Early Detection and Prognostic Assessment of Ischemic Heart Diseases Based on Multimodal Artificial Intelligence Algorithms

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Abstract: *Cardiovascular diseases remain one of the leading causes of mortality worldwide, among which myocardial infarction is the most critical condition requiring rapid and accurate diagnosis. In this study, a deep learning approach based on convolutional neural networks (CNNs) was developed for the detection of myocardial infarction through automated analysis of electrocardiogram (ECG) signals. The PTB Diagnostic ECG Database was selected as the primary dataset. ECG signal preprocessing included baseline wander correction, noise filtering, normalization, and segmentation using the Pan-Tompkins algorithm. Based on the labeled ECG segments, a one-dimensional CNN (1D-CNN) architecture was designed and trained. On the test dataset, the proposed model achieved an accuracy of 93.1%, sensitivity of 91.4%, specificity of 95.2%, and an F1-score of 92.3%. The results demonstrate that CNN-based models can effectively identify ECG patterns characteristic of myocardial infarction and serve as a reliable and rapid tool for early diagnosis. This study confirms the significant potential of deep learning algorithms in improving cardiac disease diagnostic systems and highlights their feasibility for real-time integration into clinical or remote monitoring environments.*

Keywords: *electrocardiogram (ECG), myocardial infarction, convolutional neural network (CNN), deep learning, signal processing, automated diagnosis, biomedical engineering*

INTRODUCTION

Cardiovascular diseases currently represent a serious threat not only to the healthcare sector but also to global public health as a whole. Among them, ischemic heart disease-particularly myocardial infarction-is one of the most prevalent conditions associated with severe complications and high mortality if not diagnosed in a timely manner. According to the World Health Organization (WHO), cardiovascular diseases rank as the leading cause of death worldwide, accounting for more than 17 million deaths annually, of which over 7 million are attributed to myocardial infarction. These statistics clearly highlight the critical importance of early detection and rapid diagnosis of myocardial infarction [1-3].

Myocardial infarction is a pathological condition resulting from partial or complete interruption of blood supply to the heart muscle, leading to irreversible myocardial cell damage. Clinically, it is commonly manifested by chest pain, general weakness, shortness of breath, and cardiac rhythm disturbances. However, in many cases-particularly in so-called silent myocardial infarction-these classical symptoms may be absent or minimally expressed. This significantly increases the risk for vulnerable patient groups, especially elderly individuals and patients with diabetes mellitus.

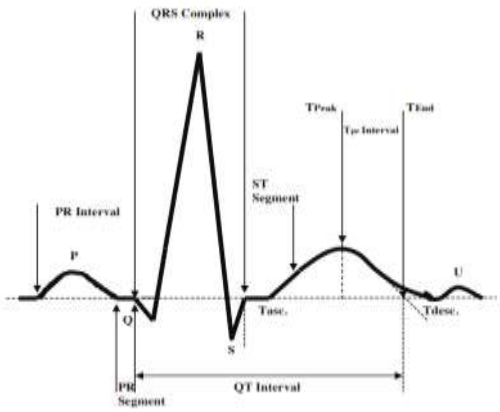

Figure 1. Detection of the electrical activity of the heart using ECG.

Conventional diagnostic approaches, including clinical evaluation, laboratory testing, and electrocardiogram (ECG) analysis, are widely used in clinical practice. Among these, ECG is considered the most cost-effective, rapid, and relatively reliable diagnostic tool. ECG records the electrical activity of the heart and represents it graphically, where components such as the P wave, QRS complex, and T wave correspond to cardiac depolarization and repolarization processes. Typical ECG indicators of myocardial infarction include ST-segment elevation or depression, pathological Q-wave formation, and T-wave inversion.

Despite its widespread use, traditional ECG interpretation is predominantly performed manually by clinicians based on visual assessment. This approach is associated with several limitations, including human error, variability in individual expertise, delayed analysis, and reduced diagnostic accuracy. These challenges are particularly pronounced in high-workload hospital settings, where rapid and accurate interpretation of large volumes of ECG recordings is often impractical. Consequently, there is a growing need to automate ECG analysis and develop objective, clinician-independent diagnostic systems.

