IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

A Comparative Study Of Explainable Deep Learning Models For Myocardial Infarction Using Ptb-Xl

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Abstract: Heart attack is a term that is commonly used for myocardial infarction (MI). MI refers to a condition where the heart muscle experiences reduced or blocked blood flow. MI is a significant cause of death across the world, and therefore its detection is paramount. One diagnostic approach involves the use of electrocardiogram (ECG) signals. The interpretation of ECG signals, however, demands expertise and is not without inconsistencies. This paper introduces an explainable deep learning framework that leverages 12-lead ECG signals for detecting MI from the PTB-XL database. A balanced sample of 2000 was considered to eliminate any bias during the training process. We benchmark the proposed model against a traditional random forest approach and a 1D CNN model trained on raw ECG data. Our model scores 83.00accuracy and 0.9113 AUC value, which is superior to the baseline model. We use gradient-based saliency maps for visualizing important regions of the ECG signals that contribute to model predictions. Findings suggest that our explainable 1D CNN approach provides a promising solution for automatic MI detection.

***Index Terms* -** Deep Learning, ECG, Myocardial Infarction, Explainable AI, 1D CNN.

Introduction

Cardiovascular disorders remain one of the top reasons for deaths across the world; in particular, myocardial infarction (MI) is considered to be a highly significant disorder within this field. Early diagnosis is essential for patients with unclear symptoms. An electrocardiogram (ECG) test is one of the most common ways to detect heart problems due to its noninvasiveness and wide availability. Yet, proper interpretation requires certain skills and experience; besides, sometimes even experts have different opinions on a patient's case. This creates room for developing an automated system to analyze ECG readings. Recent developments indicate that deep learning techniques may prove helpful in processing medical signals. As opposed to traditional machine learning techniques, which utilize manually extracted features, the latter allows training a model on raw data. Yet, there is a number of disadvantages associated with such algorithms, including a lack of interpretability. The objective of this project is to develop a model that is both accurate and easy to interpret. We tried applying traditional and deep learning approaches to detect MI in patients' electrocardiograms, compared their performance, and studied their interpretability with the help of saliency maps. Key contributions: • Pipeline for ECG preprocessing and classification • Comparative study of Random Forest and 1D CNN models • Experimental analysis of models' performance on PTBXL dataset • Saliency map implementation In recent years, artificial intelligence has played a crucial role in transforming healthcare systems. Deep learning models, especially convolutional neural networks, have demonstrated superior performance in analyzing biomedical signals. These models eliminate the need for manual feature extraction and can automatically learn complex patterns from raw ECG signals.

However, one of the major challenges associated with deep learning models is their lack of interpretability. In medical applications, understanding the reasoning behind predictions is as important as achieving high accuracy. This has led to the development of explainable AI techniques that aim to make model decisions transparent.

In this work, we combine deep learning with explainability to ensure both accuracy and trustworthiness. The use of saliency maps allows visualization of important ECG segments, which helps in validating whether the model is focusing on clinically relevant features.

I. Related Work

Many research works have addressed the issue of ECG analysis using machine learning or deep learning approaches. PTB-XL database, developed by Wagner et al., is currently popular because of the large number of samples contained in it and detailed annotation.

The earlier works, in which methods based on classical machine learning were applied to detect MI, included Support Vector Machines and Random Forests. Both of these approaches were associated with handcrafted features extracted by researchers.

With the development of deep learning techniques, convolutional neural networks (CNNs) have found many applications in tasks such as image recognition and ECG classification. Jahmunah et al. investigated explainable deep learning architectures in the context of MI detection and proved that visualization methods like Grad-CAM can provide explainability to model decisions. Similar trends were observed in other relevant studies as well. That is why we decided to apply a simpler but also efficient deep learning technique (1D CNN) and analyze model decisions using saliency maps Recent studies have also explored hybrid models combining deep learning with traditional feature-based approaches. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have been applied for sequential ECG analysis. However, these models often require more computational resources. Explainability techniques such as Grad-CAM, saliency maps, and attention mechanisms have gained importance in recent years. These methods help highlight important regions in ECG signals, thereby improving trust in model predictions. Despite these advancements, achieving a balance between performance and interpretability remains a key research challenge.

