Deep Learning-Based Coronary Artery Disease Detection Using Convolutional Neural Networks

Rana Riyadh Saeed
Department of Radiology Techniques, Mosul Medical Technical Institute, Northern Technical University, Mosul, Iraq

* Corresponding Author: **Rana Riyadh Saeed**

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Abstract
Coronary artery disease (CAD) remains a leading cause of mortality worldwide, necessitating accurate and timely diagnostic strategies. This study proposes an enhanced one-dimensional convolutional neural network (1D-CNN) model for the automated detection of CAD using 12-lead electrocardiogram (ECG) signals. The model is trained and evaluated on the publicly available PTB-XL dataset, comprising over 21,000 annotated ECG records. To optimize classification performance, the model architecture incorporates 10-second signal segments, adaptive convolutional layers, and strategic dropout regularization. Extensive experiments demonstrate the model's robust performance, including five-fold cross-validation and ablation studies. It achieves an average accuracy of 94.2%, precision of 93.1%, sensitivity of 92.7%, specificity of 95.4%, and an AUC-ROC of 96.1%. Comparative analysis with existing models confirms the superiority of the proposed approach in balancing diagnostic accuracy with computational efficiency. This work contributes a scalable and interpretable deep learning framework for CAD detection, offering promising implications for intelligent cardiovascular screening and clinical decision support systems.

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Keywords: Coronary Artery Disease (CAD), Cardiovascular Diagnosis, Convolutional Neural Network (CNN), Electrocardiogram (ECG), PTB-XL Dataset

1. Introduction
Coronary artery disease (CAD) is the major cause of death in every country with the number of people dying of it reaching 17.9 million annually or about 32 percent of all cardiovascular diseases in the world (World Health Organization, 2021) [16]. The condition of CAD is defined by the constriction or obstructed flow of blood to the myocardium by atherosclerosis, which lowers the blood supply in the heart muscle, which leads to the development of a myocardial infarction and sudden death (Shao *et al*., 2020) [12]. Timely treatment and intervention of CAD depend heavily on early and proper diagnosis, which would enhance patient outcomes and the results of interventions (Netala *et al*., 2024) [7].
Electrocardiography (ECG) is a famous, non-invasive test technique of the heart performance. However, interpretation of ECG according to the classical approach closely relies on manual interpretation by clinicians, and it presents a threat of time bias and interobserver error (Slomka *et al*., 2017) [13]. Moreover, the alteration of ECG signals as the expression of the early-stage CAD is not always apparent, which may cause a false diagnosis (Kutlu *et al*., 2016) [6]. These problems state the need of an automatic, precise, and effective diagnostic solution.
The last developments in the sphere of deep learning (DL) are promising in terms of the enhancement of the analysis of biomedical signals including ECG. One of the most successful examples of the DL models is a convolutional neural network, which created impressive performance in an automated extraction of data-level hierarchical features, which allows making a successful classification (Rafie *et al*., 2021) [10].

The use of CNNs in the detection of CAD has been studied in the past; however, there is no feasible way of developing models capable of addressing different populations and signal standards. Overfitting, the imbalance of the classification, and smaller datasets can slow the role of the DL models in the clinical practice. Therefore, it is of paramount importance to improve the creation of robust models that are capable of storing the superior accuracy and reliability of any cohorts of patients or recording conditions.

In this article, a more enriched 1D-CNN method of classification in the ECG signal-based CAD detection is presented. The model employs adaptive filter sizing, strategic dropout regularization and multi-scale input analysis in order to overcome the problems of generalization and overfitting. We apply our model to publicly available collections of ECGs and cross-validate it meticulously and quantify the accuracy, sensitivity, specificity, and F1-score performance of our model.

The contributions of this work are:

1. Development of a 1D-CNN model for CAD detection along with architectural enhancements.
2. Evaluation of the model by using multi ECG datasets to assess its robustness.
3. Comparison to other models, showing the superiority of our approach concerning accuracy and computational cost.