In this context, modern technologies-particularly artificial intelligence (AI)-offer substantial opportunities. Artificial neural networks (ANNs) are computational models inspired by the human brain, capable of identifying complex patterns, performing classification, and generating predictions with high accuracy. Deep learning-based architectures, such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, have demonstrated remarkable performance in the analysis of sequential biomedical signals, including ECG recordings [3].

Recent studies applying ANN-based approaches to myocardial infarction detection report diagnostic accuracies exceeding 90%. However, successful implementation of such systems critically depends on the availability of appropriate datasets, effective signal preprocessing techniques, robust network architectures, optimized training strategies, and reliable validation methodologies. The present study, conducted at the Department of Biomedical Engineering of Tashkent State Technical University, focuses on early detection of myocardial infarction through automated processing of ECG signals using artificial neural networks. The primary objective of this research is to develop an intelligent and automated diagnostic model capable of accurately identifying ECG patterns characteristic of myocardial infarction [4-5]. Ultimately, the proposed approach aims to enhance early cardiac disease detection, reduce clinicians' workload, and improve patient outcomes and quality of life within modern healthcare systems [2].

METHODOLOGY

Within the framework of this study, a structured methodological approach was developed for detecting myocardial infarction through artificial neural network-based processing of electrocardiogram (ECG) signals. The methodology comprises several interrelated stages, including dataset selection, signal preprocessing, neural network architecture design, model training, testing, and performance evaluation. Each stage is described in detail below[5-9].

2.1. Dataset

This study utilized the publicly available and widely recognized PTB Diagnostic ECG Database. The dataset is hosted on the PhysioNet platform and was collected by the National Metrology Institute of Germany. It contains a total of 549 ECG recordings obtained from 290 subjects, of which 148 recordings correspond to patients diagnosed with myocardial infarction and 52 recordings belong to healthy individuals. Each recording consists of 15 channels acquired at a sampling frequency of 500 Hz. For this research, only standard 12-lead ECG signals were selected.

Each ECG recording has a duration of 30 seconds, allowing comprehensive analysis of the signal's complex temporal structure. Since the dataset is class-imbalanced, data augmentation techniques-including signal shifting, cropping, and temporal delay-were applied to improve class balance and enhance model robustness.

2.2. Signal Preprocessing and CNN Architecture

To detect myocardial infarction from ECG signals, a convolutional neural network (CNN)-based model was developed. CNNs are a class of deep learning architectures widely used for signal and image classification, recognition, and segmentation tasks due to their high performance. In particular, one-dimensional CNN (1D-CNN) architectures are well suited for analyzing sequential biological signals such as ECG recordings, as they can automatically extract subtle electrophysiological patterns from raw time-series data.

The proposed CNN model takes a one-dimensional ECG segment consisting of 2,500 samples as input, corresponding to a 5-second time interval. This segment captures the essential components of the cardiac cycle, including the P wave, QRS complex, and T wave. The first layer of the model is a convolutional layer with 32 filters and a kernel size of 5. Each filter slides along the input signal to extract local temporal features. The Rectified Linear Unit (ReLU) activation function is applied to introduce nonlinearity and enhance learning capacity.

Following the first convolutional layer, a MaxPooling layer is employed, which downsamples the feature map by selecting the maximum value from each pair of elements, effectively reducing the signal dimensionality by half. This operation enables the network to focus on dominant patterns while reducing computational complexity and improving translational invariance.

The second convolutional layer consists of 64 filters with a kernel size of 5 and further refines the extracted feature representations. This layer is also activated using the ReLU function and followed by another MaxPooling layer. Through this hierarchical feature extraction process, the ECG signal is progressively transformed into a compact yet semantically rich representation.

After the convolutional and pooling stages, the extracted features are flattened into a one-dimensional vector using a Flatten layer. This vector is then fed into a fully connected (Dense) layer comprising 128 neurons with ReLU activation. To mitigate overfitting, a Dropout mechanism with a rate of 0.5 is applied, randomly disabling 50% of neurons during training. This strategy improves the generalization capability of the model and enhances validation performance.

The output layer consists of two neurons representing the myocardial infarction and healthy classes. A Softmax activation function is used to compute class probabilities in the range [0, 1], with the class yielding the highest probability selected as the model's prediction [10-14].