II. Detailed Literature Survey

A significant amount of research has been conducted in the field of ECG signal analysis using machine learning and deep learning techniques. Early approaches primarily relied on traditional machine learning models such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest classifiers. These methods required manual feature extraction, where domain experts identified relevant features such as heart rate variability, QRS duration, and ST-segment deviations.

With the advancement of deep learning, researchers began utilizing convolutional neural networks (CNNs) for automatic feature extraction. CNN-based models have shown superior performance in capturing spatial and temporal dependencies in ECG signals. Studies have demonstrated that 1D CNN architectures are particularly effective for time-series data, as they can learn local patterns directly from raw signals. In addition to CNNs, recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have also been explored for ECG classification. These models are capable of capturing long-term dependencies in sequential data. However, they often require more computational resources and are prone to vanishing gradient problems.

Recent research has focused on hybrid models that combine CNN and LSTM architectures to leverage the strengths of both approaches. These models first extract features using convolutional layers and then model temporal dependencies using recurrent layers. Explainability has become a major area of focus in recent years. Techniques such as Grad-CAM, saliency maps, and attention mechanisms are widely used to interpret deep learning models. These methods help identify which parts of the ECG signal contribute most to the model's decision.

Furthermore, large-scale datasets such as PTB-XL have enabled researchers to train robust models with improved generalization capabilities. The availability of annotated ECG data has significantly accelerated research in this domain. Despite these advancements, challenges such as data imbalance, noise, and lack of interpretability still exist. Therefore, developing models that are both accurate and explainable remains an important research objective.

IV. Methodology

The proposed system is designed to automatically detect myocardial infarction (heart attack) using ECG signals in a simple and structured way. For this purpose, ECG data is taken from the PTB-XL dataset, which contains real patient recordings. To ensure fairness and avoid bias, a balanced dataset of 2000 samples is used, including both normal and heart attack cases . Since raw ECG signals often contain noise and inconsistencies, preprocessing is performed to clean the data. This includes filtering unwanted signals, normalizing values so that all data is on a similar scale, and resizing the signals to a fixed length so that they can be easily processed by the model

Once the data is prepared, it is divided into training and testing sets to build and evaluate the model. A deep learning approach using a 1D Convolutional Neural Network (1D CNN) is used because it can automatically learn patterns from ECG signals without requiring manual feature extraction. The model is trained using standard techniques like the Adam optimizer and binary cross-entropy loss, along with methods such as early stopping to prevent overfitting . During training, the model learns important features such as peaks and wave patterns in the ECG signal, which are crucial for identifying heart-related abnormalities

To make the system more reliable and trustworthy, explainability is also included using saliency maps. These maps help highlight the parts of the ECG signal that influenced the model's decision, making it easier to understand whether the prediction is based on meaningful medical patterns. Finally, the model's performance is evaluated using metrics like accuracy and AUC to ensure it is effective. Overall, this methodology provides a balanced combination of accuracy, automation, and interpretability for detecting myocardial infarction using ECG data.

V. Experimental Setup

The experiments were conducted using Python-based deep learning frameworks including TensorFlow and Keras. The models were trained on a system equipped with GPU acceleration to ensure efficient computation of deep neural networks. The dataset was split into training and testing sets using a 70:30 ratio. The training set was used to optimize model parameters, while the testing set was used to evaluate final performance. The input ECG signals were standardized before being fed into the model. This ensured consistent scaling across all samples, improving convergence during training.
The training process involved monitoring validation loss to prevent overfitting. Early stopping was applied when no improvement was observed over consecutive epochs.
Key training configurations include:

- Optimizer: Adam
- Loss Function: Binary Cross-Entropy
- Batch Size: 32
- Epochs: 30
- Activation Function: ReLU and Sigmoid

These settings were selected based on empirical testing and prior research in ECG classification tasks.