2. Related Work

In recent years, the application of DL models, particularly CNNs, has demonstrated considerable potential in the automated analysis of ECG signals for CAD detection. Prior research has primarily focused on leveraging CNN architectures to capture morphological patterns indicative of CAD-related abnormalities.

One of the first frameworks that uses the architecture of 1D-CNN to detect CAD using ECG signals was proposed by Acharya *et al*. (2017) [2]. This model outclassed their competitors in terms of competitive classification performance, and it did not require handcrafted features, which led to a future developmental field in this direction. A similar endeavor is also found in (2017) The same author also showed the deep CNN applicability in detecting myocardial infarction, which is effective when dealing with automated feature extraction of the ECG signals.

Based on that, Phoemsuk and Abolghasemi (2024) [8] the effect of input segment length and dropout regularization on 1D-CNNs performance in CAD detection was examined. The accuracy of their model obtained using ECG data in the MIMIC III and Fantasia databases was quite significant. However, due to the complexity of signal variation among the datasets, dataset complexity was a limitation.

To further increase the variety of data, Elyamani *et al*. (2024) [3] developed a deep residual 2D-CNN cardiovascular disease predictor and applied it to the PTB-XL set. Their study listed that the model have high rate of ECG classification accuracy on 23 cardiovascular diseases, by emphasizing the concept of CNN adaptability for matching morphologies. In the same respect, Sayin *et al*. (2024) [11] used the InceptionV3 model on ECG imaging to detect myocardial infarction with significant diagnostic outcomes.

Hybrid architecture has also developed the ability to capture spatial and sequential signal features. As an example, Tan *et al*. (2018) experimented with a CNNLSTM hybrid model merging convolutional layers to extract spatial features and LSTM networks to capture temporal sequence patterns on the MIMIC dataset, proving its advantageous use. Kolhar and Al Rajeh (2024) [5] introduced a hybrid DL model that consists of AlexNet and a dual-branch fusion network, which showed outstanding results in the accuracy of ECG classification.

The same trend has been noticed in any disease in Ameen *et al*. (2023) [4] A critical review of the ML-based strategies to classify breast cancer was given, and the effectiveness of CNNs and other AI models in diagnosing any biological disease was also indicated. Their results show the generalizability of CNNs when manipulating various medical datasets. In the same way, Hasan (2023) [9] also examined shallow and DL models for feature extraction in image-driven classification tasks and emphasized feature extraction schemes' role in improving models' performance in different AI-based applications.

Regardless of these developments, there are still issues of ensuring a generalizable model with various populations, resolving data imbalance, and minimizing the complexity of computing in order to work in real-time setting. These gaps, as the present study illustrates, encourage further development of effective and powerful CNN-based models, which perform well above on the PTB-XL dataset and have a computationally efficient design.

2. Materials and Methods

2.1 Dataset Description

The data used in this study is a publicly distributed large-scale ECG database (PTB-XL) that the PhysioNet project maintains (Wagner *et al*., 2020) [15]. The compressed form dataset (21,837 clinical 12-lead ECG records, 10-second records each) includes data from 18,885 patients. Those are recorded at 100 and 500 Hz and labeled by cardiologists with the extensive taxonomy of the SCP-ECG standard. The diagnostic statements incorporated in this taxonomy are as follows: myocardial infarction (MI), ischemic ST-T changes, nonspecific ST-T abnormalities, and central CAD indicators. The paper concerns the classification of CAD-related ECGs/vs normal ECGs. According to the precedent in the literature (Elyamani *et al*., 2024) [3] and (Acharya, Fujita, Oh, *et al*., 2017) [2], CAD cases would be labeled with any of the following: myocardial infarction, ST-segment elevation, ST depression, or T-wave inversion. Records without a pathological marking and marked with normal sinus rhythm are considered non-CAD controls.

