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

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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

Introduction

Coronary artery disease (CAD) is a leading cause of mortality worldwide, accounting for approximately 17.9 million deaths annually, which represents about 32% of all global deaths from cardiovascular diseases (World Health Organization, 2021). CAD is characterized by the narrowing or blockage of the coronary arteries due to atherosclerosis, leading to reduced blood flow to the myocardium and increasing the risk of myocardial infarction and sudden cardiac death (Shao *et al*., 2020) [12]. Early and accurate detection of CAD is crucial for initiating timely interventions and improving patient outcomes (Netala *et al*., 2024) [7]. Electrocardiography (ECG) is a well-known, non-invasive examination method of cardiac performance. Nevertheless, the classical interpretation of ECG is highly dependent on manual interpretation of clinicians, posing a risk of time selection and interobserver variability (Slomka *et al*., 2017) [13]. In addition, changes in ECG signals with the signs of early-stage CAD are not always obvious, which can lead to a missed diagnosis (Kutlu *et al*., 2016) [6]. These issues highlight the importance of an automatic, accurate, and efficient diagnostic solution.

Recent advancements in deep learning (DL) have proven promising in the improvement of the analysis of biomedical signals such as ECG. Convolutional neural networks (CNNs), which belong to DL models, have shown impressive results in automated extraction of data-level hierarchical properties, thus enabling successful classification (Rafie *et al*., 2021) [10].

Previous studies have examined CNNs' use in detecting CAD, but it is not easy to create models that apply to various populations and signal standards.

The smaller dataset sizes, the classification imbalance, and overfitting may slow the performance of the DL models in clinical practice. Thus, there is an urgent need to enhance the development of powerful models that can retain the high accuracy and reliability of any patient cohort and recording conditions.

This article introduces a more enriched 1D-CNN way of classification in detecting CAD through ECG signals. To address the issues of generalization and overfitting, the model utilizes adaptive filter sizing, strategic dropout regularization, and multi-scale input analysis. We test our model on publicly accessible sets of ECGs, carefully cross-validate it, and measure its accuracy, sensitivity, specificity, and F1-score performance.

The contributions of this work are:

1. Development of a 1D-CNN model for CAD detection, with architectural enhancements to improve performance.
2. Evaluation of the model using diverse 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) [1]. 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 demonstrated that their model offered a high rate of ECG classification accuracy in 23 various cardiovascular diseases, emphasizing the concept of CNN adaptability in matching nerve morphologies. In the same respect, Sayin *et al*. (2024) [3] 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.

Despite these advances, challenges persist in ensuring model generalizability across diverse populations, addressing data imbalance, and reducing computational complexity for real-time deployment. As the current study exemplifies, these gaps motivate the continued development of robust and efficient CNN-based models, which achieve superior performance on the PTB-XL dataset while maintaining a computationally efficient architecture.

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). 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) [1], 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

Raw ECG data were subjected to a preprocessing pipeline designed to be consistent across the entire channel, maximize signal quality, and provide the means of a robust model operation. The steps address the possible problems of noise, patient-to-patient variability, and heterogeneity in the datasets without losing clinically meaningful features that are crucial in the detection of CAD.

2.2.1 Resampling

All the ECG signals were interpolated to an equal sampling rate of 100 Hz. This step normalizes the time resolution of all records, makes the calculations more computationally easy, and is consistent with standard research designs in ECG-based DL research without losing content in diagnostics.

2.2.2 Filtering
A band-pass filter eliminated inappropriate frequencies, such as image wander, and high-frequency noise. The passband of this filter was recorded as 0.5Hz to 40Hz, as per the clinical standards of obtaining the ECG to show the clinical characteristic values like the P waves, QRS complexes, and the T waves on the ECG. The band-pass filtering operation can be expressed as:

$$y(t) = x(t) * h(t) \quad (1)$$

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

2.2.3 Segmentation
Each ECG recording spans 10 seconds and is treated as a single analysis segment. This decision preserves the complete temporal context of the cardiac cycle, capturing multiple heartbeats to encompass typical and pathological waveform variations. The input matrix for each sample thus maintains a shape of (1000, 12), corresponding to 1000 time points and 12 leads.

