Deep Learning for Coronary Artery Stenosis Localization: Comparative Insights from Electrocardiograms (ECG), Photoplethysmograph (PPG) and Their Fusion

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***Abstract*—Coronary artery stenosis (CAS) is a critical cardiovascular condition that demands accurate localization for effective treatment and improved patient outcomes. This study addresses the challenge of enhancing CAS localization through a comparative analysis of deep learning techniques applied to electrocardiogram (ECG), photoplethysmograph (PPG), and their combined signals. The primary research question centers on whether the fusion of ECG and PPG signals, analyzed through advanced deep learning architectures, can surpass the accuracy of individual modalities in localizing stenosis in the left anterior descending (LAD), left circumflex (LCX), and right coronary arteries (RCA). Using a dataset of 7,165 recordings from CAS patients, three models—CNN, CNN-LSTM, and CNN-LSTM-ATTN—were evaluated. The CNN-LSTM-ATTN model achieved the highest localization accuracy (98.12%) and perfect AUC scores (1.00) across all arteries, demonstrating the efficacy of multimodal signal integration and attention mechanisms. This research highlights the potential of combining ECG and PPG signals for non-invasive CAS diagnostics, offering a significant advancement in real-time clinical applications. However, limitations include the relatively small dataset size and the focus on single-lead ECG and PPG signals, which may affect the generalizability to broader populations. Future studies should explore larger datasets and multi-lead signal integration to further validate the findings.**

***Keywords*—Coronary artery stenosis; deep learning; ECG; PPG; ECG-PPG fusion; CNN; LSTM; attention mechanism**

I. INTRODUCTION

Coronary artery stenosis, and other cardiovascular diseases, remain a major cause of death globally, and thus present a major public health concern [1]. Accurate and timely diagnosis of these conditions, as well as continuous monitoring, are crucial for effective treatment and management, ultimately improving patient outcomes [2]. Coronary artery stenosis, a common and serious manifestation of cardiovascular disease, has been the subject of extensive research, with a focus on developing accurate, non-invasive, and accessible detection methods that can enable early intervention and better disease management strategies [3], [4]. This research emphasis underscores the importance of advancing the field of cardiovascular disease diagnosis and monitoring to address this pressing global health concern.

ECG have long been used in the diagnosis and monitoring of cardiac conditions, and recent advancements in machine learning have shown promising results in ECG-based detection and classification of various cardiovascular diseases. For example, changes in the ECG waveform, such as ST-segment depression or T-wave inversion, can be indicative of myocardial ischemia caused by coronary artery stenosis [5]. A study by [6] explores cardiovascular disease (CVD) prediction using machine learning techniques on ECG and physiological data, finding that an artificial neural network (ANN) model achieves the highest predictive accuracy (90%) by utilizing significant parameters such as the R-R interval, RMSSD, blood pressure, and cholesterol levels, highlighting its potential as a non-invasive diagnostic tool for early CVD detection. Deep learning models trained on ECG data have demonstrated the ability to detect and localize specific patterns associated with different regions of coronary artery disease, such as LAD artery, LCX artery, or RCA obstructions [7].

In contrast, photoplethysmographic is an opto-electrical technique that uses light to quantify hemodynamic changes that is an important aspect of cardiovascular analysis. PPG signals can capture blood volume changes in the peripheral vasculature, which can be indicative of changes in the cardiovascular system, such as those associated with coronary artery disease [8], [9]. For example, [10] investigates photoplethysmography (PPG) as a non-invasive alternative to assess coronary artery disease (CAD) severity, finding that a Discriminant Analysis classifier achieved 88.46% accuracy in detecting severe stenosis, thus highlighting PPG's potential for CAD pre-diagnosis in resource-limited or pandemic-impacted environments. In addition, the analysis of PPG waveforms has shown potential in detecting and monitoring conditions like coronary artery stenosis, as it can provide insights into the vascular dynamics and hemodynamic changes related to this cardiovascular disorder [11].

Deep learning, a powerful subset of machine learning, has emerged as a promising approach for the analysis of various biomedical signals, including electrocardiograms and photoplethysmography [12]. These techniques have the ability to extract complex patterns and features from the data, enabling accurate classification and localization of cardiovascular conditions, such as coronary artery stenosis [13]. Among the deep learning methods, Convolutional Neural Networks have demonstrated good efficiency for identification of both ECG and PPG signals for diagnostics of coronary artery disease location [14]. By leveraging the hierarchical feature extraction capabilities of CNNs, researchers have been able to develop robust models for identifying characteristic patterns in cardiac data that are indicative of coronary artery stenosis [15].

LSTM networks, have also shown promise in the analysis of ECG and PPG signals for the detection and monitoring of coronary artery disease [16]. LSTM models overcome the limitation of capturing long range of temporal dependencies and hence suitable for processing these continuous physiological signals [17]. Some recent works have proved that LSTM networks can capture ECG and PPG patterns related to coronary artery stenosis, indicating that deep learning structures might contribute for the localization and diagnosis of this cardiovascular disease [18].