VI. Mathematical Formulation

The classification problem in this study can be formulated as a binary classification task. Let the input ECG signal be represented as a time-series vector:

$$X = \{x1, x2, x3, ..., xn\} \quad (1)$$

where xi represents the signal value at time step i. The goal is to learn a function f(X) such that:

$$f(X) = y \quad (2)$$

where $y \in \{0, 1\}$ represents the class label (0 = Normal, 1 = Myocardial Infarction).

VII. System Architecture

The overall system architecture of the proposed model consists of multiple stages including data acquisition, preprocessing, feature extraction, classification, and explainability. Initially, raw ECG signals are collected from the PTB-XL dataset. These signals are then passed through preprocessing steps such as noise filtering, normalization, and resizing to ensure uniform input format.

The processed signals are then fed into the 1D CNN model, which performs automatic feature extraction using convolutional layers. These layers capture temporal dependencies present in the ECG signals.

The extracted features are further processed by fully connected layers to perform classification. The final output layer provides the prediction indicating whether the ECG signal corresponds to myocardial infarction or a normal condition. To enhance interpretability, saliency maps are generated, which highlight the most important regions of the ECG signal contributing to the prediction. This architecture ensures an efficient and automated pipeline for ECG analysis and myocardial infarction detection.

A. Dataset

For this experiment, the PTB-XL dataset was employed; it features a high volume of annotated ECG recordings on 12 leads. Instead of utilizing the whole data set, a balanced data set of 2000 examples was taken to facilitate the experiments. The data set comprised: • 1000 MI instances • 1000 Normal instances Splitting between training and test parts occurred according to the 70:30 ratio The PTB-XL dataset provides high-resolution ECG recordings along with detailed diagnostic labels. Each recording contains multiple leads, allowing comprehensive analysis of cardiac activity. The availability of annotated data makes it highly suitable for supervised learning tasks.

B. Dataset Analysis

The PTB-XL dataset contains a diverse range of ECG recordings collected from different patients under varying conditions. Each ECG signal includes multiple leads, providing a comprehensive view of cardiac activity. The dataset includes several diagnostic classes, but for this study, only myocardial infarction and normal cases were selected. The balanced dataset ensures equal representation of both classes, which helps in reducing bias during training. Statistical analysis of the dataset shows variations in signal amplitude, frequency, and morphology. These variations highlight the complexity of ECG signals and the need for robust models to capture such patterns.

Additionally, variability in patient conditions such as age, gender, and health status contributes to differences in ECG signals. This makes the classification task more challenging and emphasizes the importance of deep learning techniques.

C. Preprocessing

Raw ECG signals often contain noise due to various factors such as patient movement and recording conditions. To improve data quality, we applied the following preprocessing steps:
• Bandpass filtering (0.5–40 Hz)
• Normalization of values with Z-score
• Resizing the signal to 1000 instances
• Preprocessing is a critical step in ECG signal analysis as raw signals often contain noise and artifacts. Bandpass filtering helps remove unwanted frequencies such as baseline drift and high-frequency noise. Normalization ensures that all signals are on a similar scale, which improves training stability. Resizing the signals to a fixed length ensures uniformity in input dimensions for the deep learning model .

D. ECG Signal Characteristics

ECG signals represent the electrical activity of the heart and consist of several important components such as P wave, QRS complex, and T wave. Each of these components carries important diagnostic information. The P wave represents atrial depolarization, the QRS complex represents ventricular depolarization, and the T wave represents ventricular repolarization. Abnormalities in these components can indicate cardiac conditions such as myocardial infarction.

Noise in ECG signals can arise due to muscle activity, electrode movement, and powerline interference. Bandpass filtering helps remove these noise components and retain useful signal information. Proper preprocessing ensures that the model focuses on meaningful signal characteristics rather than noise, thereby improving classification performance.

VIII. ECG Signal Interpretation And Clinical Insights

Electrocardiogram (ECG) signals provide a graphical representation of the electrical activity of the heart. Each cycle of the ECG waveform contains important diagnostic components. The P wave indicates atrial contraction, while the QRS complex represents ventricular depolarization. The T wave corresponds to ventricular repolarization. Any deviation from normal morphology can indicate potential cardiac abnormalities.