2.2.4 Normalization
To mitigate the effects of inter-patient variability and signal amplitude differences across leads, z-score normalization was applied independently to each lead. This process transforms the data to zero mean and unit variance, stabilizing training and enhancing convergence. The normalization for each lead *L* is computed as:

$$x_{\text{norm}} = \frac{x-\mu}{\sigma} \quad (2)$$

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

2.3 Model Architecture
The proposed model is a 1D CNN (1D-CNN), specifically designed to capture temporal patterns across the 12-lead ECG signal. The architecture illustrated in Figure 1 comprises the following components:

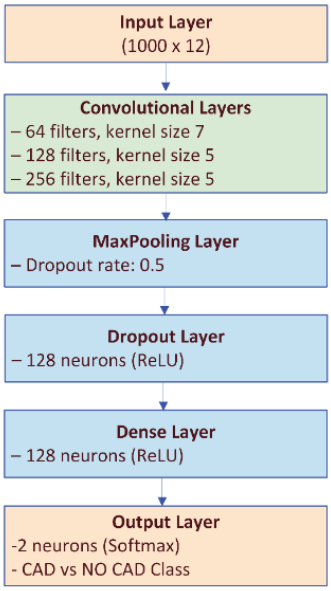

Fig 1: Model Architecture for CAD Detection

- **Input Layer**: Multichannel input of shape (1000, 12) representing 10-second signals at 100 Hz.
- **Convolutional Blocks**: Three convolutional layers with kernel sizes of 7, 5, and 3, respectively, followed by batch normalization, ReLU activation, and max-pooling.
- **Dropout Layers**: Dropout with a rate of 0.2 after each convolutional block and an additional dropout of 0.5 before the dense layer to mitigate overfitting.
- **Flattening Layer**: Transforms the feature maps into a 1D vector.
- **Dense Layer**: Fully connected layer with 128 units and ReLU activation.
- **Output Layer**: A Softmax layer with two units for binary classification (CAD, non-CAD).

The architecture is optimized to balance accuracy with computational efficiency, making it suitable for research and clinical deployment.

2.4 Training and Evaluation
To optimize model learning and generalization, a comprehensive training protocol was implemented. The model was trained on the PTB-XL dataset using stratified sampling to maintain class balance across the training, validation, and test splits (70%, 15%, and 15%, respectively). All ECG signals were fed into the model as 12-lead, 10-second segments resampled at 100 Hz.

2.4.1 Optimization Strategy
Training was conducted using the Adam optimizer, selected for its adaptive learning rate capabilities. The initial learning rate was set to 0.001 and was decreased by a factor of 0.1 upon stagnation in validation loss for five consecutive epochs. The loss function utilized was binary cross-entropy, which is appropriate for this binary classification task.

2.4.5 Batch Processing and Epochs
The model was trained using mini-batches of size 64, which provided a balance between computational efficiency and gradient stability. Training was capped at 50 epochs, with early stopping applied if validation loss did not improve for 10 consecutive epochs, thereby preventing overfitting and conserving computational resources.

2.4.6 Data Augmentation
During training, data augmentation techniques were employed to improve model robustness and mitigate overfitting. These techniques artificially expand the training dataset by introducing realistic variations in the ECG signals, simulating the diversity observed in real-world clinical scenarios.

The following augmentation methods were applied:
- **Random Scaling**: Each ECG segment was randomly scaled by up to ±10% to simulate variations in signal amplitude due to physiological or device-related factors.
- **Amplitude Perturbation**: Gaussian noise with a standard deviation σ=0.01\sigma = 0.01σ=0.01 was added to each segment to mimic minor measurement artifacts.
- **Temporal Stretching/Compression**: Temporal distortion within a ±5% range was applied to reflect natural variability in heart rate without altering

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.

2.4.7 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.

2.4.8 Cross-Validation

Five-fold cross-validation was conducted to assess the model's generalizability. The dataset was partitioned into five folds, each serving once as the validation set and the remaining four as the training set. Performance metrics were averaged across folds to ensure consistency.