Moreover, it is also understood that the application of attention-based mechanisms in deep learning systems can potentially improve the assessment and visualization of coronary artery disease based on these multiple modal signals [19]. Attention-based architectures, such as Transformer models, have shown promising results in healthcare applications by allowing the models to focus on the most relevant features and patterns in the data, which can be crucial for the precise localization of coronary artery stenosis [20].

The combination of ECG and PPG data may provide a more comprehensive understanding of the cardiovascular system, potentially leading to improved accuracy in the localization of coronary artery stenosis. This study aims to conduct a comparative analysis of deep learning approaches using ECG, PPG, and the combined ECG-PPG modalities to enable accurate and non-invasive localization of coronary artery stenosis, which could enhance early diagnosis and management of this critical cardiovascular condition.

In the following sections, this paper details the methodology for signal acquisition, dataset preparation, and preprocessing, followed by the development and evaluation of three deep learning architectures: CNN, CNN-LSTM, and CNN-LSTM-ATTN. A comprehensive comparative analysis of these models using ECG, PPG, and combined ECG-PPG signals is presented, highlighting the advantages of multimodal signal fusion and attention mechanisms. Finally, the results are discussed in relation to prior studies, and conclusion was made with insights into the clinical implications of our findings and potential directions for future research. This structure aims to provide readers with a clear roadmap of the study, fostering deeper engagement with the content.

II. Related Works

Tao et al. [21] developed an automatic ischemic heart disease (IHD) detection and localization system using magnetocardiography (MCG) signals and machine learning methods. They used 164 features derived from the MCG recordings and divide into three groups, which are time domain feature, frequency domain feature, information theory feature, and compared the performance of many classifiers. Their ensemble model of SVM and XGBoost achieved high performance in IHD detection, with an accuracy of 94.03%, precision of 86.56%, recall of 94.78%, and an AUC of 0.98. For stenosis localization in the LAD, LCX, and RCA, they employed 18 time-domain features with XGBoost, achieving accuracies of 74%, 68%, and 65%, respectively. The study demonstrated that features related to T-wave repolarization synchronicity and magnetic field patterns were critical in both detection and localization, providing a non-invasive, fast, and accurate tool for clinical use.

In their work, Huang et al. [22] propose the creation of an AI-based ECG algorithm that will help predict and indicate the location of angiography-verified CAD. The study employs a CNN model to examine 12-lead ECG data of patients with CAD who have been verified through ICA. The dataset consists of clinical data from 2303 CAD patients and ECG data of 1053 healthy patients as well as 12,954 ECG records. The CNN model provided an AUC of 0.869 to identify CAD, and specific AUC of 0.885, 0.816, 0.776 to detect stenosis in LAD, LCX, RCA respectively. The AUC of the model reached 0.973 in the case when ECGs demonstrated features of myocardial ischemia. The study proves that the AI-based algorithm on the ECG signal as the primary diagnostic tool can be effective and non-invasive for identifying severe CAD and localized stenosis.

Roopa and Harish [23] proposed an automated system for localizing thrombus in coronary arteries using 12-lead ECG signals and an Information Fuzzy Network (IFN). Their method utilizes ECG feature extraction techniques, including the Stockwell Transform and Nearest-Neighbor Interpolation, to identify key features like ST-segment deviations, time intervals, and peak amplitudes in the ECG waveform. An initial rule-based system is then used to separate ischemic and non-ischemic signals and to determine the culprit artery, which might be LAD, RCA, LCX or another artery. This experimental study showed that the proposed system has an accuracy of 92.30%; sensitivity of 87.50%; and specificity of 100%; thus, it could be a valuable noninvasive solution for diagnosing coronary artery blocks and supporting clinical decision making.

Previous studies on CAD localization have primarily focused on using single physiological signals, including MCG and ECG, alongside traditional machine learning models like XGBoost and CNNs. However, the integration of multimodal signals, particularly ECG and PPG, remains underexplored. Furthermore, while advanced deep learning techniques, such as LSTM networks and attention mechanisms, are increasingly recognized for their ability to capture both spatial and temporal dependencies, their application in CAD localization is limited.

The existing literature often lacks the incorporation of attention-based models that can dynamically focus on the most relevant signal features, potentially enhancing diagnostic accuracy. Additionally, few comparative analyses have been conducted to evaluate the relative effectiveness of ECG, PPG, and their combined modalities for CAD localization. Moreover, most studies have focused on offline models, with limited exploration of real-time clinical applications. This study addresses these gaps by employing deep learning models that integrate CNNs, LSTMs, and attention mechanisms to analyze multimodal signals, offering a comprehensive and more accurate approach to CAD localization with potential for real-time clinical implementation.

III. MATERIALS AND METHODS

A. Study Population

This research involved a cohort of patients diagnosed with significant coronary artery disease, as confirmed through angiography. Participants, aged 20 to 65 years, were selected based on the presence of severe stenosis, which was quantitatively assessed using coronary angiography. Only individuals with no prior history of CAD were included. The study received ethical clearance from the Research Ethics Committee of Universiti Kebangsaan Malaysia (UKMPPI/111/8/JEP-2020-806), and all participants provided written informed consent.

