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AI-Enhanced ECG diagnosis system for acute myocardial infarction with LBBB: Constant-Q transform and ResNet-50 integration

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This study introduces an advanced Electrocardiogram (ECG) diagnostic framework that melds signal processing techniques with deep learning models to significantly boost accuracy in identifying acute myocardial infarction (MI) and MI related to left bundle branch block (LBBB). By merging the Constant-Q Transform (CQT) with a pre-trained model, this system showcases exceptional performance, an impressive 98.99% accuracy and a remarkably low 0.0029% training loss after 100 trained epochs. Rigorous 10-fold cross-validation substantiates and fortifies these findings. This novel approach streamlines the complexities of diagnostics by consolidating 12-lead ECG data and harnessing CQT for precise time-frequency domain analysis. Notably, this methodology not only enhances MI detection accuracy but also presents potential for enhancing healthcare outcomes. It holds promise in minimizing misdiagnoses, thereby propelling advancements in patient care for critical cardiac conditions. This paradigm shift marks a significant stride in ECG-based diagnostic systems, offering far-reaching implications for improved medical practices and patient well-being.

Keywords: *AMI; LBBB; CQT; ECG; ResNet-50.*
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1. Introduction

Cardiovascular diseases are a leading cause of global mortality, resulting in an estimated annual deaths [1]. Projections indicate a concerning increase, potentially reaching by 2030 [2]. Among these diseases, Acute myocardial infarction (AMI) is particularly severe. Diagnosing a MI relies on specific changes in the electrocardiogram (ECG), such as ST-segment elevation/depression (STEMI), T-wave inversions, or pathologic Q waves. However, ECG alone may not suffice due to similar patterns in conditions like left bundle branch block (LBBB) [3]. LBBB presents diagnostic challenges as it can mask crucial ECG indicators. To address this, healthcare providers rely on additional tools, including symptoms, medical history, and imaging like echocardiography. Manual ECG interpretation can be complex and inconsistent, especially in remote or emergency settings [4]. Recent research explores the application of artificial intelligence (AI) and deep learning techniques for improving myocardial infarction (MI) diagnosis using 12-lead electrocardiograms (ECGs). In [5], researchers began by reducing noise in ECG data and utilized the ML-ResNet network to detect MI. However, the complexity of this approach posed challenges. In contrast, [6] employed deep learning, specifically ResNet-50, in medical image analysis. They conducted experiments using 12-lead ECG data from Chapman University and Shaoxing People's Hospital, transforming ECG signals into scalogram and grayscale images. They adopted a stacking ensemble method with logistic regression, support vector machine, random forest, and XGBoost as the meta learner. An innovative aspect was the introduction of a "multi-modal stacking ensemble" integrating predictions from scalogram and ECG grayscale images. Meanwhile, [7] developed a tailored MI detection model emphasizing feature fusion. Their model aimed to detect MI from 12-lead ECG images, utilizing a multi-branch network with a shallow CNN for feature extraction. However, the use of 12 separate models raised concerns about system complexity and redundancy. Our study addresses these challenges by concatenating data from all 12 leads, simplifying the diagnostic process. We also utilize the Q transform to represent data in the time-frequency domain, revealing crucial spectral characteristics of ECG signals. This approach aims to enhance MI diagnosis, contributing to improved patient outcomes and reducing the risk of misdiagnosis.

Our key contributions can be summarized as follows:

— Addressing complexity through data concatenation from all 12 leads.
— Following the removal of noise from the 12-Leads signals, the 1D ECG signals undergo a process of horizontal concentration.
— We adopt the CQT algorithm to convert the 1D ECG signal into a 2D time-frequency representation, which is then input into the pre-trained ResNet-50 CNN model.

2. Related work

Numerous studies have harnessed bodily biometric signals, such as ECG, in conjunction with AI techniques to detect cardiac problems. Some of these studies [5–7] employ the ML-ResNet network (multi-lead residual neural network), multibranch fusion network, and multiple feature-branch convolutional neural network to detect myocardial infarction (MI) using a 12-lead ECG. In [5], the authors applied the ECG data to undergo an initial noise reduction. The ML-ResNet network has been harnessed for the purpose of detecting and pinpointing myocardial infarction (MI). This network architecture encompasses a total of 13 layers, integrating a distinctive lead feature branch within its structure. Specifically, this single feature branch is composed of three residual blocks, each containing three convolutional layers. However, it is important to note that this approach encounters a challenge in terms of complexity, as it involves a substantial number of parameters that need to be carefully managed and optimized.

