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An Improved Myocardial Infarction Detection using Convolutional Neural Network and Graph Neural Network Algorithm

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ABSTRACT

Myocardial infarction (MI) is a crucial health problem and its mortality rate is higher than that of cancer. It is the damage and death of heart muscle from the sudden blockage of a coronary artery by a blood clot. Although lots of researches have been carried out with impressive performance record for detection of MI, however, existing approaches for MI detection can be improved upon for better performance. A vital piece of medical technology that aids in the diagnosis of a number of heart-related disorders in patients is an electrocardiogram (ECG). To find significant episodes in long-term ECG data, an automated diagnostic method is needed. Cardiologists face a very difficult problem when trying to quickly examine long-term ECG records. To pinpoint critical occurrences, a computer-based diagnosing tool is necessary. In this study we employ Convolutional Neural Network (CNN) algorithm with Graph Neural Network (GNN) to select best features and make appropriate classifications. The result of the study gave f1 score of 99.58%, precision of 99.5% and an accuracy of 99.72%. Our proposed model have shown a significant improvement in the detection of MI, this will aid in effectively addressing the challenge of performance drawback in this domain of research.

Keywords: Convolutional Neural Network (CNN); machine learning; myocardial infarction; Graph Neural Network (GNN); feature selection; deep learning

1. INTRODUCTION

Myocardial infarction (MI) also known as heart attack is the damage and death of heart muscle from the sudden blockage of a coronary artery by a blood clot. Coronary arteries are blood vessels that supply the heart muscle with blood and oxygen. (Pustjens et al., 2020). The hardening process starts early and progresses gradually as time goes on. A complex chain of events involving several blood cells, cholesterol, proteins, and hormones results in the development of a hardening plaque in the blood channel walls (Degerli et al., 2021). From a thin coating, this plaque expands into a mass of tissue that blocks the arterial lumen and restricts blood flow across it (Menyar, 2006).

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The risk associated with MI is that it frequently comes on suddenly for the patient, and needed quick action to end the crisis out of concern for death or serious cardiac injury. In order to effectively treat a MI, early diagnosis is therefore important (Degerli et al., 2021). A test called an electrocardiogram (ECG) enables the advancement of an electrical wave that controls the activity of the heart muscle. This electrical wave travels through the atria of a normal pacemaker, forcing them to constrict and facilitating blood flow from the atria to the ventricles (Hammad et al., 2022). Once the heart chambers have contracted as a result of the electrical signal, blood flows from the right ventricle to the lungs and from the left ventricle to the body tissues via the aorta. An ECG test can be used to identify any irregularities in the generation and transmission of electrical waves, which may be caused by issues with the heart conduction system (Hammad et al., 2020). Furthermore, whether they are recent or old, alterations in the ECG may be a sign of MI. The ECG processing methodology, in brief, can aid in order to create an accurate methodology for the automatic detection of MI, researchers are working on it. As previously indicated, the prior techniques can be divided into two groups: machine learning and deep learning approaches. Support vector machine (SVM) and K-nearest neighbor (KNN) (Sharma & Sunkaria, 2018), Fourier decomposition method (FDM) with SVM (Fatimah et al., 2021), and others are some of the different machine learning techniques that are described in the literature. To recognize various types of heart problems , convolutional neural networks (CNNs), recurrent neural networks (RNNs) (Jahmunah et al., 2021), residual networks (Śmigiel et al., 2021a) and capsule networks (Prakash et al., 2021) are also used .

However, only deep learning-based approaches that are pertinent to the scope of the work presented have been included by the authors (Gupta et al., 2021). Three deep learning techniques were created by (Śmigiel et al., 2021b) to automatically categorize main ECG signals. The first technique used CNN as its foundation, the second method used SincNet as its foundation, and the last way used CNN with entropy-based characteristics as its foundation. Using a CNN with entropy, they worked on five superclasses from the PTB-XL dataset and got the best overall accuracy of 76.50%. (Śmigiel et al., 2021a) further used R-peak detection and deep learning techniques to automatically classify the ECG signals. They used the same database (PTB-XL) to work on five superclasses, and their best overall accuracy was 76.20%. Few-Shot Learning (FSLapplicability)'s for categorizing ECG signals was determined by (Pałczyński et al., 2022). They took the QRS complex out of the ECG signals and classified the data with a deep CNN. They worked with the five superclasses in the PTB-XL database and achieved the best overall accuracy of 79%. (Prabhakararao & Dandapat, 2021) developed a method for classifying arrhythmias into multiple categories using a CNN ensemble. To lessen the computing load and remove baseline artefacts, they employed data augmentation techniques and preprocessing. They assessed the 12-lead of the PTB-XL database on the five superclasses and found that their technique had an overall accuracy of 85%. A multi-lead fusion approach for multi-class arrhythmia classification was proposed by (Zhang et al., 2021). The five superclasses from the PTB-LX database that they worked on yielded an aggregate accuracy of 93.10%. Utilizing the five superclasses for classification resulted in low accuracy for all of these earlier techniques. When compared to these methods, the suggested method on the five superclasses had the best accuracy. A comparison of related literatures using various criteria is shown in Table 1.