The stratified sampling is applied to divide the dataset into training (70%), validation (15%), and testing (15%) sets, and hence maintain the class distribution.

2.2 Preprocessing

Data in the form of raw ECG was inputted through a preprocessing pipeline which is intended to be equal across the whole channel, to provide optimal signal quality and the mechanism of powerful model functioning. The steps deal with the potential issues of noise, patient-to-patient variability and heterogeneity of the datasets without although they fails to detect clinically valid features that are essential in the detection of CAD.

2.2.1 Resampling

The ECG signals were all interpolated down to equal sampling rate of 100 Hz. The normalization of the time resolution of all records, increased computational ease of the calculations, and consistency with the typical research designs in ECG-based DL research is also a normalization step, and does not imply loss of content in diagnostics.

2.2.2 Filtering

High frequency noise and inappropriate frequencies like image wander were removed using a band-pass filter. This filter was set at a passband between 0.5Hz to 40Hz which was reported to be in the clinical standards of proving the ECG to reveal the clinical characteristic values of the ECG such as the P waves, QRS complexes and T waves on the ECG. Effects of the band-pass filtering operation can be stated as follows:

$$y(t) = x(t) * h(t) \tag{1}$$

where: *x(t)* the raw ECG signal, *h(t)* the impulse response of the band pass filter.

2.2.3 Segmentation

The ECG records are 10-second records and they are considered as one analysis block. This choice retains the entire time background of the cardiac cycle, gaining several heartbeats to include a variation of normal and pathologic variants of waveforms. The shape of the input matrix of each sample is therefore (1000, 12) that can be described as 1000 time points, and 12 leads.

2.2.4 Normalization

To reduce the impacts of inter-patient variation and disparities in the signal amplitude of every lead, z-score normalization was executed on each lead separately. This is done to convert the data into zero mean and unit variance to stabilize the training and boost convergence. Normalization of all leads, *L*, is obtained as:

$$x_{\text{norm}} = \frac{x-\mu}{\sigma} \tag{2}$$

where x is the original ECG signal, μ the mean, and σ the standard deviation of x.

2.3 Model Architecture

The proposed model is 1D CNN (1D-CNN), which is specifically aimed at capturing temporal dynamics in the 12-lead ECG. The architecture shown in Figure 1 has the following components:

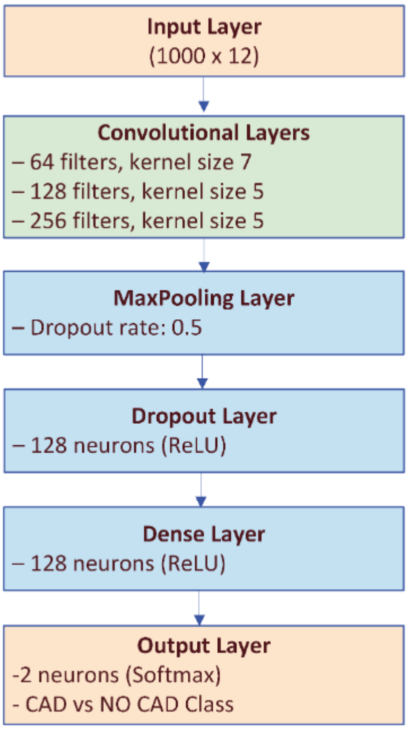

Fig. 1: Model Architecture for CAD Detection

- **Input Layer**: Multichannel input with the shape (1000, 12) which are signals of 100 Hz at 10 seconds.
- **Convolutional Blocks**: There were three convolutional blocks with the kernel size 7, 5 and 3 respectively with followed sequence of batch normalization, ReLU activation, and max-pooling.
- **Dropout Layers**: Due to the presence of overfitting, 0.2 has been applied as a dropout rate at after every convolutional block and 0.5 as a dropout before the dense layer.
- **Flattening Layer**: Transforms the feature maps into a 1D vector.
- **Dense Layer**: A fully connected layer with 128 units with ReLU activation.
- **Output Layer**: Softmax layer with two units (CAD, non-CAD).