Similarly, [7] adopts a 1D-ECG signal within a deep learning framework for MI diagnosis. The MFB-CNN approach involves 12 independent feature branches, each operating on a single lead from the 12-lead ECG. This study introduces an innovative method for the detection and localization of automated myocardial infarction (MI) using 12-lead electrocardiogram (ECG) data. The Multiple-Feature-Branch Convolutional Neural Network (MFB-CNN) capitalizes on the integrity and diversity of ECG signals, as each feature branch captures distinct lead-related data. The integration of these features through a global softmax layer obviates the necessity for manual feature crafting. However, a notable challenge arises due to the high complexity when dealing with the separate analysis of 12 leads.

In contrast, the study [6] introduces a model tailored for myocardial infarction detection using 12-lead electrocardiogram (ECG) images. Their proposed methodology encompasses a multi-branch network, feature fusion, and a classification network. Following thorough experimentation, they opted for a shallow CNN as the multi-branch network to extract features from individual leads. The fusion of feature maps was accomplished through depth fusion, and these integrated features were subsequently channeled into a classification network founded on the DenseNet architecture. The resultant model exhibited exceptional sensitivity and specificity in the realm of myocardial infarction screening. Nonetheless, a notable drawback of this approach lies in its complexity, and there is a lack of data preprocessing incorporated within the method.

Further advances include [8], which introduces an innovative approach to medical diagnosis using ResNet-50 for the automatic classification of 12-lead ECG data encompassing multiple cardiovascular diseases. They presented an efficient DL model designed for the automatic diagnosis of 12-lead electrocardiogram (ECG) signals categorized into 27 classes. These classes include 26 different types of CVD and a normal sinus rhythm. The proposed model is built on the Residual Neural Network (ResNet-50) architecture and is evaluated through experimentation using combined public databases from the USA, China, and Germany as a proof of concept.

In [9], an updated ResNet-18 model is introduced, showcasing the potential of deep learning to revolutionize ECG signal analysis. This novel approach addresses the limitations of conventional methods and aims to categorize ECG signals more effectively. To achieve precise identification and classification of five AAMI heartbeat classes using the MIT-BIH arrhythmia database, the article presents an enhanced ResNet-18 model. This model leverages the unique characteristics of lead ECG data, treating it as one-dimensional time series. By adopting this approach, the model can extract multiple features from the same input, efficiently capturing the internal structural nuances within the ECG data. Consequently, this enhancement significantly bolsters the model's classification accuracy. Dealing with expansive datasets presents challenges in neural network training. As the input data volume increases, so does the necessity for additional neurons to enhance classification accuracy. Unfortunately, expanding the model's size, especially in fully connected neural networks, results in an abundance of parameters, which can impede training speed. To address this challenge, the article introduces a Convolutional Neural Network (CNN) characterized by local connectivity and parameter sharing. This CNN design effectively reduces model parameters while accelerating training, making it well-suited for large datasets. The study employed the MIT-BIH dataset, which primarily consists of 2-lead ECG recordings. However, this limited dataset may not fully harness the potential benefits of utilizing all 12 leads available in a comprehensive ECG. In addition, it is worth noting that the ResNet architecture, particularly its residual blocks, can face challenges related to gradient vanishing during training. This issue can impede the network's ability to effectively learn and represent complex patterns in the data.