B. Data Collection

The study followed a protocol for recording both ECG and PPG signals concurrently from participants, as illustrated in Fig. 1. A total of 60 patients with confirmed significant coronary artery disease through angiography were included, resulting in a dataset containing 7,156 simultaneous single-lead ECG and PPG recordings. The patients were categorized into three groups based on their angiography findings: All those patients who had stenosis in LAD, LCX, and RCA arteries were included in this study.

In the LAD group, 27 patients provided 3,884 concurrent single-beat ECG and PPG recordings. The LCX group consisted of 16 patients, contributing 1,565 recordings, while the RCA group included 17 patients, resulting in 1,707 recordings. Fig. 2 displays sample single-beat ECG and PPG signals for each artery group (LAD, LCX, and RCA).

The dataset was derived from the MAX86150EVS ECG/PPG module, which recorded standard single-lead ECG and PPG signals at a 400 Hz sampling rate for 10 minutes per patient. Signal processing techniques, such as baseline wander removal, smoothing, and segmentation, were applied to isolate individual cardiac cycles and enhance the quality of single-beat signals. This resulted in a final dataset of 7,165 simultaneous single-beat ECG and PPG waveforms, each consisting of 187 data points per sample. This dataset is used in the next sections to develop and evaluate various deep learning models.

C. Dataset Preparation and Preprocessing

Prior to proceeding with the deep learning models, the collected data is partitioned into three distinct datasets: the ECG dataset, the PPG dataset, and the combined ECG and PPG dataset. These datasets share the same number of samples and targets. The purpose of this division is to enable the training and evaluation of deep learning models on the individual modalities as well as the combined modality. For the combined ECG and PPG dataset, each sample comprises a concatenation of both the ECG and PPG signals into a single feature vector. This integration aims to leverage the complementary information present in the ECG and PPG signals to potentially enhance the overall performance of the CAD stenosis localization task. Fig. 3 shows examples of the concatenated ECG and PPG signals belonging to the classes, namely LAD, LCX, and RCA.

In the experiment, the datasets are split into subsets with the training, validation, and test data that should not overlap, 70% of the dataset for training, 10% for validation and the remaining 20% for testing. It is noteworthy to mention that the training and test sets are completely disjoint in terms of patient-wise separation, adhering to best practices for evaluating deep learning models. All three groups of datasets are subjected to the same train-validation-test split ratios.

The three datasets seem to be unbalanced, with the LAD group containing a significantly larger number of samples compared to the LCX and RCA groups. Such distribution skew could result into biased deep learning models and performance of the models when trained and tested on the datasets [22]. As a result, to address this problem, we resorted to applying down sampling where we sampled a proportionate sample of the majority class to create a new smaller set of samples that was equivalent in size to the other two classes. Fig. 4 shows bar chart representations of the distribution of samples before and after the down-sampling process for each group.

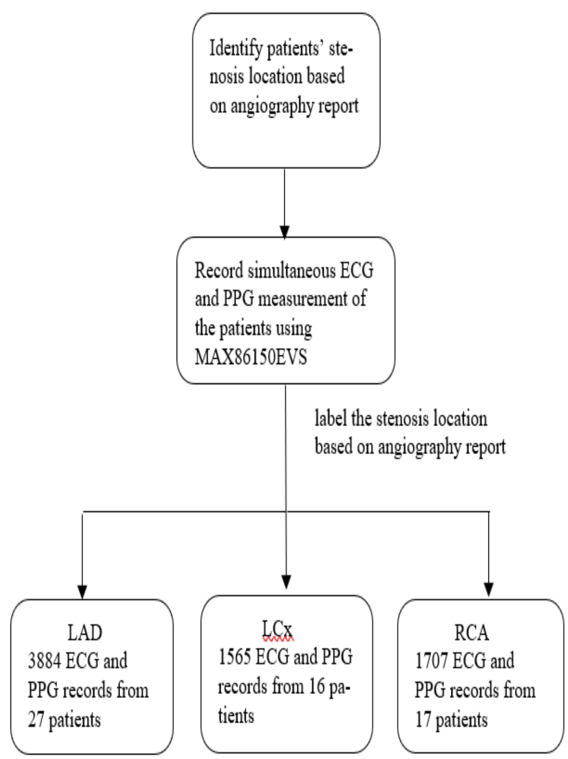

Fig. 1. Data collection procedure.