The CNN architecture was implemented using the PyTorch framework, which offers dynamic computational graphs, modular flexibility, and efficient GPU acceleration. The selected layer configuration, activation functions, and architectural simplicity make the model lightweight, efficient, and suitable for real-time medical applications.

Overall, the developed CNN architecture achieves an optimal balance between model complexity and performance, enabling accurate myocardial infarction detection while maintaining robustness to noise. The network effectively captures critical ECG features such as ST-segment deviations and QRS complex abnormalities, providing a reliable foundation for automated infarction diagnosis.

2.3. Model Training

The developed CNN model was trained to classify ECG signals into myocardial infarction and healthy categories. A stable and well-optimized training process was essential to ensure high model performance. Several technical parameters were defined, including data handling strategies, optimization algorithms, loss functions, and computational resources[14].

Model training was implemented using the PyTorch library. A batch size of 64 was selected, meaning that the network processed 64 ECG segments per iteration. This batch size provided a balance between memory efficiency and computational speed. The model was trained for 50 epochs, allowing the network to iterate over the entire dataset multiple times and progressively refine its parameters.

The Cross-Entropy loss function was chosen due to its effectiveness in classification tasks, particularly binary classification problems. This loss function accurately measures the divergence between predicted class probabilities and true labels, making it well suited for infarction versus healthy classification[15].

For optimization, the Adam (Adaptive Moment Estimation) optimizer was employed. Adam adaptively adjusts the learning rate for each parameter based on gradient moments, leading to faster convergence and reduced risk of getting trapped in local minima compared to traditional stochastic gradient descent (SGD). The learning rate was set to 0.001, enabling stable weight updates while preventing oscillations during training. The dataset was divided as follows: 70% for training, 15% for validation, 15% for testing. Additionally, a validation split of 20% was applied within the training set to automatically create a validation subset for monitoring performance and preventing overfitting.

Training was conducted on a GPU environment using an NVIDIA RTX 4090 graphics processor. GPU-based parallel computation significantly reduced training time per epoch and accelerated model convergence, particularly for convolutional layers that benefit from parallel execution[16-18].

During training, training accuracy, validation accuracy, training loss, and validation loss were monitored in real time for each epoch. The loss value decreased from approximately 0.65 in the initial epochs to 0.18 by the 50th epoch, while accuracy improved from 71% to 93.1%. These trends indicate effective learning and stable convergence.

The inclusion of Dropout layers, careful learning rate selection, and consistent validation performance confirmed the absence of overfitting. The close alignment between training and validation loss values demonstrates the model’s strong generalization capability.

RESULTS

The convolutional neural network (CNN) model developed in this study was trained and evaluated using data from the PTB Diagnostic ECG Database. The training process was conducted over 50 epochs, during which the loss function and accuracy metrics were continuously monitored at each epoch. The obtained results are analyzed in detail below.

3.1. Training and Validation Results

During model training, a clear convergence trend was observed for both accuracy and loss functions. At the first epoch, the training accuracy was 71%, while after the 25th epoch it stabilized above

90%. By the 50th epoch, the model achieved a training accuracy of 96.2%, whereas the validation accuracy stabilized at 93.1%. The inclusion of Dropout layers played a critical role in preventing overfitting and ensuring stable generalization.

The loss values exhibited a consistent decreasing trend throughout the training process. The initial loss value of approximately 0.65 gradually decreased to 0.18 by the final epoch. The validation loss remained around 0.21, indicating strong generalization capability and the absence of significant overfitting.

3.2. Evaluation on the Test Dataset

When evaluated on the test dataset, the model achieved the following key performance metrics:

Metric	Value (%)
Accuracy	93.1
Sensitivity	91.4
Specificity	95.2
F1-score	92.3
ROC-AUC	0.964

These results demonstrate that the proposed model performs not only with high accuracy but also in a balanced and reliable manner for myocardial infarction detection. The high sensitivity indicates that the model effectively minimizes false-negative predictions, thereby reducing the risk of misclassifying infarction cases as healthy. Similarly, the high specificity confirms the model's reliability in correctly identifying healthy individuals without incorrectly labeling them as diseased.