The application of deep learning in medical image analysis, particularly ResNet-50, is shown in [5], where The study conducted experiments utilizing 12-lead electrocardiogram (ECG) databases sourced from Chapman University and Shaoxing People's Hospital. To fine-tune the pretrained ResNet-50 model for each lead, the ECG signals were transformed into scalogram images and ECG grayscale images. The ResNet-50 model served as the base learner for a stacking ensemble method. The meta learner, used for combining predictions from the base learner, employed logistic regression, support vector machine, random forest, and XGBoost. This study introduced a novel approach termed "multimodal stacking ensemble," which integrates predictions from two modalities: scalogram images and ECG grayscale images. In scenarios involving MI associated with left bundle branch block (LBBB), and disruptions in the heart's electrical conduction, the Constant Q Transform (CQT) emerges as crucial. LBBB-related changes often appear in the lower frequency spectrum (ST-segment) of cardiac signals, making CQT more adept at uncovering these alterations compared to linear methods. While ResNet excels in various computer vision tasks, it is not immune to challenges. A primary one is vanishing gradients, which hinder learning in deep architectures. ResNeXt, an extension of ResNet, overcomes this through "cardinality." Using grouped convolutions, ResNeXt facilitates efficient information flow across paths. By partitioning input channels into groups, it enhances network capacity without overburdening parameters, ultimately increasing accuracy and robustness, especially in scenarios with limited training data.

3. Methodology

We introduce a new system for ECG diagnosis by integrating a pre-trained model with the Constant-Q Transform (CQT), leading to improved accuracy and efficiency in analyzing ECG signals. The model stages, including signal preprocessing, 12 leads Horizontal data concatenation, CQT transformation, and the ResNet-50 model, are illustrated in Figure 1. This innovative approach combines signal processing techniques and deep learning models to enhance ECG analysis and improve healthcare outcomes. Additionally, the incorporation of k-fold cross-validation strengthens the credibility and reliability of our experimental results, providing a comprehensive evaluation of the integrated ECG diagnosis system (see Figure 1).

3.1. Data set and preprocessing

For this research, we obtained electrocardiograms (ECGs) from the publicly available PTB database, which comprises ECG signals from 191 participants in both AMI and AMI associated with LBBB categories. The records last 10 seconds, are labeled by cardiologists. Most records may have multiple annotations, and the signal is sampled at 500 Hz [3].