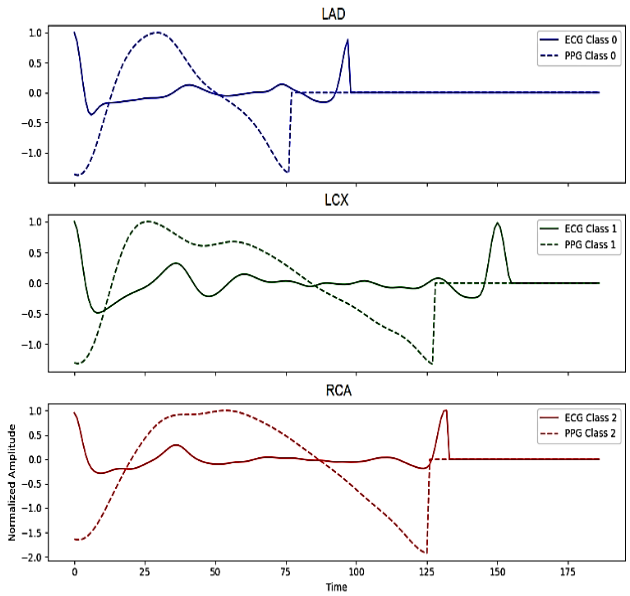

Fig. 2. ECG and PPG data samples for a patient with blockages in the LAD, LCX, and RCA arteries.

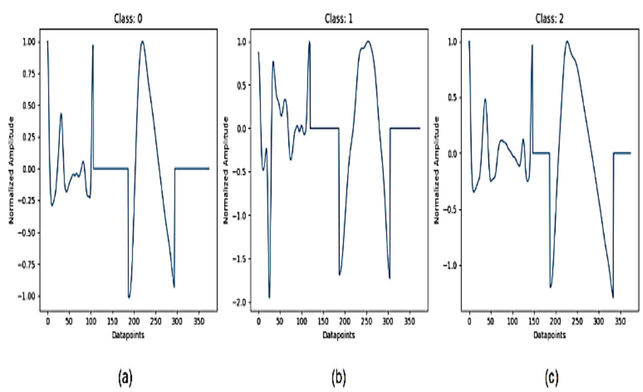

Fig. 3. Combined ECG and PPG samples for a patient with blockages in (a) LAD, (b) LCX, and (c) RCA arteries.

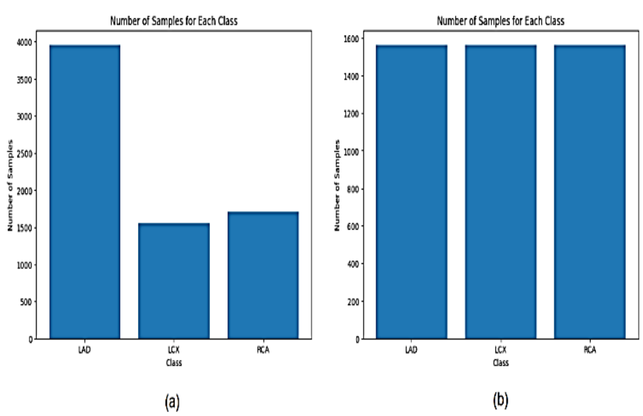

Fig. 4. (a) Dataset showing class imbalance prior to the balancing process, and (b) Dataset with balanced classes after the data balancing procedure.

D. Model Build-up

In this study, a series of deep learning models were developed to classify CAD stenosis location using ECG, PPG the combination of both signals. These models were developed using Google Colaboratory (Colab), a cloud-based platform that provides access to powerful GPU resources and comprehensive deep learning libraries, such as TensorFlow and PyTorch. To effectively process the complex time-series data, three models were explored: a CNN-based model, a hybrid CNN-LSTM model, and an advanced CNN-LSTM-ATTN model. Each architecture was designed to leverage different aspects of deep learning, namely spatial feature extraction, temporal dependency modeling, and attention-based focus mechanisms, to improve classification accuracy.

The initial model utilizes a CNN, designed to automatically extract features from raw ECG and PPG signals. This is a simple sequence model starting with one-dimensional convolutional layer (Conv1D) with 32 filters and 3×1 kernel, that is then passed through a max-pooling (MaxPooling1D) to minimize the dimensionality of the formed feature maps. The convolutional layers identify local features in the input signals; max-pooling reduces dimensionality and masks significant characteristics. Further, subsequent feature maps are subjected to flatten layer and then fed to the fully connected layer containing 128 units with ReLU activation followed by softmax output layer for classification into three diagnostic categories. This CNN model efficiently captures spatial patterns in the signals, establishing a strong baseline for coronary artery disease classification.

The second model enhances the CNN by incorporating LSTM layers to capture temporal dependencies in the sequential ECG and PPG data. Following the convolutional and max-pooling layers, two LSTM layers, each with 50 units, are added. The first LSTM layer is set to return sequences, enabling the second LSTM layer to process both short- and long-term dependencies within the signal data. This combination of CNN and LSTM layers allows the model to extract spatial features while also understanding their temporal progression, thereby boosting its ability to classify coronary artery disease based on dynamic signal changes. A final dense layer with softmax activation generates a probability distribution across the three diagnostic categories.

The third and most advanced architecture incorporates an attention mechanism to further enhance the model's ability to focus on the most relevant portions of the input signals. The model begins with a convolutional layer with 32 filters and a max-pooling layer, followed by an LSTM layer with 50 units and return_sequences=True. After the LSTM layer, an attention mechanism is applied to dynamically weigh the importance of each time step in the signal, allowing the model to focus on the most significant information. This attention mechanism improves the interpretability of the model by highlighting the critical sections of the ECG and PPG signals that contribute to the classification. The attention-weighted features are then flattened and passed to a softmax output layer for final classification. The architectural representation of the model is represented in Fig. 5 after performing data balancing process and the overall flow of the study is represented in Fig. 6.

