (CNN) model in classifying electrocardiogram (ECG) traces as either "Normal" (arrhythmia) or "Abnormal" (other disturbances). The matrix demonstrates 166 true positives (correctly identified normal traces), 118 true negatives (correctly identified abnormal traces), 15 false positives, and 16 false negatives. The substantial number of true positives and true negatives indicates the model's efficacy in distinguishing between arrhythmia and other disturbances, while the misclassifications suggest areas for potential model refinement.

Graphs 1. Examples of True and False Classifications in ECG Trace Analysis.



These graphs illustrate examples of ECG trace classifications by the model, showing true positives, true negatives, false positives, and false negatives. A) False Positive: An example of a trace classified as having arrhythmia when none was present, likely due to interference mimicking arrhythmic patterns. C) True Positive: A correctly identified arrhythmic trace, where the model accurately detected the presence of arrhythmia. B) False Negative: An example of a trace with undetected arrhythmia, possibly due to subtle variations or noise masking the arrhythmic signals. D): A correctly classified non-arrhythmic trace, accurately identified as normal by the model.

These examples highlight the model's challenges, particularly with traces containing interference and disturbances that can mimic arrhythmic patterns, leading to occasional misclassifications.

Step 3 – Arrhythmia Detection: Differentiating Between Interferences and True Arrhythmias Using Signal Analysis. Preliminary results.

ABSTRACT:

Accurate arrhythmia detection in electrocardiogram (ECG) signals is crucial for timely diagnosis and intervention. However, interferences in ECG recordings can impede accurate diagnosis. This study investigates machine learning (ML) methodologies to effectively differentiate true arrhythmias from interferences. Utilising an extensive ECG database of 1,050 samples (588 true arrhythmias and 462 interferences), three analytical approaches are explored, each incorporating convolutional neural networks (CNNs), heart rate variability (HRV) feature extraction, and diverse ML models. Results indicate that the HRV-based approach with feature selection and Random Forest classification achieves the highest diagnostic accuracy (92.01%), demonstrating its significant potential for clinical application as a decision-support tool.

Key words: Arrhythmia detection, ECG signal analysis, machine learning, heart rate variability, Random Forest, convolutional neural networks, feature selection, diagnostic accuracy.

Key Takeaways:

1. The study investigates machine learning methodologies to differentiate true arrhythmia from interferences in ECG signals.
2. Three analytical approaches were explored:
    a. Full-signal analysis using Convolutional Neural Network (CNN)
    b. Heart Rate Variability (HRV)-based feature extraction and selection
    c. Time and frequency domain HRV features without selection
3. The dataset comprised 1,050 ECG samples (588 true arrhythmias and 462 interferences).
4. The HRV-based approach with feature selection and Random Forest classification achieved the highest diagnostic accuracy (92.01%).
5. Random Forest model demonstrated superior performance in terms of accuracy (92.01%), specificity (97.41%), and sensitivity (88.75%).
6. Feature selection proved essential for improving model specificity and optimizing computational efficiency.
7. CNN models, while robust in capturing full-signal patterns, did not match the Random Forest model's overall diagnostic performance when paired with HRV metrics.
8. The study highlights the importance of HRV features in capturing essential cardiac dynamics that traditional models may overlook.
9. The findings suggest that integrating HRV with Random Forest offers a balanced approach to clinical decision support systems for arrhythmia detection.
10. Future research will focus on enhancing model robustness with larger datasets and improving computational efficiency for real-time clinical implementation.

1. INTRODUCTION

Cardiac arrhythmias, defined as irregular heart rhythms, pose a significant health risk due to their association with adverse cardiovascular events, including stroke and heart failure. Early detection of arrhythmias is thus essential, yet it is often complicated by artifacts or signal interferences within electrocardiogram (ECG) readings, which can mimic arrhythmic patterns and lead to misdiagnosis [1]. Traditional ECG analysis relies on visual inspection and manual interpretation, which, although useful, is limited by its subjective nature and the high susceptibility to error in the presence of noisy data [2].

Recent advancements in machine learning (ML) have introduced novel methods for ECG analysis, offering the potential to improve the accuracy and reliability of arrhythmia detection. These techniques, particularly those employing deep learning architectures such as convolutional neural networks (CNNs), can autonomously identify and classify complex patterns within large datasets, rendering them valuable for real-time diagnostic support [3, 4]. Heart rate variability (HRV) analysis has also emerged as a key feature in arrhythmia detection, as it reflects autonomic modulation and provides insights into the physiological state of the heart [5, 6]. By leveraging HRV-based feature extraction in conjunction with ML models, it becomes feasible to enhance diagnostic accuracy while reducing false positives caused by signal interference. This study evaluates three distinct ML approaches to determine the most effective method for arrhythmia detection, with the aim of establishing an optimal model for clinical applications.