TABLE 1.
Related works Comparison

Literature	Year	Database	Classifiers	Remarks (Accuracy in %)
(Śmigiel et al., 2021b)	2021	PTB-XL	CNN SincNet	72.00 73.00
(Śmigiel et al., 2021a)	2021	PTB-XL	Neural networks	76.20
(Pałczyński et al., 2022)	2022	PTB-XL	Neural networks	80.20
(Prabhakararao & Dandapat, 2021)	2022	PTB-XL CinC-training	DMSCE	84.50 88.30
(Zhang et al., 2021)	2021	China Physiological Signal Challenge 2018	MLBF-Net	87.70
(Prakash et al., 2021)	2021	PTB	GABORCNN	98.84
(Tadesse et al., 2021)	2020	PTB	VGG-Net	99.20
(Anand et al., 2022)	2022	PTB-XL	CNN	95.80
(He et al., 2021)	2021	Combination of PTB and PTB-XL	Multi-feature-branch lead attention neural network (MFB-LANN)	94.19

Therefore, the goal of this work is to develop a unique method for MI detection based on deep learning approaches that will address the aforementioned shortcomings. Deep learning techniques have recently demonstrated success in a variety of applications, including pattern recognition (Khan et al., 2021; Srinivasu et al., 2021), internet of things (IoT), and medical (Almadhor et al., 2021).

Based on the study of ECG signals, several artificial intelligence (AI) techniques are used to identify MI by (Fatimah et al., 2021; Ibrahim et al., 2020; Sharma & Sunkaria, 2018). These are divided into two categories: machine learning and other techniques (Cho et al., 2020; Jahmunah et al., 2021; Sharma & Sunkaria, 2020) and for the deep learning approaches (Anand et al., 2022; He et al., 2021; Ramaraj, 2021). Particularly when working with massive amounts of data, deep learning techniques are regarded to be more dependable than traditional machine learning techniques. Deep learning techniques' multi-layer architecture also offers capabilities for efficient feature interpretation and pattern detection, both of which are essential for classifying sizable unstructured datasets. Although they have superior features, standard deep learning networks are known to have a number of disadvantages, such as the following:

- Misclassification in several circumstances of considerable interclass disparity.

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- Decreasing detection accuracy and, notably, sensitivity as a result of increasing data over-fitting caused by the depletion of datasets.

- Utilising ineffective MI detection techniques and sophisticated signal processing techniques.

- Implementing these strategies in real-time applications leads to low accuracy.

- Requiring the QRS complex to be found.

2. MATERIAL AND METHODS

In this study, we first filter out the noise from the ECG readings. Then, extract the deep features from the input signals, with a deep learning model based on a convolutional neural network (CNN). The characteristics from the convolutional layers are then optimized and chosen. The CNN-GNN classifier is then fed the chosen characteristics to detect MI. The examination and inquiry of the PTB-XL database revealed that the suggested method surpasses current deep learning techniques (Wagner et al., 2020). This section provides a thorough explanation of the methodology and dataset (PTB-XL) used to assess the effectiveness of the proposed technique. The dataset contains several different diagnostic groups as well as a sizeable percentage of healthy records. PTB-XL is a sizeable dataset with exceptional variation that stands out for its superior signal quality. Rarely do clinical databases contain samples with such a wide range of pathologies, a wide variety of co-occurring disorders, and a high number of healthy controls. PTB-XL is an excellent option for training and testing algorithms in the real world, where machine or deep learning algorithms must perform consistently regardless of the recording environment or the caliber of the data.

In order to identify Myocardial Infarction (MI), the proposed CNN-enhanced GNN based MI detection model in Deep Learning and GNN analyzes 12-lead ECG signals. Following the preprocessing stage, the ECG signal pictures are normalized in accordance with the input specifications of the suggested models for greater research accuracy. ECG images of various sizes that are appropriate for the model are collected as input, divided into train, validation, and test portions, and then sent to the CNN model. Convolutional, pooling, and fully connected layers make up the majority of the CNN model's layers. The max-pooling layer does image subsampling and image size reduction, while the convolutional layer is utilized to create tensors by applying filters. The data is flattened and then passed through a compressed fully connected neural network for quick and accurate classification of MI affected class, normal class, history class, and abnormal class based on the ECG images after passing through a number of convolutional and max-pooling layers. A flow chart representation of the model that categorizes two classes is shown in Figure 1.