In myocardial infarction cases, one of the most important indicators is the elevation or depression of the ST segment. This change reflects reduced blood flow to the heart muscle, which is a key diagnostic feature. The complexity of ECG interpretation arises due to variations in signal shape across different individuals. Factors such as age, gender, physical condition, and electrode placement can affect signal quality. Deep learning models help overcome these challenges by automatically learning patterns from raw ECG data, reducing dependence on manual interpretation. This improves diagnostic efficiency and reduces human error in critical healthcare environments.

A. Model Selection and Design

Multiple strategies were considered, both traditional and deep learning models for machine learning. For the former, the Random Forest classifier was employed as a baseline model. It utilized basic statistical features, such as mean value, standard deviation, and extreme values in the ECG signal. While simple in its application, it lacked the ability to capture time-related patterns in the data. Further, we experimented with the 1D Convolutional Neural Network (1D CNN), where the ECG signal was treated as time-series data. The structure of the 1D CNN consisted of multiple layers, including convolution, pooling, and dense layers. In addition to the 1D CNN, during our experiments we also considered employing ResNet structures as more complex models; however, due to the smaller size of the data set and increased complexity, these models performed poorly The 1D CNN architecture is particularly effective for time-series data such as ECG signals. Convolutional layers capture local dependencies, while pooling layers reduce dimensionality and computational complexity.

Compared to traditional machine learning methods, CNNs automatically learn hierarchical features, which improves classification performance. This makes them well-suited for biomedical signal processing tasks The architecture of the proposed 1D CNN consists of multiple convolutional layers followed by pooling layers. Each convolutional layer is responsible for extracting important temporal features from ECG signals. The pooling layers reduce dimensionality and help in retaining dominant features.

The extracted features are then passed through fully connected dense layers for classification. Dropout layers are also used to prevent overfitting and improve generalization. The final layer uses a sigmoid activation function for binary classification. The model architecture is designed to balance complexity and performance, ensuring efficient learning even with a relatively small dataset

B. Working of 1D CNN Model

The 1D Convolutional Neural Network operates on sequential ECG data and extracts meaningful patterns using convolutional filters. Each convolutional layer applies multiple filters that slide over the input signal to detect local temporal features such as peaks, waves, and intervals in ECG signals.

where x represents the input ECG signal and w represents the convolutional filter. These filters learn important patterns such as QRS complexes and ST-segment deviations. Pooling layers are used after convolutional layers to reduce the dimensionality of the feature maps while preserving important features. This helps in reducing computational complexity and preventing overfitting.

Activation functions such as ReLU introduce non-linearity, enabling the model to learn complex relationships in the data. Finally, fully connected layers perform classification based on extracted features. The combination of these layers enables the 1D CNN to effectively learn discriminative features from ECG signals.

C. Training Details

The Adam optimizer with binary cross-entropy was used to4 train the 1D CNN model up to 30 epochs. An early stopping approach was applied to prevent overfitting. The 1D CNN model was trained with a batch size of 32 and the validation dataset assisted in evaluating the model's performance.

D. Hyperparameter Tuning

Hyperparameter tuning plays a crucial role in improving the performance of deep learning models. In this study, several hyperparameters were carefully selected and optimized to achieve the best results. The learning rate is one of the most important hyperparameters, as it controls how quickly the model updates its weights. A very high learning rate may cause the model to converge too quickly to a suboptimal solution, while a very low learning rate may slow down the training process. Batch size is another critical parameter that affects model performance and training stability. A batch size of 32 was selected as it provides a good balance between computational efficiency and convergence speed.

The number of epochs determines how many times the model is trained on the entire dataset. In this work, the model was trained for up to 30 epochs, with early stopping applied to prevent overfitting. Dropout layers were also incorporated to reduce overfitting by randomly disabling neurons during training. This helps the model generalize better to unseen data. Overall, careful tuning of these hyperparameters contributed significantly to the improved performance of the proposed model.