2. METHODS

The dataset comprises ECG records from 588 patients with confirmed arrhythmias and 462 patients with noise-induced false positives. ECG signals represent the amplitude (mV) over a 6-second period with 125 samples per second (750 samples total). The analysis incorporates three primary methodological approaches (Table 1).

2.1 First Approach: Full-Signal Analysis Using Convolutional Neural Network (CNN)

This approach utilises the full ECG signal as input to a CNN model, which autonomously learns spatial and temporal patterns for differentiating arrhythmias from interferences. CNN's architecture enables it to leverage feature extraction across the entire signal span, capturing morphological nuances that may distinguish true arrhythmia from artefacts [7].

2.2 Second Approach: Heart Rate Variability (HRV)-Based Feature Extraction and Selection

This method focuses on HRV due to its established connection to cardiac autonomic modulation:

- Feature Extraction: An initial set of 19 HRV features is extracted.
- Feature Selection: Utilising Random Forest, the 10 most relevant HRV features are selected, optimising performance while reducing computational demands.
- ML Models: Four ML models—Random Forest, Support Vector Machine (SVM), Multilayer Perceptron (MLP), and CNN—are applied to the reduced feature set.

2.3 Third Approach: Time and Frequency Domain HRV Features without Selection

This approach includes HRV feature extraction in both time and frequency domains:

- Time Domain: 15 HRV features such as MeanNN, SDNN, RMSSD, and pNN50 are extracted.
- Frequency Domain: 7 features, including total power, very low frequency (vLF), low frequency (LF), high frequency (HF), and LF/HF ratio, are analysed.
- ML Models: Random Forest, SVM, MLP, and CNN are trained on these HRV features without feature selection [5].

3. HEART RATE VARIABILITY (HRV) FEATURES

HRV metrics are fundamental in distinguishing arrhythmic from non-arrhythmic patterns. Time domain metrics quantify variability between heartbeats (e.g., MeanNN, SDNN), whilst frequency domain metrics indicate the autonomic nervous system's balance (e.g., LF/HF ratio) [6,8].

4. RESULTS

Each approach was evaluated for accuracy, specificity, and sensitivity (Table 2 and Graph 1).

- First Approach (Full Signal with CNN):

  The CNN achieved an accuracy of 0.9060, specificity of 0.9171, and sensitivity of 0.8806, demonstrating the model's efficacy in recognising arrhythmic patterns across the entire signal.

- Second Approach (HRV-Based with Feature Selection):
  - *CNN:* Accuracy 0.9087, Specificity 0.9161, Sensitivity 0.8912
  - *Random Forest:* Accuracy 0.9201, Specificity 0.9741, Sensitivity 0.8875 [9]
  - *Support Vector Machine (SVM):* Accuracy 0.8973, Specificity 0.9482, Sensitivity 0.8571
  - *Multilayer Perceptron (MLP):* Accuracy 0.8821, Specificity 0.9051, Sensitivity 0.8639

Random Forest attained the highest accuracy (92.01%), indicating its effectiveness in differentiating arrhythmias.

- Third Approach (Time and Frequency Domain HRV without Feature Selection):
  - *CNN:* Accuracy 0.8213, Specificity 0.9052, Sensitivity 0.7551
  - *Random Forest:* Accuracy 0.9087, Specificity 0.9396, Sensitivity 0.8843 [10]
  - *SVM:* Accuracy 0.6612, Specificity 0.9655, Sensitivity 0.4218
  - *MLP:* Accuracy 0.6844, Specificity 0.8448, Sensitivity 0.5578

The third approach exhibited reduced sensitivity and accuracy, particularly in SVM and MLP models.

5. DISCUSSION

The findings underscore that the HRV-based approach with feature selection, especially using Random Forest classification, delivers superior diagnostic accuracy in distinguishing arrhythmias from ECG noise. This approach’s success highlights the importance of HRV features in capturing essential cardiac dynamics that traditional models may overlook [1]. Feature selection also proved essential for improving model specificity, thereby minimizing false positives and optimizing computational efficiency, crucial for potential clinical applications [2]. CNN models, while robust in capturing full-signal patterns, did not match the Random Forest model’s overall diagnostic performance when paired with HRV metrics (Graph 2). These results suggest that while deep learning methods like CNN are valuable for comprehensive data analysis, integrating HRV with Random Forest offers a balanced approach to clinical decision support systems [3].