2.1 DESCRIPTION OF ECG DATASET

The training and validation sets for this study were taken from the publicly available PTB-XL dataset (Wagner). 21,837 clinical 12-lead ECGs from 18,885 patients are included in the PTB-XL dataset. Each ECG signal lasts for 10 seconds. Only the 500-Hz ECGs were used as the dataset since the neural network required 4,096 samples from the signal of each ECG lead. The ptbxl database.csv file was extracted for the MI diagnosis.

2.2 MI DETECTION PROCESS

2.2.1 DATA PREPROCESSING

Each of the ECG is a 12 5,000 matrix, where the first (12) denotes the space dimension and the second (5, 000) denotes the time dimension (12 leads, 10 s length, 500 Hz sampling). From the signal of each ECG lead, we took 4,096 samples to utilize as the neural network's input. Prior to training, the raw ECG data were pre-processed. We first used a low-pass filter on the raw data to create a baseline and then zeroed the average value to make the baseline flat in order to remove ECG signal baseline drift and low-power noise. After that, we filtered the high-frequency signals to denoise the data.

2.2.2 DATA SPLITTING

30% of the PTB-XL data were used to validate the model, while the remaining data were utilized to train the model.

2.2.3 DEVELOPMENT OF MODEL

We employed a residual network with a convolutional neural network-like topology (He et al., 2016). Using this architecture, it is possible to train a deep neural network efficiently while including the graph convolutional layer with non linear activation. The network had four residual blocks, each with four convolutional layers, and a convolutional layer (Conv). The final block's output was returned to a dense fully linked layer with a sigmoid activation function. Batch normalization was used to rescale each convolutional layer's output before being fed into a rectified linear activation unit (ReLU).

3. RESULT AND DISCUSSION

The experimental environment for this study was on google collaborative platform and is essentially a python development environment. In this study, Keras was employed. On the machine learning platform Tensorflow, Keras is a high-level deep learning API. It is a platform for solving machine learning issues that focuses on contemporary deep learning. Keras can process enormous volumes of complex data with ease. It is user-friendly and allows users to concentrate more on certain aspects of the issue without experiencing a cognitive load. Low level TensorFlow operations on GPU and CPU are also reduced by Keras and TensorFlow.

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TABLE 2.
Summary of Results

		Precision	Sensitivity	Specificity	F1 Score	Accuracy
Training	MI	0.9894	0.9930	0.9945	0.9912	0.9938
	Non-MI	0.9906	0.9946	0.8364	0.9926	0.9155
Validation	MI	0.9657	0.9669	0.9680	0.9663	0.9675
	Non-MI	0.9669	0.9686	0.7337	0.9677	0.8512
Testing	MI	0.9950	0.9966	0.9978	0.9956	0.9972
	Non-MI	0.9963	0.9969	0.8960	0.9966	0.9465

The precision score achieved from the experimental analysis is 0.9894, 0.9657, and 0.9963 for training, validation, and testing respectively. While, sensitivity score of 0.9930, 0.9669, and 0.9969 was obtained for training, validation, and testing phase respectively. Specificity score of 0.9945, 0.9680, and 0.9978 was achieved for training, validation and testing respectively, 0.9912, 0.9663, and 0.9956 was achieved for F1 score, respectively for training, validation, and testing. Accuracy performance of 0.9938, 0.9675, and 0.9972 was achieved for training, validation, and testing respectively. The performance analysis summary of the study experiment is further presented in Figure 2.