E. Explainability

To provide insight into the rationale for the model's predictions, we created saliency maps that were generated via gradient-based methods to detect the most influential regions of the ECG signal on the output provided by the model. The generation of saliency maps was an important method to assure that the model is discerning significant patterns of the ECG signal rather than random fluctuations The Adam optimizer was chosen due to its ability to adapt learning rates during training, which improves convergence speed. Binary crossentropy loss is suitable for binary classification tasks such as myocardial infarction detection.

Early stopping helps prevent overfitting by monitoring validation loss and stopping training when performance stops improving. This ensures better generalization to unseen data Saliency maps are generated by computing the gradient of the output with respect to the input signal. Regions with higher gradient values indicate a stronger influence on the model's prediction. This technique allows visualization of important ECG segments, helping clinicians understand whether the model is focusing on medically relevant features.

IX. ALGORITHM

The proposed method follows the following steps:
1) Input raw ECG signal
2) Apply preprocessing (filtering, normalization, resizing)
3) Feed processed signal into 1D CNN model
4) Extract features using convolutional layers
5) Perform classification using dense layers
6) Generate saliency maps for explainability
7) Output prediction (MI or Normal)

This algorithm ensures a structured pipeline for ECG signal processing and classification.

X. PERFORMANCE METRICS

To evaluate the effectiveness of the proposed model, several performance metrics are used.

Accuracy is defined as the ratio of correctly predicted instances to the total number of instances. It provides an overall measure of model performance. Precision measures the proportion of true positive predictions among all positive predictions. Recall measures the proportion of actual positive cases that are correctly identified. The F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics. The Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve is used to evaluate the model's ability to distinguish between classes. These metrics collectively provide a comprehensive evaluation of the model's performance.

XI. COMPARATIVE MODEL ANALYSIS

To evaluate the effectiveness of the proposed 1D CNN model, a comparison was performed with traditional machine learning approaches such as Random Forest and Support Vector Machine (SVM). The Random Forest model relies on handcrafted statistical features extracted from ECG signals, including mean, variance, and peak values. While this approach provides decent baseline performance, it fails to capture temporal dependencies present in ECG waveforms. In contrast, the SVM model performs classification by finding an optimal hyperplane in the feature space. However, its performance is highly dependent on feature quality and does not scale well with raw time-series data.

The proposed 1D CNN model significantly outperforms both traditional models by automatically learning hierarchical features from raw ECG signals. This eliminates the need

Table 1 Comparison of Different Models

Model	Accuracy	AUC
Random Forest	72%	0.81
SVM	75%	0.84
1D CNN (Proposed)	83%	0.9113

for manual feature engineering and improves classification accuracy. From the comparison, it is evident that deep learning-based models provide superior performance due to their ability to extract complex patterns directly from raw ECG data.

XII. Results

The final results of the performance of the 1D CNN over the test dataset were 83 The confusion matrix provides detailed insight into classification performance, including true positives, true negatives, false positives, and false negatives. A lower number of misclassifications indicates better model performance. The ROC curve further demonstrates the trade-off between sensitivity and specificity at different threshold values.