6. CONCLUSION

This study demonstrates that machine learning models, particularly Random Forest combined with HRV feature selection, can reliably distinguish between true arrhythmias and ECG interferences. Subsequent research will focus on enhancing model robustness with larger datasets and improving computational efficiency to support real-time clinical implementation.

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Table 1. Summary of Approaches for ECG Signal Analysis in Arrhythmia Detection

Approach	**Description**	**Details**
First Approach	Using the whole signal to ascertain differences,	Artificial Intelligence (AI): Convolutional Neural Network (CNN)
Second Approach	Extracting features from the signal based on Heart Rate Variability (HRV)	AI Models: Random Forest, Support Vector Machine (SVM), Multilayer Perceptron (MLP), CNN. Using all 19 features with feature selection (Random Forest): 10 most important features
Third Approach	Extracting features from the signal based on Heart Rate Variability (HRV) without feature selection	AI Models: Random Forest, SVM, MLP, CNN. Time domain: 15 features, Frequency domain: 7 features, No feature selection

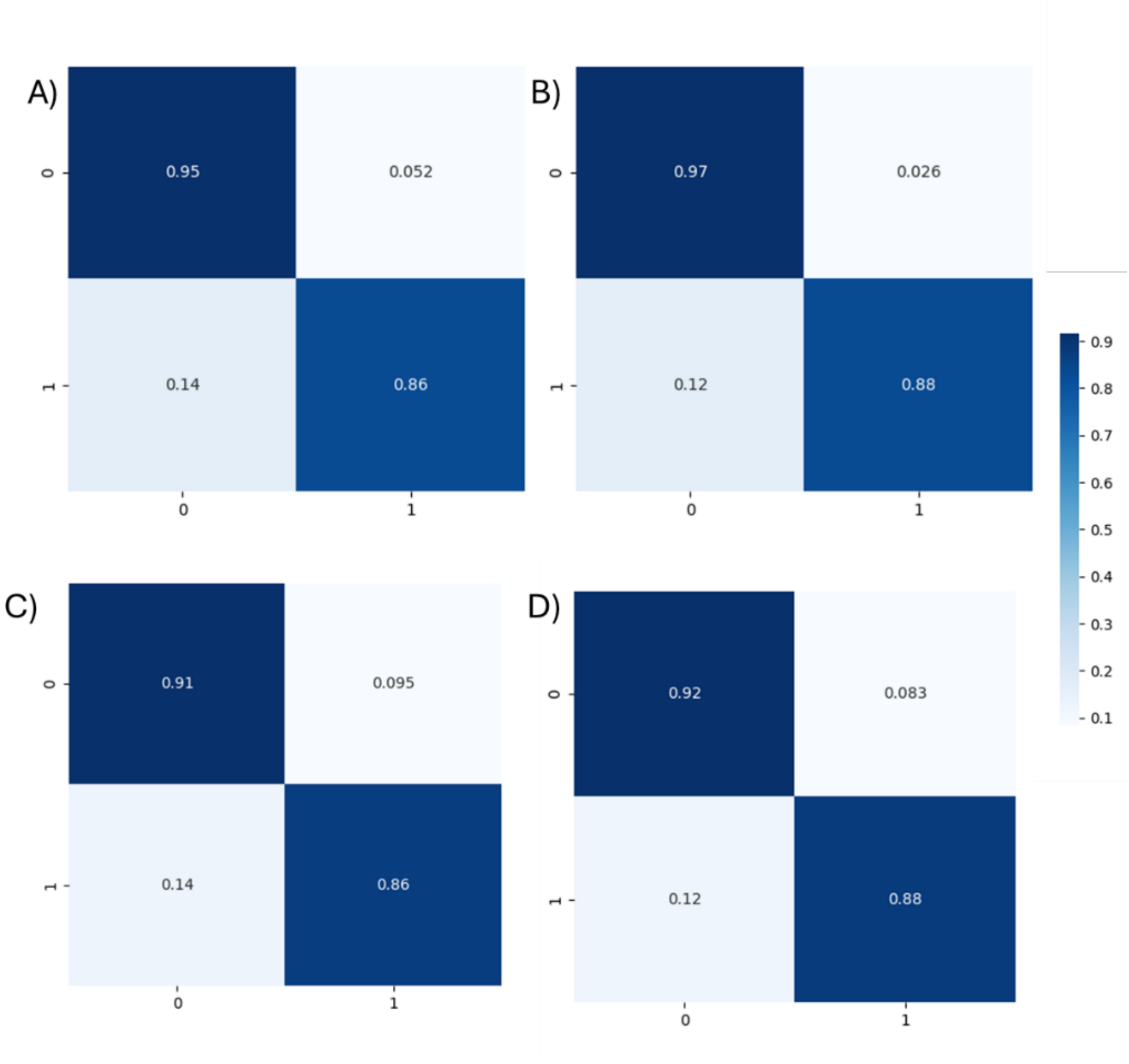
Table I shows the three approaches used for ECG signal analysis for arrhythmia detection. The first approach uses the entire signal to identify differences through a Convolutional Neural Network (CNN). The second approach involves feature extraction based on Heart Rate Variability (HRV) and applies various artificial intelligence models (Random Forest, Support Vector Machine, Multilayer Perceptron, and CNN) after selecting the 10 most relevant features from an initial set of 19 features. The third approach extracts HRV features in the time domain (15 features) and frequency domain (7 features) without feature selection and applies the same artificial intelligence models as the second approach.