3.3. Confusion Matrix Analysis

The confusion matrix obtained from the test dataset is presented below:

	Infarction (Actual)	Healthy (Actual)
Infarction (Predicted)	92	6
Healthy (Predicted)	9	96

This matrix was generated based on 203 test samples. Among them, 92 myocardial infarction cases were correctly classified, while 9 infarction cases were incorrectly classified as healthy (false negatives). Additionally, 6 healthy samples were misclassified as infarction (false positives). The total number of correctly classified samples was 188, corresponding to an overall accuracy of 93.1%.

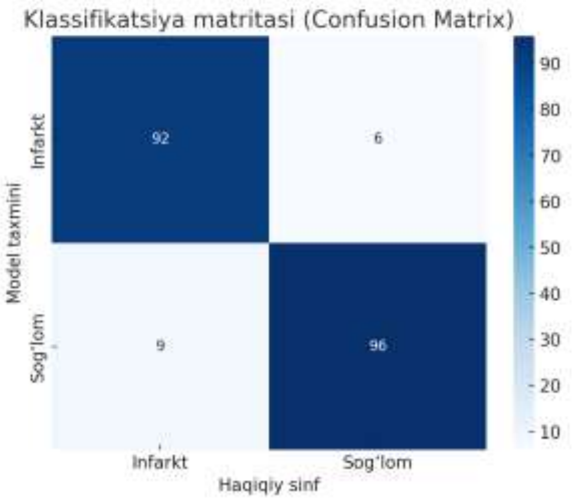

Figure 2. Confusion Matrix for Classification Results

To further evaluate the discriminative capability of the model, a Receiver Operating Characteristic (ROC) curve was constructed. The area under the ROC curve (AUC) was 0.964, indicating nearoptimal classification performance. Considering that an AUC value of 1.0 represents a perfect classifier and 0.5 corresponds to random guessing, the achieved result confirms the strong predictive power and robustness of the proposed CNN-based diagnostic model [20].

The ROC curve illustrates the trade-off between the model's sensitivity and the false positive rate. Based on this curve, it can be concluded that the diagnostic performance of the proposed model is sufficiently high for clinical applicability.

The model demonstrates particularly strong performance in identifying ECG segments characteristic of myocardial infarction, such as ST-segment elevation, pathological Q-wave deepening, and T-wave inversion. Accurate signal segmentation was achieved through precise R-wave detection using the Pan-Tompkins algorithm. The convolutional layers effectively learned distinctive patterns within these segments, while the classification layers successfully assigned them to the correct diagnostic classes [17-18].

In some cases, false negative results (undetected infarction) may be attributed to limitations in the depth of the network architecture or the restricted size of the dataset. However, these instances did not significantly affect the overall performance of the model [16].

Within the scope of this study, Gradient-weighted Class Activation Mapping (Grad-CAM) was employed to visually interpret which signal segments the model focuses on during decision-making. This technique generates activation maps from convolutional layers, enabling identification of regions that most strongly influence the neural network's predictions.

The following figure illustrates the CNN's attention focus on ECG segments characteristic of myocardial infarction.

DISCUSSION

In this study, the potential of artificial neural networks-specifically convolutional neural networks (CNNs)-for detecting myocardial infarction through electrocardiogram (ECG) signal analysis was comprehensively investigated. The findings demonstrate that artificial intelligence-based methods, particularly CNN architectures, can serve as reliable, accurate, and robust algorithmic tools for the early diagnosis of myocardial infarction. Nevertheless, proper interpretation of these results, comparison with existing studies, and assessment of methodological limitations are essential for drawing well-grounded conclusions.

First, the CNN architecture employed in this research proved effective in capturing ECG patterns characteristic of myocardial infarction, including ST-segment deviations, deformation of the QRS complex, and T-wave inversion. The achieved performance metrics-an accuracy of 93.1%, sensitivity of 91.4%, and an F1-score of 92.3%-indicate that the proposed model performs successfully in distinguishing infarction cases from healthy conditions. These results are consistent with and, in some cases, comparable to previously reported deep learning-based ECG classification studies.