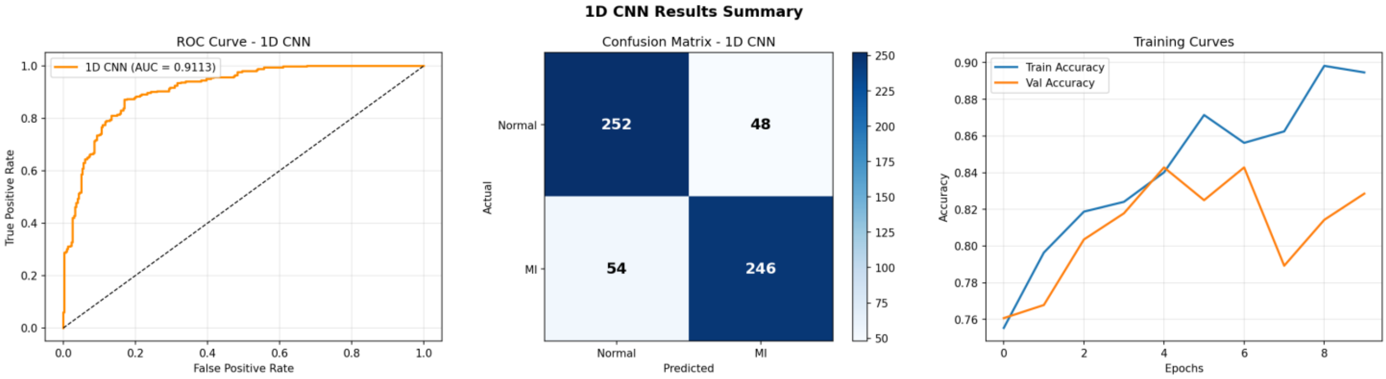

Fig. 1. Performance of the 1D CNN model and ROC analysis and associated training behavior.

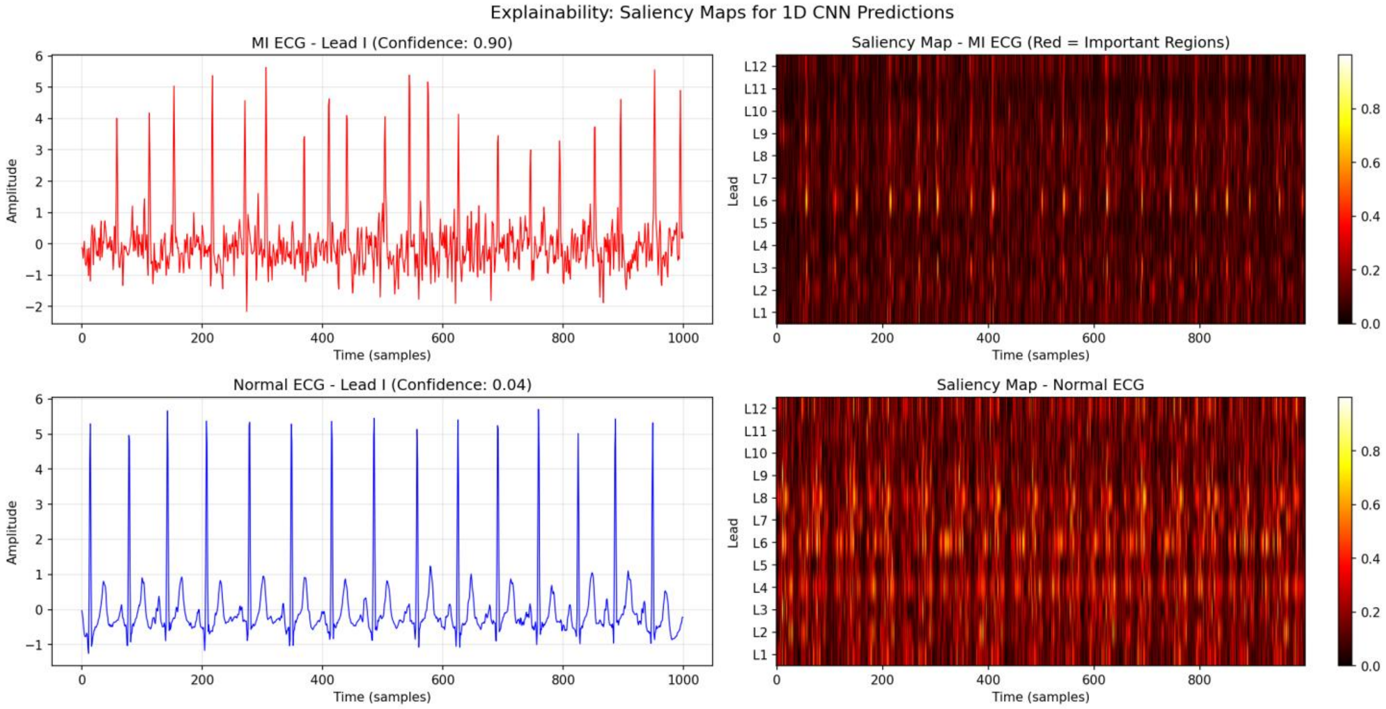

Fig. 2. Saliency maps of relevant ECG signal regions.