Table 2. Performance of Machine Learning Models for Arrhythmia Detection Across Different Approaches

Approach	Model	Accuracy	Specificity	Sensitivity
First	CNN	0.9060	0.9171	0.8806
Second	CNN	0.9087	0.9161	0.8912
Second	Random Forest	0.9201	0.9741	0.8875
Second	Support Vector Machine	0.8973	0.9482	0.8571
Second	Multilayer Perceptron	0.8821	0.9051	0.8639
Third	CNN	0.8213	0.9052	0.7551
Third	Random Forest	0.9087	0.9396	0.8843
Third	Support Vector Machine	0.6612	0.9655	0.4218
Third	Multilayer Perceptron	0.6844	0.8448	0.5578

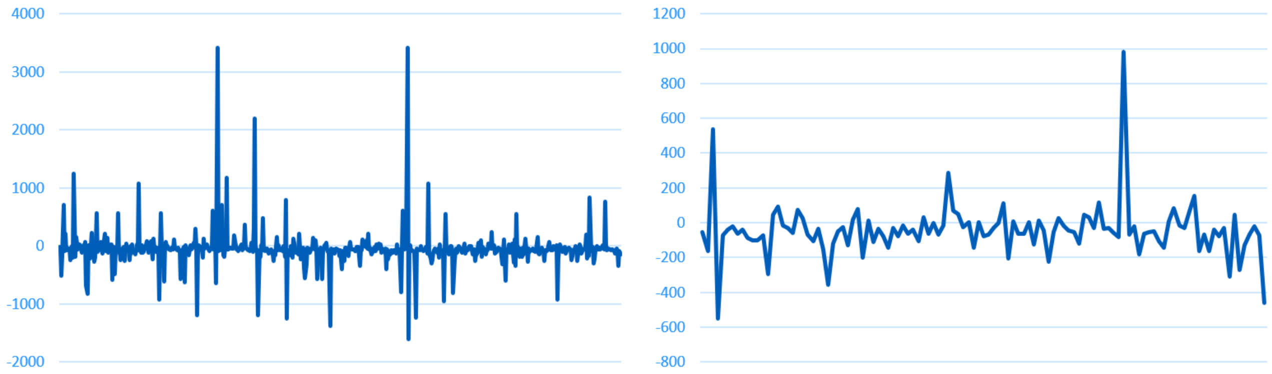
Table 2 describes the performance metrics—accuracy, specificity, and sensitivity—of various machine learning models applied in three approaches for arrhythmia detection. The first approach utilizes the entire ECG signal with a Convolutional Neural Network (CNN). The second approach involves feature extraction based on Heart Rate Variability (HRV) with models such as CNN, Random Forest, Support Vector Machine, and Multilayer Perceptron, with feature selection applied to retain the 10 most relevant features. The third approach also utilizes HRV-based features but without feature selection, applying the same models. Notably, the Random Forest model in the second approach achieves the highest accuracy (0.9201) and specificity (0.9741).

Graph 1. Confusion Matrices for Arrhythmia and Interference Classification



The confusion matrices (A, B, C, D) illustrate the performance of different models in classifying arrhythmias and interferences. Each matrix shows the true negative rate (bottom-left), true positive rate (top-right), false negative rate (bottom-right), and false positive rate (top-left). In total, 19 signals that should have been classified as arrhythmia were misclassified as interference, and 2 signals that should have been classified as interference were misclassified as arrhythmia. These matrices provide insights into the model's ability to accurately distinguish between true arrhythmic events and interference within ECG signals.

Graph 2. Misclassification of Arrhythmias as Interference in ECG Analysis



The graph shows examples of ECG signals where arrhythmias, specifically fibrillation events, were incorrectly classified as interference by the model. This misclassification indicates that the signal characteristics of fibrillation can sometimes resemble interference patterns, leading to challenges in accurate differentiation. The plots highlight the signal variability and irregularities associated with fibrillation, which could be refined for better model performance in future studies.

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