By combining CNNs for spatial feature extraction, LSTMs for temporal modeling, and attention mechanisms for focused learning, these architectures present a robust approach to CAD classification. The CNN-based model provides a solid baseline by capturing local signal patterns, while the CNN-LSTM hybrid improves the model's ability to learn temporal dependencies. The CNN-LSTM-ATTN model further enhances performance by focusing on the most relevant parts of the signals, making it the most comprehensive and accurate architecture for the task of CAD diagnosis based on ECG and PPG signals.

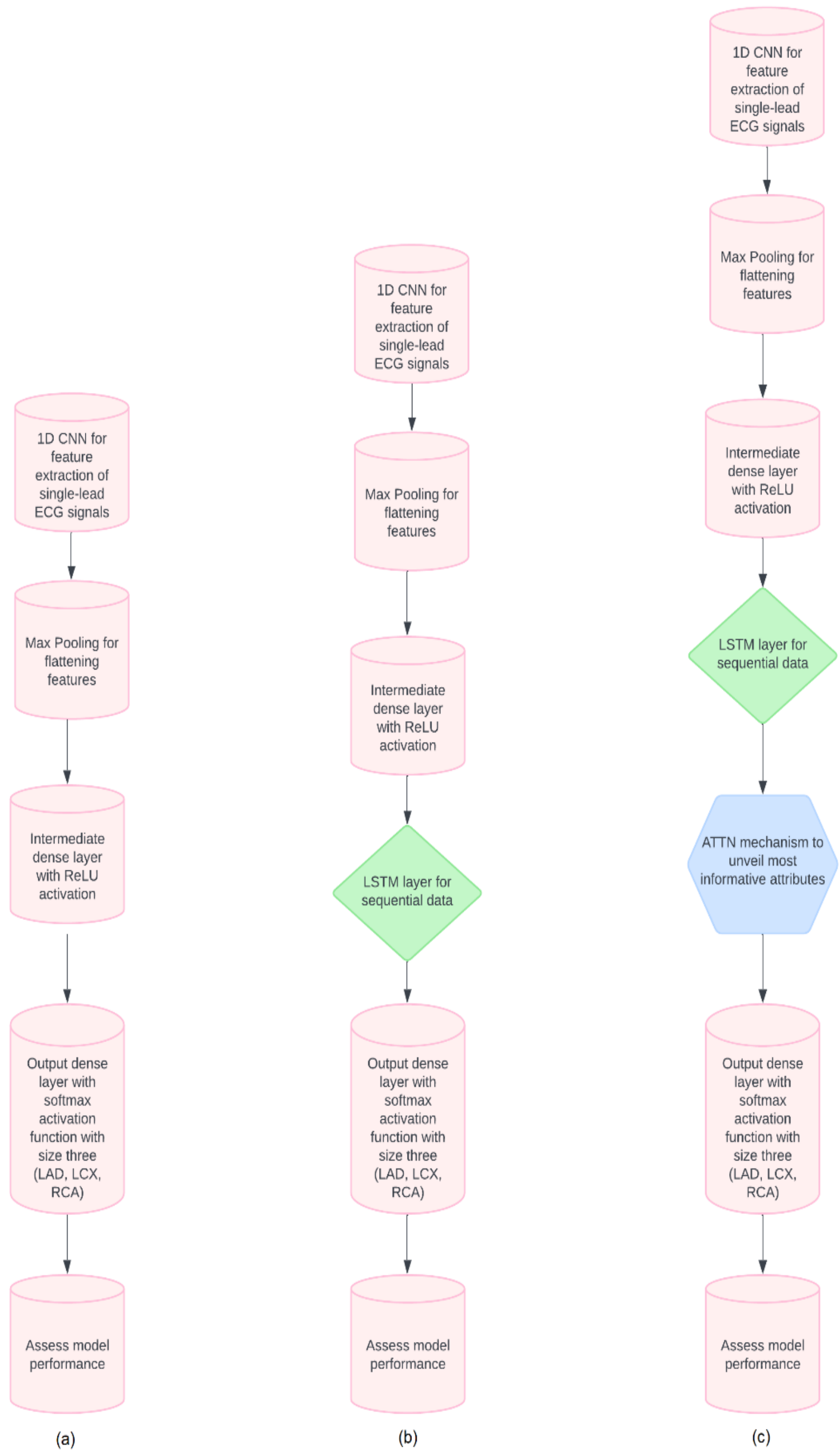

Fig. 5. Architecture for coronary artery blockage localization prediction model for (a) CNN, (b) CNN+LSTM, (c) CNN+LSTM+ATTN.