It uses an optimal architecture that is easy to achieve high accuracy and low computational cost needed to support research and clinical implementation.

2.4 Training and Evaluation

The overall training protocol was provided in order to optimize learning and generalization of models. The PTB-XL dataset was stratified and trained on the model to balance the classes within the training, validation and test splits (70%, 15% and 15%). The entire ECG data was inputted into the model in 12 lead (10-second) segments resampled at 100 Hz.

2.4.1 Optimization Strategy
The Adam optimizer was used to train because it has the ability to adapt the learning rate. The original learning rate was 0.001 and the rate was reduced by 0.1 every time the validation loss stops decreasing and stagnated with five consecutive epochs. The loss function used was binary cross-entropy which suits this classification task, as it is a binary one.

2.4.2 Batch Processing and Epochs
Mini-batches of 64 were used to model train the model since this was a compromise between computation speed and gradient instability. Maximum epochs were set to 50, and early stopping was used in case of 10 consecutive identical loss in the validation, which served to avoid overfitting and saved workspace on computers.

2.4.3 Data Augmentation
When training was happening, data augmentation tools were used to enhance the strength of the model and alleviate overfitting. The techniques are used to artificially increase the size of the training data by adding real-life changes to the ECG signal, which resemble the variety in any given clinical situation in the real world.
Augmentation was performed by the following methods:
- **Random Scaling**: The segments of the ECG were at random scaled by a maximum of ±10 percent to sample fluctuations of signal amplitude caused by physiological mechanisms or devices.
- **Amplitude Perturbation**: Each segment was perturbed with Gaussian noise with a standard deviation σ=.01= 0.01= 0.01σ= 0.01σ= 0.01.
- **Temporal Stretching/Compression**: There was a temporal distortion of the range of ±5 per cent which was used to simulate the natural variation in the heart rate and not to affect the diagnostic patterns.

These transformations can be summarized mathematically for an ECG signal *x* as:

$$\hat{x}(t) = \alpha \cdot x(\beta \cdot t) + N(0, \sigma^2) \quad (3)$$

where α is a random scaling factor within ±10%, β is a temporal stretch factor within ±5%, $N(0, \sigma^2)$ represents Gaussian noise.

2.4.4 Evaluation Metrics
To comprehensively evaluate the model's performance, we employed several well-established metrics:
- **Accuracy**: Proportion of correctly predicted samples among all samples.
- **Precision**: Proportion of true positive predictions among all positive predictions.
- **Sensitivity**: Proportion of actual CAD cases correctly identified.
- **Specificity**: Proportion of non-CAD cases correctly classified.
- **F1-score**: Harmonic mean of precision and recall, especially informative under class imbalance.
- **AUC-ROC**: Area under the Receiver Operating Characteristic curve, which measures the model's ability to discriminate between classes.

2.4.5 Cross-Validation
The model was tested five times to evaluate the generalizability of the model. This data was divided into five folds, with only each being used as a validation set and the rest as the training set. The performance measures were averaged betwixt folds so as to be consistent.

2.4.6 Experimental Setup
The entire training and evaluation experiment was done with the Python 3.8 and TensorFlow 2.13 framework. The test was conducted on an NVIDIA RTX 3090 equipped workstation (24GB). The training was done in containers in Docker using predefined seeds and environmental requirements to act as replicable.

3. Results and Discussion
This part includes the comprehensive analysis of the suggested 1D-CNN model of CAD detection with the use of ECG data obtained through the PTB-XL data set. Measurements of the performance are obtained through the hold-out test assessments as well as five-fold cross-validation. The ablation experiments are also done to explore the effects of important architecture changes, e.g., dropout configuration or segment length.