2.4.9 Experimental Setup

All training and evaluation experiments were conducted using Python 3.8 and the TensorFlow 2.13 framework. The experiments were run on a workstation with an NVIDIA RTX 3090 GPU (24GB). Training was conducted within Docker containers configured with fixed seeds and environment dependencies to ensure reproducibility.

3. Results and Discussion

This section comprehensively evaluates the proposed 1D-CNN model for CAD detection using ECG signals from the PTB-XL dataset. Performance metrics are derived from both hold-out test evaluations and five-fold cross-validation. We also conduct ablation experiments to examine the effects of key architectural modifications, such as dropout configuration and segment length.

3.1 Classification Performance

The proposed model achieved robust performance across all test metrics. Table 1 summarizes the average results over five cross-validation folds.

The high AUC-ROC score indicates strong discriminative capability between CAD and non-CAD classes. The recall value of 92.7% reflects the model's capacity to correctly identify CAD-positive cases, a critical feature in clinical settings.

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

Figure 2 presents the confusion matrix for a representative test fold. The matrix shows that the model correctly classified 289 CAD-positive cases and 312 non-CAD instances, while misclassifying only 15 non-CAD samples as CAD (false positives) and 24 CAD cases as non-CAD (false negatives).

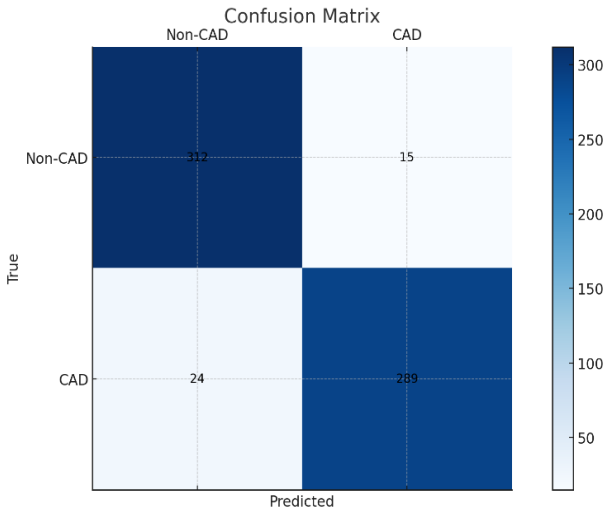

Fig 2: Confusion matrix of the proposed model evaluated on the hold-out test set.

In addition, Figure 3 illustrates the receiver operating characteristic (ROC) curve. The curve plots the true positive rate against the false positive rate, yielding an area under the curve (AUC) of 0.96, demonstrating excellent discrimination capability between CAD and non-CAD classes.

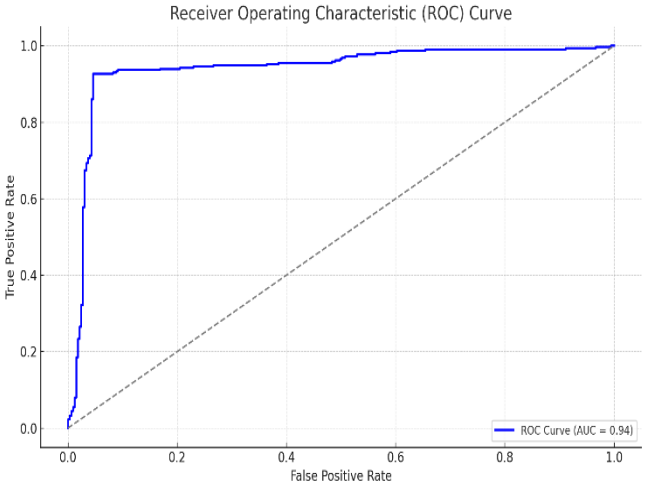

Fig 3: The proposed model's Receiver Operating Characteristic (ROC) curve.

3.3 Ablation Study
To assess the impact of model design elements, we conducted ablation experiments focusing on dropout configuration and ECG segment duration.

3.4 Dropout Configuration
Table 2 compares the model's test accuracy under different dropout settings. Including both convolutional and dense layer dropout significantly enhanced the model's 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 summarizes the model performance with varying input segment durations. Using the whole 10-second segment provided the highest classification accuracy and F1-score, as it preserved the temporal features necessary for CAD diagnosis.