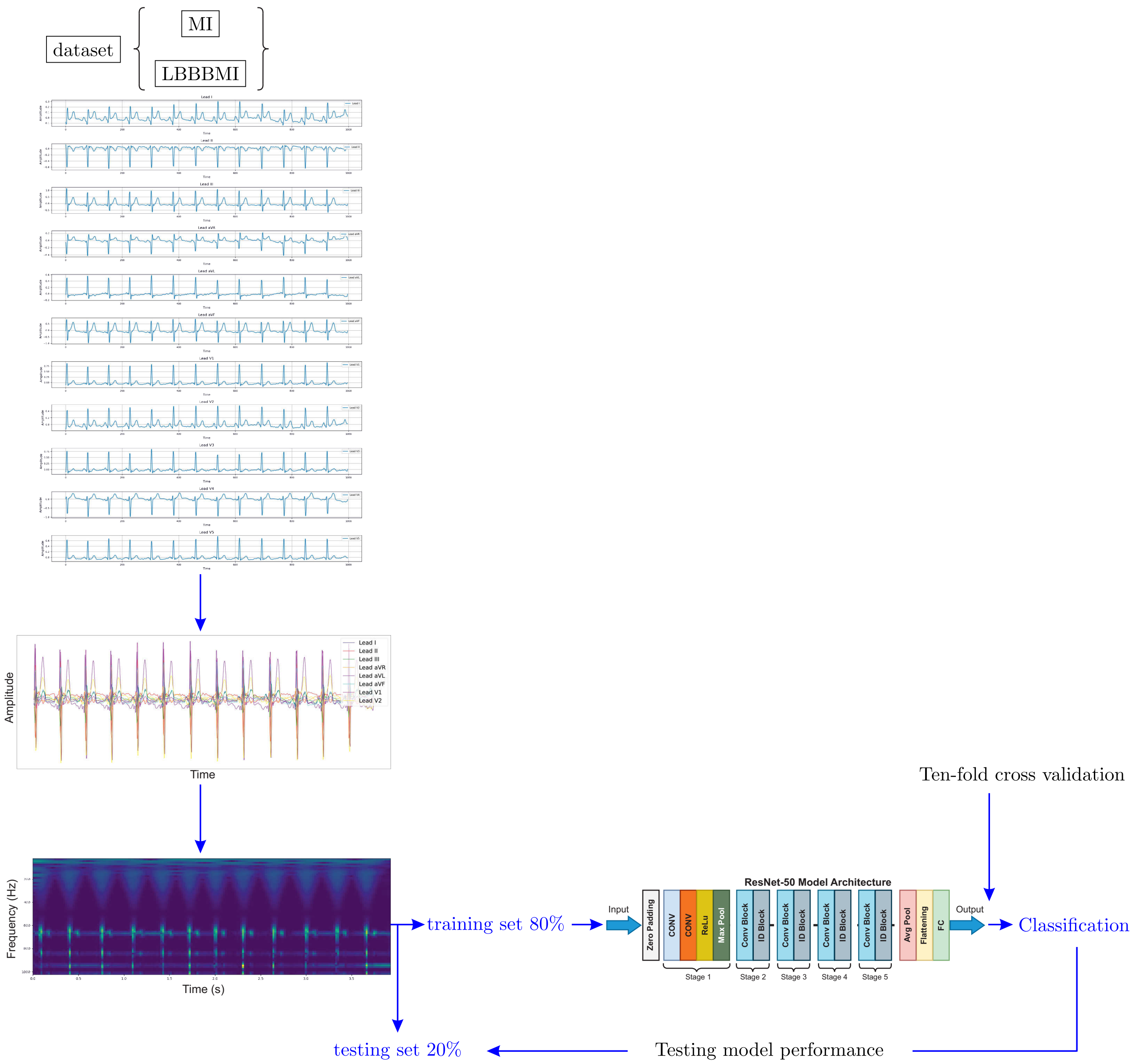

Fig. 1. The proposed method.

However, ECG signals often suffer from various types of noise that can adversely affect the accuracy of the diagnostic results. These noise types include power line interference, baseline wander, and electrode contact noise, which must be adequately addressed before applying machine learning algorithms to diagnose MI. Thus, ECG signal denoising and preprocessing become a discriminative need [10]. In our study, several filters are applied to an electrocardiogram (ECG) signal to improve its quality. Firstly, a bandpass filter is applied to remove static noise and high-frequency noise. This filter uses a Butterworth filter of order 5 with a lowcut frequency of 0.5 Hz and a highcut frequency of 100 Hz. Next, a median filter with kernel size of 3 is applied to remove burst noise. The signal is then processed to remove baseline drift by subtracting the moving average of the signal using a window size of 0.2 seconds. Finally, any obvious outliers in the signal that may be caused by electrode problems are removed by manually replacing values greater than 2.0 or less than -2.0 with the mean of the filtered signal. The resulting signal is then ready for further analysis or interpretation.

3.2. 12-Lead data concatenation and 2D transformation

12 leads horizontally concatenating allows us to represent multiple leads in a single waveform, which can be useful for visualization or further processing. It enables you to consider the interactions between

the leads and analyze the combined information. By applying the CQT to the ECG data, essential features can be extracted with high precision, enabling more accurate diagnosis of cardiac conditions. The CQT, a signal processing technique, offers variable frequency resolution, making it particularly suitable for non-stationary signals like ECG. Figure 2 illustrates the horizontal concatenation of the 12 leads, followed by the representation of the concatenated signal in the time-frequency domain.

As input, the model takes an ECG signal $X \in \mathbb{R}^{N*12}$ after the horizontal concatenation the new data format is a matrix of N samples and 12 columns, each column represents a lead. The perceptually motivated CQT [11, 12] approach to the spectro-temporal analysis of a discrete signal $x(n)$ is defined by

$$X_{CQ}(k,n) = \sum_{l=n-\left\lfloor \frac{Nk}{2} \right\rfloor}^{n+\left\lfloor \frac{Nk}{2} \right\rfloor} x(j) \cdot a_k^* \left(l - n + \frac{Nk}{2} \right). \tag{1}$$

This equation represents the computation of $X_{CQ}(k,n)$, which signifies the CQT coefficients for a given frequency scale k and time index n. The summation involves the signal $x(l)$ multiplied by the scale-related factor a_k and k within a specific range determined by N and k, n represents the sample index within the signal; k ranges from 1 to K and stands for the frequency bin index; $a_k(n)$ denotes the basic functions, which are functions of both n (sample index) and k (frequency bin index); the symbol '$*$' denotes the complex conjugate operation; N_k refers to the frame length specific to the frequency bin k.