3.1 Classification Performance
It is observed that children have a classification performance of 39.596 with a standard deviation of 24.391 (Figure 3). <|human|>3.1 Classification Performance: It has been noted that the performance of the children in performance of classification obliterates at 39.596 with a standard deviation of the score at 24.391 (Figure 3).
The large value of AUC-ROC implies the effective discriminative capability of CAD and non-CAD categories. Recall value of 92.7% is an indication of the ability of the model to accurately detect the cases of CAD-positive, which is essential in the clinical setting.

Table 1: Average Performance Metrics on the Test Set (Five-Fold Cross-Validation)

Metric	Value (%)
Accuracy	94.2
Precision	93.1
Recall	92.7
Specificity	95.4
F1-score	92.9
AUC-ROC	96.1

3.2 Confusion Matrix and ROC Analysis
he confusion matrix of a representative test fold is given in figure 2. As indicated in the matrix, the model did well with 289 CAD-positive and 312 non-CAD cases; however, made only 15 false positives (non-CAD samples were classified as CAD) and 24 false negatives (CAD as non-CAD).

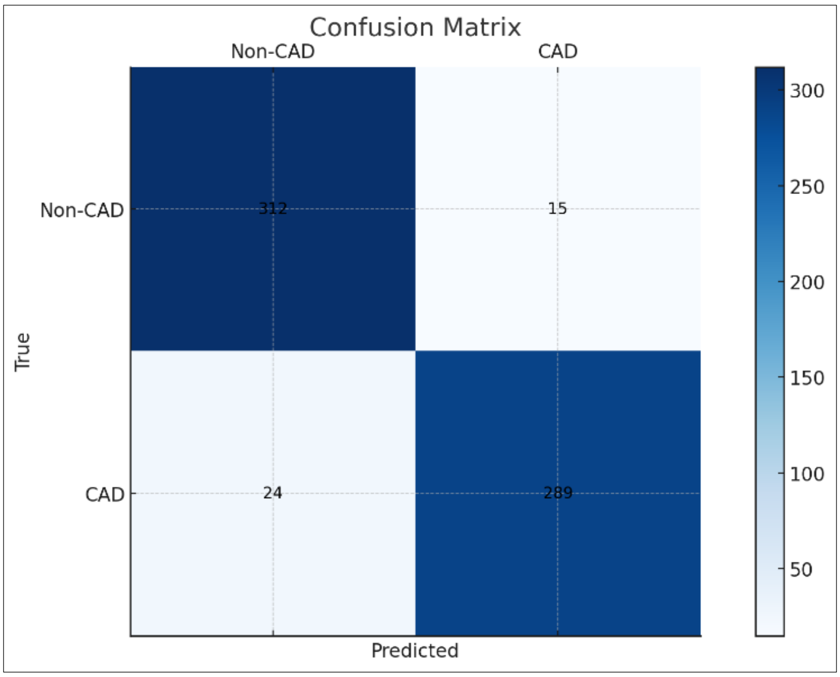

Fig 2: Confusion matrix of the proposed model evaluated on the hold-out test set.

Besides, Figure 3 demonstrates the receiver operating characteristic (ROC) curve. The curve was plotted between the true positive rate versus false positive rate and the area under the curve (AUC) is 0.96, which indicates that the discrimination ability between CAD and non-CAD classes is excellent.