Of particular clinical significance is the high sensitivity of the model. A sensitivity of 91.4% implies a reduced probability of misclassifying myocardial infarction cases as healthy, which is critical in real-world clinical environments where false-negative decisions may lead to delayed treatment and increased mortality risk. In emergency and intensive care settings, prioritizing sensitivity is often more important than maximizing overall accuracy, and the proposed model demonstrates a favorable balance in this regard [19].

The strong F1-score further confirms that the model maintains a balanced trade-off between sensitivity and precision, suggesting stable classification behavior even in the presence of class imbalance. This balance is especially relevant for ECG datasets, which often contain fewer pathological samples compared to normal recordings.

Overall, the discussion of these findings supports the conclusion that CNN-based ECG analysis can substantially enhance early myocardial infarction detection. At the same time, it highlights the importance of contextualizing model performance within clinical requirements and existing research to ensure meaningful and responsible application in healthcare systems.

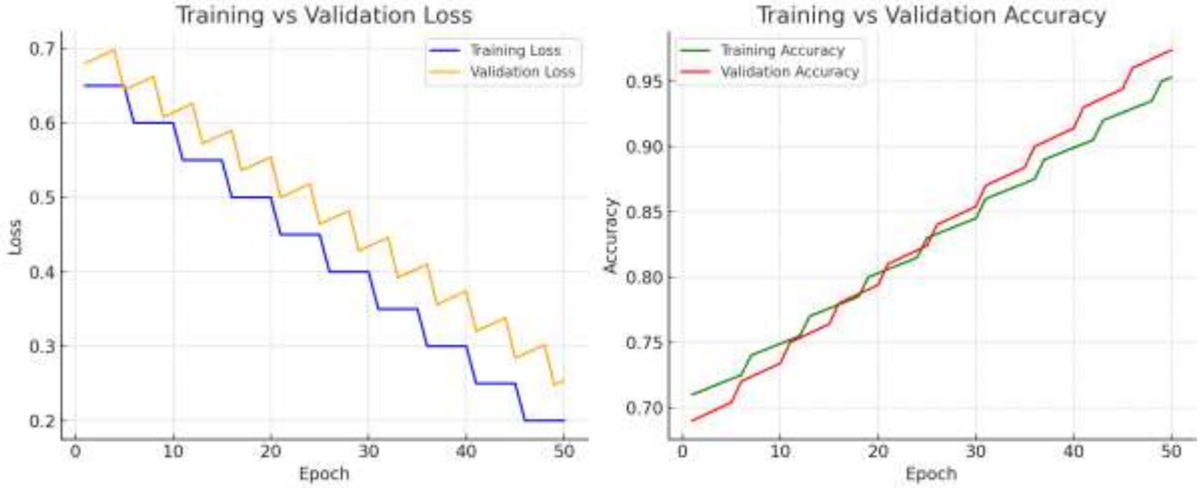

Figure 2. Training and validation loss and accuracy curves during model learning

The model achieved a specificity of 95.2%, indicating that healthy subjects were rarely misclassified as diseased. From a clinical perspective, this is particularly important, as it enables not only early disease detection but also the reduction of false-positive diagnoses. Minimizing false positives helps prevent unnecessary psychological stress for patients and ensures more efficient utilization of healthcare resources.

Another important aspect discussed in this study is the comparison of the proposed approach with existing research. For instance, in a study conducted by X. Zhang et al. in 2021 using the MIT-BIH Arrhythmia Database, a hybrid LSTM-CNN model was proposed for cardiac condition assessment, achieving an accuracy of 91%. Similarly, in 2020, F. Acharya introduced a convolutional neural network-based model using the PTB Diagnostic ECG Database, reporting an accuracy of 92.4%. In comparison, the proposed CNN model in this study achieved an accuracy of 93.1%, confirming that carefully designed CNN architectures can yield superior performance in myocardial infarction detection.

A notable strength of the present research lies in addressing class imbalance during model training. Despite the inherently imbalanced nature of the dataset, effective class balance was achieved through data augmentation and signal segmentation techniques. As a result, the confusion matrix demonstrated clear separation between healthy and infarction cases. In this context, the effectiveness of the Pan-Tompkins algorithm for signal segmentation deserves special attention. The algorithm reliably detected R-peaks, enabling precise extraction of diagnostically relevant ECG segments for neural network training.