In the CQT context, the basic functions $a_k(n)$ are specifically defined as complex-valued functions that depend on both the sample index n and the frequency bin index k. These functions play a crucial role in decomposing a signal into its frequency components across different time intervals, facilitating analysis in the time-frequency domain (see Figure 2).

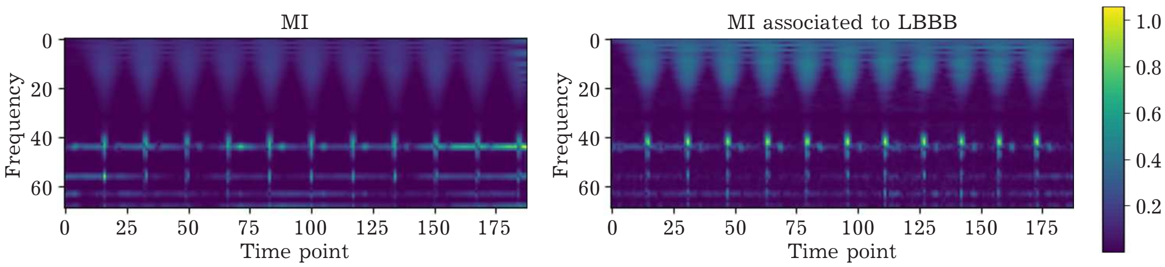

Fig. 2. ST-segment in low-frequency representation.

However, it has been observed that the quality of the leads may differ, leading to variations in the extracted features and subsequent analyzes. To address this issue, we used the novel approach that involves horizontally concatenating the data from multiple leads before applying the CQT transform. This technique aims to leverage the complementary information across leads and enhance the overall quality of the signals. By concatenating the leads, the resulting signal benefits from an improved signal-to-noise ratio and a reduction in artifacts and noise that may have been present in individual leads. Consequently, when the CQT transform is applied to the concatenated signal, the extracted features exhibit improved consistency and reliability compared to those obtained from individual leads. This approach has demonstrated promising results in various signal analysis tasks, such as classification or anomaly detection, where the concatenation of leads before the CQT transform has led to enhanced performance and more accurate results. Figures 3, 4 illustrate the differences between applying the Constant-Q Transform (CQT) to each lead individually and applying it to the horizontally concatenated 12-lead ECG signals.

In the first approach, the CQT transformation is independently applied to each lead of the 12-lead ECG signals. This results in obtaining separate time-frequency representations for each lead, capturing specific temporal and frequency patterns in individual leads. On the other hand, in the second approach, the 12-lead ECG signals are horizontally concatenated before applying the CQT transform. This novel technique aims to leverage the complementary information present across multiple leads simultaneously. By concatenating the leads, the resulting signal benefits from improved signal-to-noise ratio and a reduction in artifacts and noise that may have been present in individual leads. Therefore, the proposed approach of concatenating leads before applying the CQT transform offers a valuable method to address the variability in lead quality and improve the overall efficacy of signal processing and analysis.

3.3. ResNet-50

ResNet-50 is a variant of the ResNet architecture, which is a deep convolutional neural network commonly used for computer vision tasks. It is known for its depth and remarkable performance in image recognition tasks. The ResNet building block consists of a main pathway with convolutional layers, batch normalization, and activation functions. It also includes a shortcut connection that allows the network to learn residuals or differences between the current layer's output and the desired output. This architecture addresses the vanishing gradient problem and enables the training of very deep networks. It has proven highly effective in various computer vision tasks, including image classification and object detection [5]. In the context of a 2D convolutional neural network (CNN), similar operations to those in the 1D scenario are performed, but considering two-dimensional data. Here is an adaptation of the provided description for a 2D CNN.

A 2D convolutional layer (Conv2D) is applied to the input data, followed by a batch normalization layer (BatchNorm) and rectified linear unit activation (ReLU). Subsequently, a Max Pooling layer is used to downsample the features extracted by the Conv2D layer.

In this setup, 16 residual blocks are employed to extract deep features. There exist two types of residual blocks:

The residual Block Type 1: Composed of three Conv2D layers, three BatchNorm layers, and two ReLU activation layers. One Conv2D layer and one BatchNorm layer are utilized to match dimensions, facilitating skip connections.