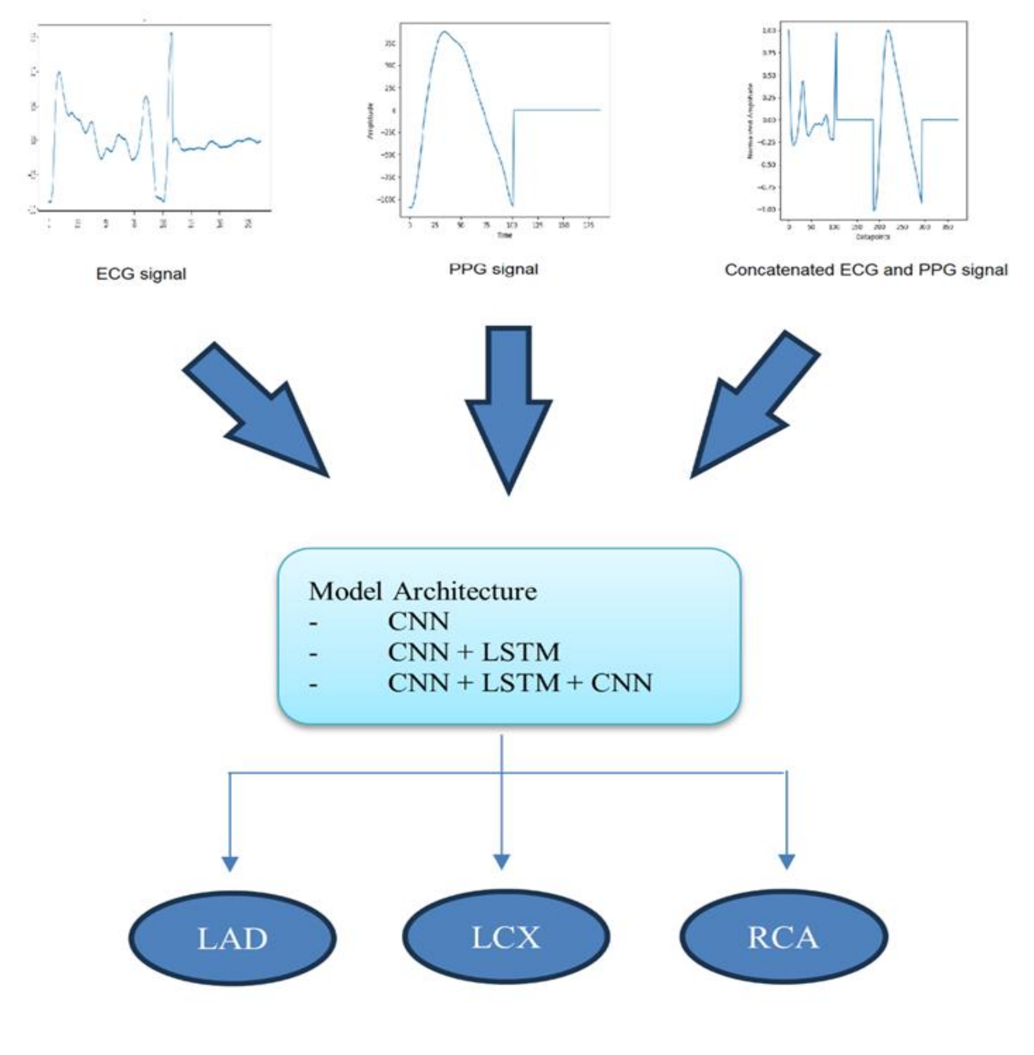

Fig. 6. Model architecture for predicting the localization of coronary artery blockages.

E. Training Process

The training process for each model involves the use of the Adam optimizer with a learning rate of 0.001 and a batch size of 32. The categorical cross-entropy loss function is applied to optimize the models during training. To reduce the risk of overfitting, a dropout layer with a 0.2 rate is introduced after the first fully connected layer in all models. Moreover, the practice of early stopping is used to terminate the learning process when there is a failure to get any improvements in the validation error. The models are trained for up to 100 epochs, with the best-performing model, based on validation accuracy, saved for final evaluation on the test set.

F. Evaluation Metrics

The study aimed to evaluate an AI-enhanced ECG as a means of identifying the location of coronary artery stenosis from single-lead standard ECG recordings, together with comparison based on full lead set. The testing and the performance of the proposed deep learning models was assessed in terms of accuracy metric, area under the receiver operating characteristic curve (AUC-ROC) and the confusion matrix.

The measurement of accuracy is the extent to which samples have been classified correctly; it is the number of correctly predicted over the total samples. This is the ratio of true positive calculated by dividing it by all the positive cases that have been identified as positive by the application. Precision and recall are measurement indicators used in this study. Precision deals with the number of actually positive cases found to be positive by the application, calculated by dividing the true positive value by the actual positive samples. The true positive rate depicts the ratio of the actual positive samples to the total numbers of positive samples that were classified as such the false positive rate depicts the ratio of the negative samples that were classified as positive. Also, the true negative rate expresses the share of real negative patterns that correctly classified and the false negative rate describes the percentage of actual positive patterns that misleading classified as negative.