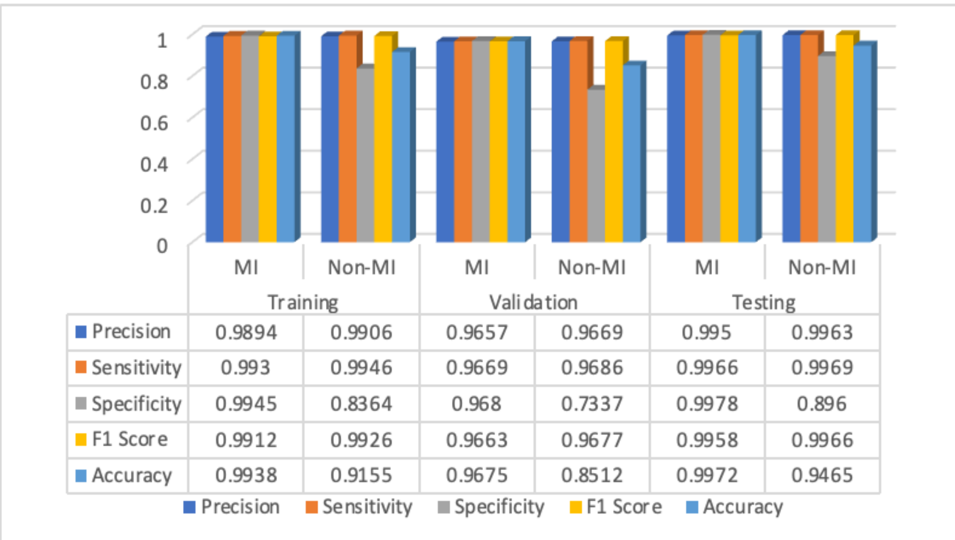

FIGURE 2. Summary of Results

When we compared our results with other recent related works, our new model was observed to have a batter performance in terms of accuracy, precision and f1score as shown in Table 3.

3.1 ACCURACY

The proposed model in our study achieved an optimal accuracy performance of 99.72% compared to 89.14%, 76.20%, 79.00%, 85.65%, 93.10%, and 99.20% respectively for Śmigiel et al. (2021b), Śmigiel et al. (2021a), Pałczyński et al. (2022), Prabhakararao & Dandapat (2021), Zhang et al. (2021), and Hammad et al. (2022). The performance of our proposed model indicates the efficiency in terms of accurately been able to detect MI as against the preceding listed baseline articles.

3.2 PRECISION

The precision score of 71.40%, 66.70%, 70.60%, 84.25%, 94.30%, and 98.20% was achieved by the following baseline articles Śmigiel et al. (2021b), Śmigiel et al. (2021a), Pałczyński et al. (2022), Prabhakararao & Dandapat (2021), Zhang et al. (2021), and Hammad et al. (2022), respectively. While our proposed model achieved an outperforming precision score of 99.50% which is far better than the score achieved by baseline article.

3.3 RECALL

The recall score of 99.66% was achieved by our proposed model for MI detection, which outperform the precision score of baseline articles of Śmigiel et al. (2021b), Śmigiel et al. (2021a), Pałczyński et al. (2022), Prabhakararao & Dandapat (2021), Zhang et al. (2021), and Hammad et al. (2022) which scored 66.20%, 66.70%, 70.60%, 85.21%, 93.10%, and 99.20% respectively.

3.4 F-SCORE

The F-score of 68.00%, 68.30%, 70.60%, 84.55%, 92.80%, and 98.60% was achieved by Śmigiel et al. (2021b), Śmigiel et al. (2021a), Pałczyński et al. (2022), Prabhakararao & Dandapat (2021), Zhang et al. (2021), and Hammad et al. (2022) respectively, however, the F-score of our study outperforms the performance of all baseline article, with a record of 99.58%.

TABLE 3.
Comparison of our proposed work with other works

Literature	Year	Database	Technique	*Acc* (in %)	*Pre* (in %)	*Rec* (in %)	F-Score
Śmigiel et al. (2021b)	2021	PTB-XL	CNN and entropy-based features	89.14	71.40	66.20	68.00
Śmigiel et al. (2021a)	2021	PTB-XL	Deep learning and R-peak detection	76.20	66.7	66.7	68.30
Pałczyński et al. (2022)	2022	PTB-XL	Deep CNN and QRS complex detection	79.00	70.60	70.60	70.60

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Prabhakararao & Dandapat (2021)	2021	PTB-XL	CNN ensemble	85.65	84.25	85.21	84.55
Zhang et al. (2021)	2021	PTB-XL	Multi-lead-branch fusion network	93.10	94.30	93.10	92.80
Hammad et al. (2022)	2022	PTB-XL	Deep CNN model with SVM classifier	99.20	98.20	99.20	98.60
Proposed Model	2022	PTB-XL	Deep CNN enhanced GNN	99.72	99.5	99.66	99.58

4. CONCLUSION

In this study, our proposed model have shown a significant improvement in the detection of MI, this will aid in effectively addressing the challenge of performance drawback in this domain of research, furthermore health institution can implement the proposed model in its health sector for effective performance output in terms of MI detection. Our model shows that f1 score, precision, and accuracy achieved optimal record using the proposed CNN enhanced-GNN model based on PTB-XL dataset. We further compared the result with other related works and it was observed to have a better performance.

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