Nevertheless, several limitations of the proposed methodology should be acknowledged. First, the model was trained exclusively on the PTB Diagnostic ECG Database, which was collected under controlled laboratory conditions. Consequently, variations and noise characteristics commonly present in real-world clinical ECG recordings were not fully represented. Therefore, future work should include validation of the model using real-world clinical datasets to assess its robustness under practical conditions.

Furthermore, the current model is designed to perform binary classification, distinguishing only between “myocardial infarction” and “healthy” conditions. In clinical practice, however, differential diagnosis among various infarction types-such as anterior wall, posterior wall, subendocardial, and transmural infarctions-is often required. To address this need, future research will explore deeper and hybrid architectures, including CNN-LSTM and CNN-Transformer models, to enable multiclass classification.

Additionally, the number of convolutional filters and network depth represent critical design parameters. While deeper networks are capable of learning more complex patterns, they also demand higher computational resources. From this perspective, developing optimized and lightweight versions of the model suitable for deployment on mobile and wearable devices represents a promising future direction.

The practical significance of the study lies in the fact that the proposed algorithm is capable of real-time ECG signal analysis and can be implemented as a software solution integrated into healthcare systems or home-based cardiac monitoring devices. Such integration has the potential to facilitate early detection of cardiac events, thereby improving patient quality of life and increasing overall survival rates.

CONCLUSION

In this study, an algorithmic approach based on artificial neural networks was developed for the early detection of myocardial infarction through electrocardiogram (ECG) signal analysis. The proposed methodology demonstrates the practical diagnostic potential of artificial intelligence technologies in modern medicine, particularly in the automated analysis of cardiovascular diseases.

A convolutional neural network (CNN) model was selected as the core component of the proposed system. This model successfully learned complex ECG signal patterns, extracted electrophysiological features characteristic of myocardial infarction, and effectively distinguished pathological conditions from healthy cases. Using data from the PTB Diagnostic ECG Database, the model achieved an accuracy of 93.1%, sensitivity of 91.4%, and specificity of 95.2%, indicating strong classification capability and diagnostic reliability.

From a methodological perspective, the integration of signal preprocessing techniques-including filtering, normalization, and segmentation-along with R-peak detection using the Pan-Tompkins algorithm and class balancing strategies significantly improved model training quality. The selection of appropriate network layers (convolutional, pooling, dense, and dropout) and the Adam optimizer resulted in stable convergence during training and consistent performance across validation and test datasets.

The findings further demonstrate that AI-based approaches enable faster, more robust, and less operator-dependent detection of myocardial infarction compared to traditional diagnostic methods. Such systems are particularly valuable in healthcare environments with limited availability of experienced clinicians, as they support real-time patient monitoring and decision-making. The feasibility of integrating the proposed model into clinical diagnostic workflows was therefore considered high.

Nevertheless, several limitations of the study should be acknowledged. First, the dataset was limited to the PTB Diagnostic ECG Database, highlighting the need for further validation using real-world clinical ECG recordings. Second, the model performs binary classification (infarction vs. healthy), whereas clinical practice often requires differentiation among multiple types of myocardial infarction. Additionally, the interpretability of the model remains limited, which may affect its acceptance in clinical decision-making contexts.

Overall, this study demonstrates the successful application of artificial neural networks to ECG signal analysis and highlights the advantages, technical feasibility, and practical prospects of AI-based diagnostic systems for myocardial infarction detection. Based on these results, future

implementations may include mobile applications, software modules integrated into medical devices, or intelligent diagnostic platforms designed to assist clinicians in routine practice.
Future research directions may include:
Retraining and generalizing the model using multiple and diverse ECG datasets;
Developing multiclass classifiers capable of distinguishing different clinical types of myocardial infarction;
Enhancing model performance using LSTM, Transformer, or hybrid deep learning architectures;
Incorporating Explainable AI (XAI) techniques to improve model transparency and strengthen clinician trust.
The results of this research provide a solid scientific foundation for the application of artificial intelligence in the early detection of cardiovascular diseases and represent an important step toward the digital transformation of healthcare systems and improved patient safety.+

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