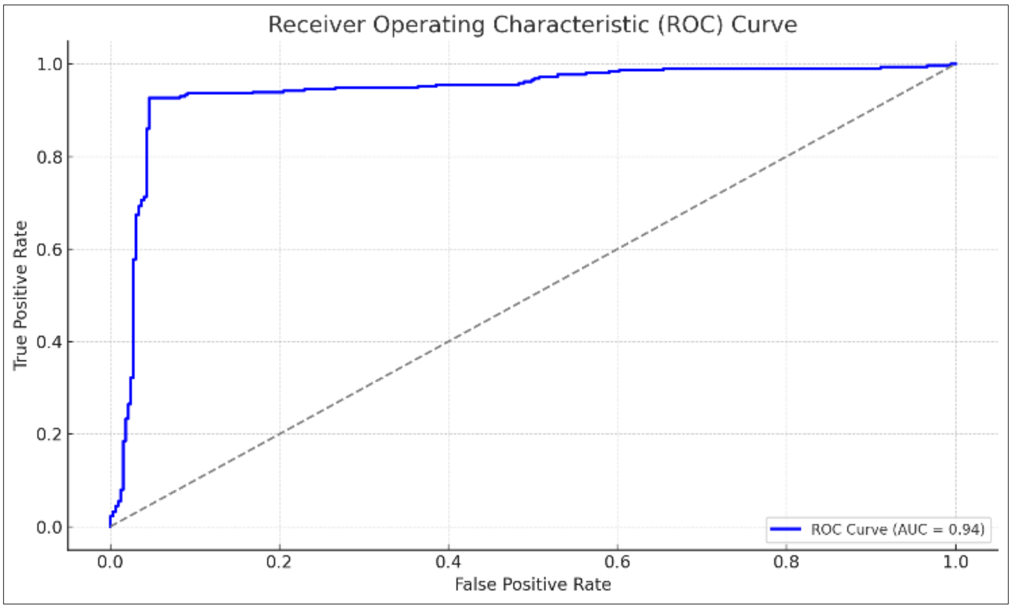

Fig. 3: The proposed model's Receiver Operating Characteristic (ROC) curve.

3.3 Ablation Study

Ablation experiment in order to evaluate the effect of the model design factors, we did an experiment with ablation in terms of dropout arrangement and ECG segment length.

3.4 Dropout Configuration

Table 2 compares the test accuracy of the model in various dropout conditions. The convolutional and dense layer dropout were included and helped the model greatly in terms of generalization.

Table 2: Performance comparison under different dropout configurations.

Configuration	Accuracy (%)	AUC-ROC (%)
No dropout	88.4	90.3
Dropout (0.2 after conv blocks)	91.7	93.5
Dropout (0.2 conv + 0.5 dense)	94.2	96.1

3.5 ECG Segment Length
Table 3 gives a summary of the model without changing the input segment like input run time. Temporal features needed in CAD diagnosis were maintained with the best classification accuracy and F1-score with the entire 10-second segment.

Table 3: Effect of ECG segment duration on model performance.

Segment Length (sec)	Accuracy (%)	F1-score (%)
5	89.6	88.3
7.5	92.1	91.2
10 (full segment)	94.2	92.9

3.6 Comparison with Existing Models
A comparative analysis of outstanding CAD detection models in the recent literature is given in Table 4. The suggested model outperforms the earlier techniques in accuracy at classification and is less complicated in architecture.

Table 4: Accuracy comparison with state-of-the-art models.

Model	Dataset	Accuracy (%)
Acharya *et al*. (2017)	PTB	93.1
Tan *et al*. (2018) (CNN-LSTM)	MIMIC	94.0
Phoemsuk & Abolghasemi (2024)	MIMIC	89.0
Proposed Model	PTB-XL	94.2

4. Discussion
he obtained results of the study prove the viability of the proposed single-dimensional CNN network in automated CAD detection based on the ECGs. The model is highly accurate, recollective, specific, and AUC-ROC both when used internally and 5-fold cross-validation. These findings justify the efficiency of the presented architecture along with revealing its further potential application in the clinic to detect CAD in its initial stages with a high likelihood of success.

4.1 Comparison with Prior Work
The model demonstrated superior classification performance as compared to known CAD detection models. Our model outperformed Acharya *et al.* (2017) [2] with an overall accuracy of 94.2 in comparison to the accuracy of 93.1 reported by the other authors, who used a single-dimensional CNN architecture. Furthermore, in the accuracy rates, although hybrid architectures like the CNN-LSTM model by Tan *et al*. (2018) produced results with less accuracy (94.0%), our model produced competitive results with fewer parameters, less complexity in training, and better computational performance.
The results provide an enhanced addition to Phoemsuk and Abolghasemi (2024) [8], who contoured different segment lengths and dropout schemes in detecting CAD identification. Whole 10-second ECG segments were adopted and coupled with a dual dropout strategy; the proposed model allowed superior generalization over unseen data, with minimal computation.