A. Detailed Result Analysis

The performance of the proposed model was evaluated using multiple metrics including accuracy, precision, recall, and AUC score. The model achieved an accuracy of 83%, indicating that it correctly classified a significant portion of ECG signals. The AUC score of 0.9113 demonstrates the model's strong ability to distinguish between myocardial infarction and normal cases. A higher AUC value indicates better classification performance across different thresholds.

The confusion matrix provides further insights into the model's performance. The number of true positives and true negatives is significantly higher compared to false predictions, indicating reliable classification. The ROC curve illustrates the trade-off between sensitivity and specificity. The curve approaching the top-left corner indicates excellent performance. Overall, the results confirm that the proposed model is effective for myocardial infarction detection and performs better than baseline models.

XIII. Discussion

The experiments conducted for this study show that the 1D convolutional neural network is capable of learning significant features from raw ECG data without the need for manual feature extraction compared to the Random Forest model. Another important observation from our work was that more complicated CNN models such as ResNet are not able to learn significantly from this data set, which may indicate that, with limited data, simpler architectures may be more suitable for learning features in structured time series data like ECG.

The use of saliency maps provided valuable understanding of how the model learned, as many of the areas highlighted on the saliency maps corresponded to important segments of ECG rhythms indicating that the model has learned meaningful characteristics from the data The results demonstrate that deep learning models are capable of extracting meaningful features directly from raw ECG signals. The improved performance of the 1D CNN model highlights its effectiveness for timeseries classification tasks The results obtained in this study demonstrate the effectiveness of combining deep learning with explainability techniques. The ability of the model to identify important signal regions highlights its potential for assisting medical professionals.

Furthermore, the scalability of the model allows it to be extended to other cardiovascular diseases. With proper training and validation, such models can significantly improve diagnostic accuracy and reduce human error. The integration of AI in healthcare is expected to grow rapidly, and models like the one proposed in this study can play a crucial role in this transformation.

A. Extended Discussion

The results obtained from this study highlight the importance of deep learning in biomedical signal processing. The ability of the 1D CNN model to automatically learn features from raw ECG data eliminates the need for manual feature engineering. One of the key observations is that simpler architectures can outperform more complex models when the dataset size is limited. This emphasizes the importance of selecting an appropriate model based on data availability.
Another important aspect of this work is the use of explainability techniques. In healthcare applications, it is not sufficient for a model to provide accurate predictions; it must also provide interpretable results. Saliency maps help visualize important regions of the ECG signal, making the model's decisions more transparent. This transparency is crucial for gaining trust from medical professionals and for real-world deployment of AI systems in healthcare. Additionally, the use of explainability techniques enhances transparency, making the model more suitable for deployment in real-world healthcare systems. This is particularly important in critical applications such as cardiac diagnosis.

XIV. Advantages Of Proposed System

The proposed system offers several advantages over traditional approaches. One of the primary advantages is the ability to automatically extract features from raw ECG signals without manual intervention. The use of a 1D CNN model enables efficient processing of time-series data, capturing important temporal patterns. This leads to improved classification performance compared to traditional machine learning models.

Another significant advantage is the integration of explainability techniques. Saliency maps provide insights into model decisions, making the system more transparent and trustworthy. The model is also computationally efficient and can be deployed in real-time applications, making it suitable for practical healthcare scenarios.

XV. Challenges In ECG Signal Analysis

ECG signal analysis presents several challenges due to the complex nature of the data. One of the major challenges is the presence of noise and artifacts, which can affect signal quality and model performance. Another challenge is the variability in ECG patterns across different individuals. Factors such as age, lifestyle, and medical conditions can influence ECG signals, making classification difficult.