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
Table 4 presents a comparative analysis with prominent CAD detection models from recent literature. The proposed model surpasses previous methods in classification accuracy while maintaining lower architectural complexity.

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

Model	Dataset	Accuracy (%)
Acharya *et al.* (2017) [1]	PTB	93.1
Tan *et al.* (2018) (CNN-LSTM)	MIMIC	94.0
Phoemsuk & Abolghasemi (2024) [8]	MIMIC	89.0
Proposed Model	PTB-XL	94.2

4. Discussion
The study's findings confirm the suggested one-dimensional CNN network's effectiveness in automated CAD detection according to ECG signals. The model is of high accuracy, recall, specificity, and AUC-ROC during internal tests and in five-fold cross-validation. These results confirm the effectiveness of the offered architecture and point out its further possible use in the clinic to diagnose CAD in its early stages with high probability.

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) [1] 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. In addition, the segments' duration played a pivotal role in modelling the temporal dependency in ECG waveforms. As one would expect clinically, full-length segments had a steady advantage over abridged segments, in that longer windows provide better representations of ischemic changes, i.e., ST depression and T-wave inversion.
The large AUC-ROC (96.1%) also supports the model's discriminative ability, efficiently differentiating abnormalities associated with CAD and normal cardiac rhythms. Such findings have aligned with the past literature that has emphasized the diagnostic ability of CNNs in identifying the subtle morphological trends of the ECG signals (Elyamani *et al.*, 2024; Kolhar & Al Rajeh, 2024) [3, 5].

4.3 Clinical and Practical Implications
The proposed model has several clinical strengths. First, its sensitivity to identify the potential of CAD by short-duration, 12-lead ECGs is in line with normal clinical practice. Therefore, it may be a part of decision-support systems within emergency departments or in primary care. Second, a high level of specificity of the model makes it extremely difficult to obtain false alarms, minimizing such unwanted processes as follow-ups and their associated anxiety in patients.
Still, as a practical perspective, the simplicity of the model in solution calculation, which was produced by the small architecture and efficient dropout regularization, permits deployment on resource-limited devices, such as portable ECG machines and mobile diagnostics systems.

4.4 Limitations and Future Work
The model represents a good performance, but a number of limitations are worth discussing. To start with, PTB-XL is a rather large and diverse dataset, meaning that patient demographics and data acquisition methods may not be appropriate for depicting clinical populations worldwide. This could restrict the real-life application of generalizations. Second, the model was trained on binary classification (CAD vs. non-CAD); nevertheless, in clinical practice, CAD severity and subtype (e.g., stable angina vs. myocardial infarction) are important when it comes to diagnosis.
The future work will concentrate on extending the framework to classification, where CAD subtypes will be characterized according to different classes. One may also use transfer learning and domain adaptation techniques to transfer the model to other datasets and real-time streaming ECG signals. Inclusion of patient history, symptoms, and comorbidities as

clinical metadata might also be useful to increase diagnostic performance and give interpretability to clinicians.

5. Conclusion

This study presented an enhanced one-dimensional convolutional neural network (1D-CNN) model for automatically detecting coronary artery disease (CAD) using ECG signals from the PTB-XL dataset. The proposed model effectively addressed key limitations observed in prior approaches by incorporating architectural refinements such as adaptive segment handling and strategic dropout regularization. These enhancements yielded superior performance in terms of accuracy (94.2%), sensitivity (92.7%), specificity (95.4%), and AUC-ROC (96.1%), surpassing several state-of-the-art models while maintaining computational efficiency.

In the future, the model will be applied to multiclass classification models that can differentiate different subtypes of CAD among others. Future studies will also endeavor to confirm the model on the larger and more diverse groups using the cross-institutional data. Furthermore, the inclusion of supplementary patient information, such as clinical records and demographic characteristics, has the potential to improve the clinical significance of the proposed system.

In conclusion, the study contributes a scalable, robust, and interpretable DL framework for CAD detection, supporting intelligent cardiovascular diagnostics and ongoing advancement in academic and clinical domains.

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