The area that the curve corresponding to the ROC forms, in short AUC-ROC serves as a rich measure that encapsulates the ability of a classification model in terms of its ability of class separation. Also known as Receiver Operating Characteristic, this metric measures the true positives along the true negatives across the range of classification thresholds that gives a balanced measure of a model's discriminative abilities.

The confusion matrix is used to display accuracy of the model in terms of the three diagnostics types. It gives an account of the right and wrong classifications made by the model, which aids in determination of its efficiency for each class. This characteristic of the confusion matrix helps to analyze the advantages and disadvantages of the model in terms of identifying the various conditions of coronary artery disease.

IV. Results And Discussion

To enhance the model's performance, we carried out several experiments to assess the effectiveness of various deep learning architectures in classifying CAD stenosis locations using ECG, PPG and combination of ECG and PPG signals. The architectures examined in this study comprised a baseline CNN network, a hybrid CNN-LSTM model, and a CNN-LSTM-ATTN model. Table I provides a summary of the performance metrics, including classification accuracy and AUC, for each of these models on the test set. Additionally, the corresponding ROC curve and confusion matrix based on the best model obtained are illustrated in Fig. 7.

In Table I, the results highlight the comparative performance of three deep learning models for CAD stenosis localization using ECG, PPG, and their combined signals. These models include a CNN, a hybrid CNN-LSTM model, and an advanced CNN-LSTM-ATTN.

TABLE I. Performance Metrics of the Three Models Utilized in this Study

Signal	Model	Accuracy	AUC		
			LAD	***LCX***	***RCA***
ECG	CNN	94.25%	0.99	0.98	0.99
	CNN + LSTM	95.53%	0.99	0.99	0.99
	CNN + LSTM + ATTN	97.61%	0.99	0.98	0.99
PPG	CNN	86.10%	0.95	0.96	0.96
	CNN + LSTM	91.97%	0.97	0.99	0.98
	CNN + LSTM + ATTN	92.25%	0.97	0.98	0.98
Combined ECG & PPG	CNN	94.69%	0.96	0.97	0.97
	CNN + LSTM	92.47%	0.98	0.99	0.98
	CNN + LSTM + ATTN	98.12%	1.00	1.00	1.00

For ECG-based detection, the CNN model achieved an accuracy of 94.25%, AUC scores ranging from 0.98 to 0.99 across the three coronary arteries: LAD, LCX, and RCA. Integrating the LSTM layer improved accuracy to 95.53%, indicating the added value of temporal feature extraction, while AUC scores remained consistently high.

The introduction of the attention mechanism (CNN-LSTM-ATTN) led to a significant performance boost, achieving 97.61% accuracy and maintaining near-perfect AUC values for all three arteries, underscoring the ability of the attention mechanism to focus on the most relevant features in the data.

For PPG signals, the CNN model started with a lower accuracy of 86.10%, yet the inclusion of LSTM and attention mechanisms progressively improved the results. The CNN-LSTM model raised accuracy to 91.97%, and the CNN-LSTM-ATTN model further increased it to 93.32%, while AUC scores improved, especially for the LCX and RCA arteries.

When the ECG and PPG signals were combined, the results demonstrated the most substantial improvement. The CNN model reached 94.69% accuracy, and while the CNN-LSTM model saw a slight dip in accuracy to 92.47%, the addition of the attention mechanism significantly enhanced performance, resulting in 98.12% accuracy and perfect AUC scores of 1.00 for all three coronary arteries. This illustrates the clear advantage of combining both signal modalities, which, coupled with advanced deep learning techniques, maximized diagnostic accuracy and precision.

Overall, the results indicate that while individual signals (ECG or PPG) provide valuable diagnostic insights, combining both signals with sophisticated deep learning architectures, especially with attention mechanisms, offers superior performance in localizing coronary artery stenosis. The CNN-LSTM-ATTN model demonstrates exceptional potential for clinical application, offering a non-invasive, highly accurate method for detecting blockages in major coronary arteries.

Table II presents a comparative analysis between the best model obtained from the study and three previous studies—Tao et al. [21], Huang et al. [22], and Roopa and Harish [23]—in terms of accuracy and Area Under the Curve (AUC) for coronary artery stenosis (CAS) localization. The proposed model, which employs a CNN-LSTM-ATTN architecture integrating both ECG and PPG signals, achieves an impressive overall accuracy of 98.12%, substantially outperforming earlier models. In terms of AUC, the model demonstrates exceptional performance, achieving perfect scores of 1.00 for detecting stenosis in LAD, LCX, and RCA. However, Tao et al.'s XGBoost based model, which employed magnetocardiography, yielded lower AUC of 0.74, 0.68, and 0.65 for these arteries, respectively. Huang et al.'s CNN model, only with ECG signals, achieved the AUCs of 0.89, 0.82, and 0.78 for LAD, LCX, and RCA respectively. At the same time, Roopa and Harish proposed an ECG-based model that yielded an accuracy of 92.3%, but AUC values were not disclosed. The exceptional performance of the proposed model achieved because the proposed model relies on the fusion of the ECG and PPG signals; the two methods improve both the feature extraction and temporal models. Moreover, attention mechanisms help to pay more attention to useful signal characteristics, which in turn contributes to better definition of the location of blockages in coronary arteries.