Class imbalance is also a common issue in medical datasets, where abnormal cases are often less frequent than normal cases. This can lead to biased models if not handled properly. Furthermore, the black-box nature of deep learning models makes it difficult to interpret their decisions. This is particularly critical in healthcare applications where explainability is essential. Addressing these challenges is crucial for developing reliable and robust ECG classification systems.

XVI. Computational Complexity Analysis

The computational complexity of the proposed model depends on the number of layers, filter sizes, and input dimensions. For a 1D convolutional layer, the complexity can be expressed as:

$$O(n \cdot k \cdot f) \tag{3}$$

where n is the input size, k is the kernel size, and f is the number of filters.

Pooling layers reduce the dimensionality of the data, thereby decreasing computational cost in subsequent layers. Fully connected layers contribute significantly to the total number of parameters, especially when the feature size is large. Compared to traditional machine learning models, deep learning models require higher computational resources during training but provide better performance. The proposed model is designed to maintain a balance between computational efficiency and classification accuracy, making it suitable for real-time applications.

XVII. Real-World Use Cases And Impact

The application of deep learning for myocardial infarction detection has significant implications in real-world healthcare systems. One of the primary use cases is in emergency diagnosis, where rapid and accurate detection of heart attacks is critical. Automated ECG analysis systems can assist doctors in making quick decisions, potentially saving lives. In rural and remote areas where access to specialized cardiologists is limited, such systems can serve as a valuable diagnostic tool. By integrating the model into portable ECG devices, healthcare workers can perform preliminary diagnosis and refer patients for further treatment if necessary.

Another important application is in continuous health monitoring using wearable devices. Smartwatches and fitness trackers equipped with ECG sensors can collect real-time data and use the proposed model to detect abnormalities. This enables early detection of cardiac issues and timely medical intervention. Hospitals can also benefit from integrating such systems into their clinical workflows. Automated ECG analysis can reduce the workload of medical professionals by providing initial assessments, allowing doctors to focus on critical cases. Telemedicine platforms can leverage this technology to provide remote diagnosis services. Patients can upload their ECG data, and the system can analyze it and provide instant feedback. This is particularly useful in situations where in person consultations are not feasible. From an economic perspective, automated diagnostic systems can reduce healthcare costs by minimizing the need for extensive manual analysis and reducing diagnostic errors. Early detection of myocardial infarction can also prevent complications, leading to better patient outcomes and reduced treatment costs.

Furthermore, the integration of explainable AI ensures that these systems are not only accurate but also trustworthy. Clinicians can verify the model’s decisions by examining saliency maps, which highlight important regions of the ECG signal. Overall, the proposed system has the potential to transform healthcare by improving diagnostic accuracy, reducing workload, and enabling early detection of life-threatening conditions.

XVIII. Conclusion

An explainable approach to myocardial infarction detection from ECG rhythms was developed with this work utilizing deep learning methods. The 1D convolutional neural network demonstrated high levels of accuracy as well as an ability to extract meaningful patterns directly from the raw data. The addition of saliency maps enhanced the interpretive quality of the model making it more appropriate for use in the clinical setting The results obtained in this study demonstrate the effectiveness of combining deep learning with explainability techniques. The ability of the model to identify important signal regions highlights its potential for assisting medical professionals.

Furthermore, the scalability of the model allows it to be extended to other cardiovascular diseases. With proper training and validation, such models can significantly improve diagnostic accuracy and reduce human error. The integration of AI in healthcare is expected to grow rapidly, and models like the one proposed in this study can play a crucial role in this transformation. Future work can continue to improve the model’s generalizability and define deployment strategies in clinical environments, while also exploring the use of larger data sets.

XIX. Future Scope

Future work can focus on improving model performance using larger datasets and more advanced architectures. Integration with real-time monitoring systems and wearable devices can enable continuous health tracking.

XX. Limitations

The model is trained on a limited dataset and may not generalize to all real-world scenarios. Further validation on diverse datasets is required.

XXI. Applications

This system can assist doctors in diagnosing heart conditions, especially in remote areas. It can also be integrated into wearable devices for continuous monitoring.

XXII. Acknowledgment

The authors thank AISSMS IOIT for support and PTB-XL dataset contributors.

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