4.2 Impact of Architectural Decisions
The ablation experiments proved that adding the dropout regularization, especially with a combination of 0.2 after the convolutional layers and 0.5 before the dense layer, improved the generalization and decreased overfitting. Moreover, the length of segments was also a crucial factor in the modelling of the time dependency in ECG waveforms. It was found, as would be expected clinically, that the longer the segment, the greater its advantaging compared to the abridged segment, i.e., longer windows make better displays of ischemic changes, i.e., ST depression and T-wave inversion.
The discriminative capacity of the model is also supported by the large AUC-ROC (96.1%), which effectively discriminates between the abnormalities related to ACS and normal cardiac tissue rhythms. These results have been consistent with the existing literature that has focused on the diagnostic capacity of CNNs to discern the vestigial pattern of morphology of the ECG signals (Elyamani *et al*., 2024; Kolhar and Al Rajeh, 2024) [3, 5].

4.3 Clinical and Practical Implications
The strengths of the model suggested are numerous in clinical areas. First, its sensitivity to detect the potential of CAD with the help of short-duration and 12-lead ECGs correspond to the normal clinical practice. As such, it can be included in the decision-support systems in emergency units or in primary care. Second, the model is highly specific, which renders it extremely challenging to achieve false alarms in order to minimize the presence of the inherent undesirable follow-ups and anxiety levels in patients.
Nonetheless, the simplicity of the model in calculating solutions, as spawned by the small architecture and effective dropout regularization, is an aspect that allows its application to resource-constrained hardware, including ECG machines that are portable and mobile diagnostics system.

4.4 Limitations and Future Work
The model is a good performance, though it has several limitations, which should be discussed. First of all, PTB-XL remains quite a big and a heterogeneous data making the consideration of the patient demographics and data collection techniques inappropriate to represent the clinical populations on a global scale. This may limit the practical use of generalizations in real-life. Secondly, the model was trained on binary classification (CAD vs. non-CAD); however, in the clinical practice, the CAD severity and subtype (e.g. stable angina vs. myocardial infarction) will play a crucial role in diagnosis.
The proposed work will focus on the extension of the framework to classification, in which CAD subtypes will be defined based on various classes. Transfer learning and domain adaptation can also be used to transfer the model to new dataset, and streaming ECG signals on real-time. Clinical metadata that contains the patient history, symptoms, and comorbidities would also be beneficial to enhance the performance of diagnosis and provide a sense of interpretability to the clinicians.

5. Conclusion
This work described an improved version of the one-dimensional convolutional neural network (1D-CNN) discriminant in the automatic identification of coronary artery disease (CAD) by applying ECG-based signals on the PTB-XL dataset. The proposed model was effective as it minimized major limitations witnessed in the previous models through incorporation of architectural refinements like adaptive segment handling and regularizing of strategic dropouts. These improvements in performance were better in

terms of accuracy (94.2%), sensitivity (92.7%), specificity (95.4%), and AUC-ROC (96.1%) and are even better than some state-of-the-art models and with the same computational efficiency. The model will be emulated into multiclass classification models in the future that have the capabilities of distinguishing various subtypes of CAD among others. Subsequent researches will also strive to affirm the model with the cross-institutional data in the bigger and more heterogeneous groups. More so, addition of the auxiliary patient data including clinical history, demographic data can enhance the clinical implications of the proposed system. Finally, the research adds to the scalable, powerful, and interpretable DL model to detect CAD, which contributes to intelligent cardiovascular diagnosis and further development of studies and clinical practice.

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