The residual Block Type 2: Comprising three Conv2D layers, three BatchNorm layers, and two ReLU activation layers.

The Conv2D layers serve the purpose of feature extraction, while the BatchNorm layers contribute to accelerating convergence and stabilizing the model. The ReLU layers introduce non-linearity for enhanced representational power.

The features extracted through the residual blocks undergo pooling, typically using Average Pooling, where the pooled results are collected and directed to the output layer. The output layer utilizes the sigmoid activation function to produce predictions based on the learned features (see Figure 3).

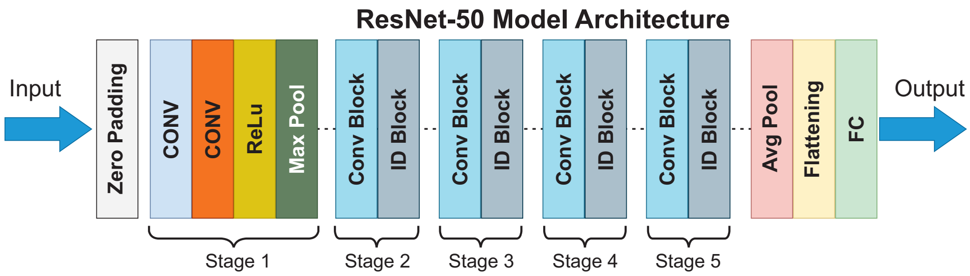

Fig. 3. ResNet-50 architecture.

3.4. K cross validation

K-fold cross-validation is a widely used technique in machine learning for evaluating classification algorithms. It involves dividing the data into k subsets, using $k-1$ subsets for training and one subset for testing, resulting in k accuracy scores for assessment. This technique is essential for estimating the performance of models, preventing overfitting, and optimizing data utilization. It also aids in model selection, hyperparameter tuning, and algorithm comparison. K-fold cross-validation provides insights into the stability and suitability of models for real-world applications [13].

3.5. Performance evaluation

We employed the specificity, sensitivity, and accuracy metrics – all widely used in the field of pattern recognition, to assess the performance of each class. In order to calculate these metrics, the values of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) were used, which were stated in the appropriate way in the equations (2), (3), and (4). These are their definitions:

$$\text{specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}, \tag{2}$$

$$\text{sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{3}$$

$$\text{Accuracy} = \frac{\text{Total correctly classified signals}}{\text{Total number of signals}} \times 100. \tag{4}$$

4. Result and discussion

Our paper significantly advances ECG diagnosis, specifically in the detection and characterization of acute myocardial infarction (MI) and acute MI associated with left bundle branch block (LBBB). By integrating a pre-trained model with the Constant-Q Transform (CQT), we achieve improved accuracy and efficiency in analyzing ECG signals related to AMI and LBBB. Our model utilizes the cross-entropy loss function and demonstrates outstanding performance, achieving an impressive training accuracy of 98.99% with a training loss score of only 0.0029% after 100 epochs of training (see Figures 4, 5).

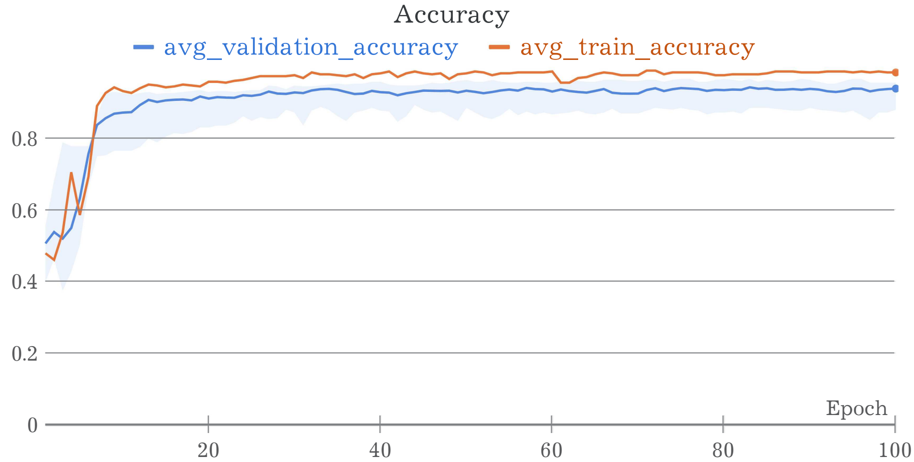

Fig. 4. Our Model Mean Accuracy Scores for 10-Fold Cross-Validation.

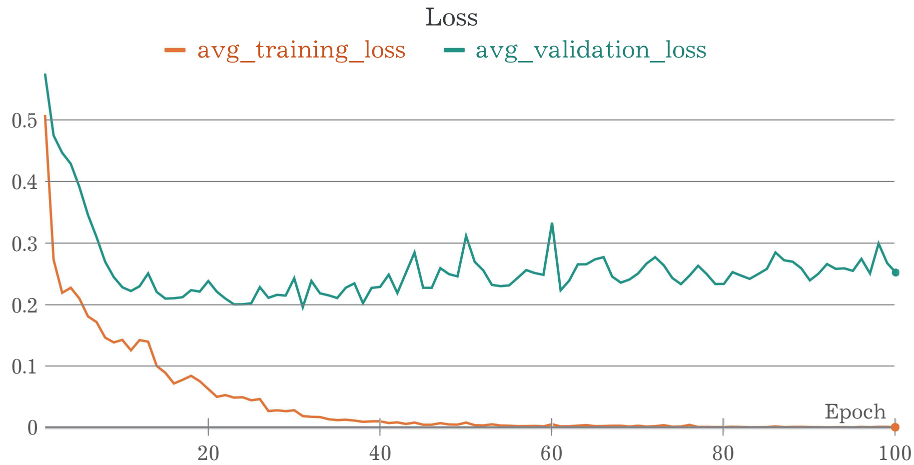

Fig. 5. Our Model Mean Loss Scores for 10-Fold Cross-Validation.

As depicted in Figure 4, these exceptional performances validate the effectiveness and reliability of our model in accurately classifying ECG signals. The high accuracy and low training loss score highlights the robustness and precision of our approach in addressing the given task (see Table 1).

Table 1. Comparative results.

Method	Dataset	Accuracy	Sensitivity	Specificity
ML-ResNet [5]	PTB	95.49%	94.85%	97.37%
Multi-Modal Stacking Ensemble and Resnet-50 [6]	PTB-XL	93.97%	94.0%	–
Multi-branch fusion network [7]	ECG images	94.73%	96.41%	95.94%
Proposed methode	PTB-XL	98.99%	98.75%	97.69%

Accurate detection of MI and LBBB in MI cases is of significant clinical importance as it enables timely diagnosis and appropriate treatment, leading to improved patient outcomes and better cardiac care. Our results demonstrate the potential of the proposed ResNext50 model as an effective tool to improve cardiac diagnosis and patient management, thus contributing to the advancement of cardiology research and clinical practice. Further validation and exploration on larger datasets and real-world scenarios are warranted to assess the generalization and practicality of our proposed approach in clinical settings.

5. Conclusion

In conclusion, our research introduces a novel ECG diagnosis system that combines signal processing techniques and deep learning models. This integration enhances the accuracy and efficiency of analyzing ECG signals, specifically in the detection and characterization of acute myocardial infarction (MI) and AMI associated with left bundle branch block (LBBB). The use of the Constant-Q Transform (CQT) and a pre-trained model results in an impressive performance, achieving a remarkable accuracy of 98.99% and minimal training loss of 0.0029% after 100 epochs. The utilization of this novel approach benefits patient care and healthcare technology, enhancing the diagnosis and management of these critical cardiac conditions. Moreover, the inclusion of 10-fold cross-validation strengthens the credibility of our findings, ensuring reliable performance evaluation and providing valuable insights for further advancements in ECG-based diagnostic systems.

[1] Ibrahim L., Mesinovic M., Yang K.-W., Eid M. A. Explainable Prediction of Acute Myocardial Infarction using Machine Learning and Shapley Values. IEEE Access. **8**, 210410–210417 (2020).

[2] Laslett L. J., Alagona P., Clark B. A., Drozda J. P., Saldivar F., Wilson S. R., Poe C., Hart M. The Worldwide Environment of Cardiovascular Disease: Prevalence, Diagnosis, Therapy, and Policy Issues: A Report From the American College of Cardiology. Journal of the American College of Cardiology. **60** (25, Supplement), S1–S49 (2012).

[3] Benjamin E. J., Muntner P., Alonso A., Bittencourt M. S., Callaway C. W., et al. Heart Disease and Stroke Statistics-2019 Update: A Report From the American Heart Association. Circulation. **139** (10), e56–e528 (2019).

[4] Hollander G., Nadiminti V., Lichstein E., Greengart A., Sanders M. Bundle branch block in acute myocardial infarction. American Heart Journal. **105** (5), 738–743 (1983).

[5] Han C., Shi L. ML-ResNet: A novel network to detect and locate myocardial infarction using 12 leads ECG. Computer Methods and Programs in Biomedicine. **185**, 105138 (2020).

[6] Sakli N., Ghabri H., Soufiene B. O., Almalki F., Sakli H., Ali O., Najjari M. ResNet-50 for 12-lead electrocardiogram automated diagnosis. Computational Intelligence and Neuroscience. **2022**, 7617551 (2022).

[7] Hao P., Gao X., Li Z., Zhang J., Wu F., Bai C. Multi-branch Fusion Network for Myocardial Infarction Screening from 12-lead ECG Images. Computer Methods and Programs in Biomedicine. **184**, 105286 (2020).

[8] Hawkins D. M. The problem of overfitting. Journal of Chemical Information and Computer Sciences. **44** (1), 1–12 (2004).

[9] Xie S., Girshick R., Dollar P., Tu Z., He K. Aggregated Residual Transformations for Deep Neural Networks. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 5987–5995 (2017).

[10] Berkaya S. K., Uysal A. K., Gunal E. S., Ergin S., Gunal S., Gulmezoglu M. B. A survey on ECG analysis. Biomedical Signal Processing and Control. **43**, 216–235 (2018).

[11] Youngberg J., Boll S. Constant-Q signal analysis and synthesis. ICASSP'78. IEEE International Conference on Acoustics, Speech, and Signal Processing. 375–378 (1978).

[12] Brown J. C. Calculation of a constant Q spectral transform. Journal of the Acoustical Society of America. **89** (1), 425–434 (1991).

[13] Barut Z., Altuntaş V. Comparison of Performance of Different K Values with K-Fold Cross Validation in a Graph-Based Learning Model for lncRNA-Disease Prediction. Kirklareli Üniversitesi Mühendislik Ve Fen Bilimleri Dergisi. **9** (1), 63–82 (2023).

ЕКГ-діагностична система зі штучним інтелектом для гострого інфаркту міокарда з БЛНПГ: перетворення Constant-Q та інтеграція з ResNet-50

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У цьому дослідженні представлено розширену діагностичну структуру електрокардіограми (ЕКГ), яка поєднує методи обробки сигналів із моделями глибокого навчання, щоб значно підвищити точність ідентифікації гострого інфаркту міокарда (ІМ) та ІМ, пов'язаного з блокадою лівої ніжки пучка Гіса (БЛНПГ). Завдяки поєднанню перетворення Constant-Q (CQT) із попередньо навченою моделлю ця система демонструє виняткову продуктивність, вражаючу точність у 98.99% і надзвичайно низькі втрати під час навчання 0.0029% після 100 епох навчання. Сувора 10-кратна перехресна перевірка підтверджує та підсилює ці висновки. Цей новий підхід спрощує складність діагностики шляхом консолідації даних ЕКГ у 12 відведеннях і використання CQT для точного аналізу в частотно-часовій області. Примітно, що ця методологія не тільки підвищує точність виявлення ІМ, але й представляє потенціал для покращення результатів медичної допомоги. Вона дає надію на мінімізацію помилкових діагнозів, тим самим сприяючи прогресу в догляді за пацієнтами з критичними серцевими захворюваннями. Ця зміна парадигми знаменує значний крок у діагностичних системах на основі ЕКГ, що має далекосяжні наслідки для покращення медичної практики та благополуччя пацієнтів.

Ключові слова: *AMI; LBBB; CQT; ECG; ResNet-50.*