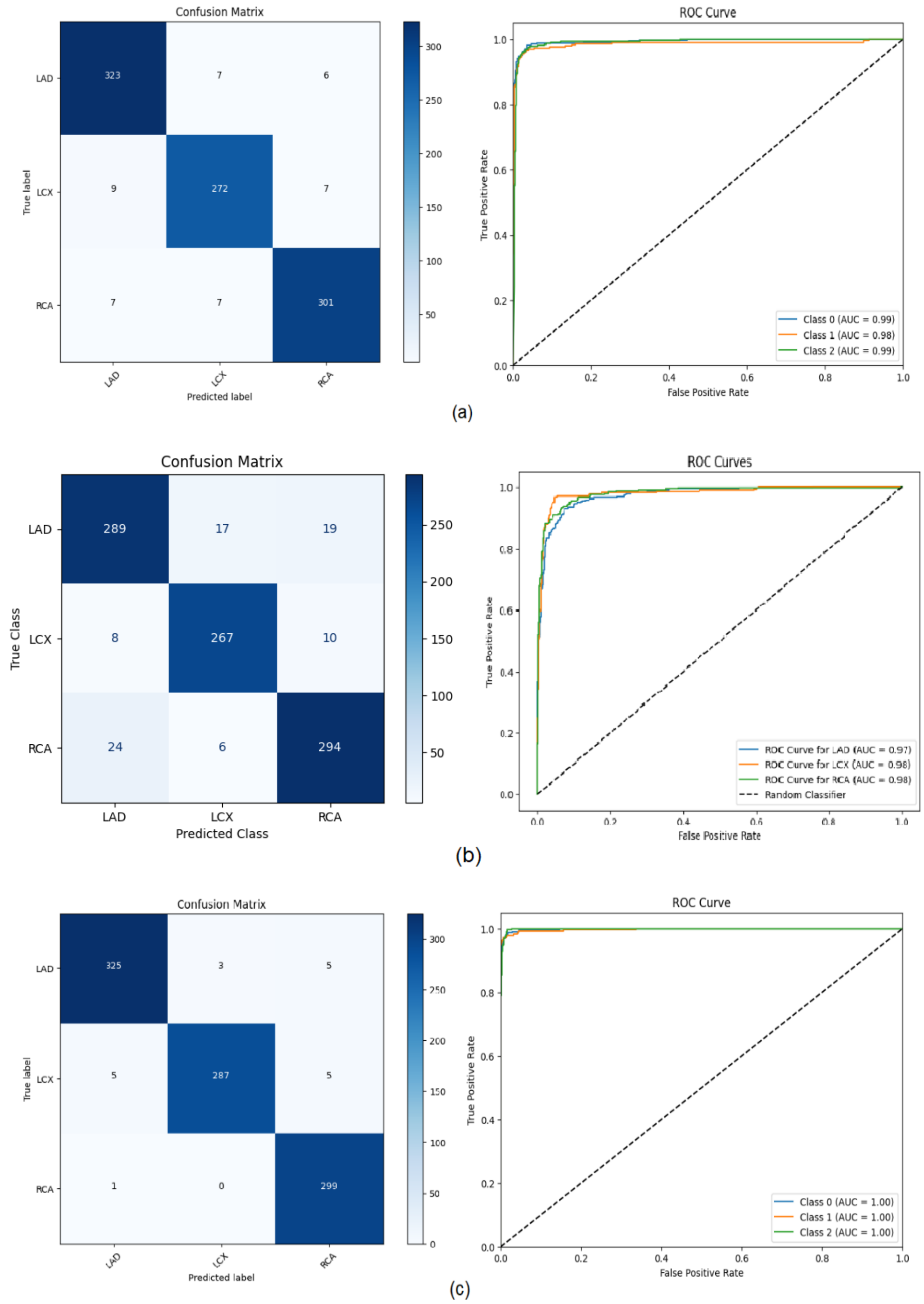

Fig. 7. Confusion matrices and ROC curves of the best models obtained (CNN+LSTM+ATTN) for (a) ECG, (b) PPG, and (c) combination of ECG and PPG signals.

TABLE II. COMPARISON OF PERFORMANCE WITH PRIOR STUDIES

Author, Year	Data	AI Model	Acc.(%)	AUC		
				LAD	*LCX*	*RCA*
Tao et al., 2018 [21]	MCG	XGBoost	NA	0.74	0.68	0.65
Huang et al., 2022 [22]	12 lead ECG	InceptionV3		0.89	0.82	0.78
Roopa and Harish, 2019 [23]	12 lead ECG	IFN	92.3	NA		
Proposed work	Combined simultaneous single lead ECG and PPG	CNN + LSTM + ATTN	98.12	1.00	1.00	1.00

V. Conclusion

This paper proposes a method to diagnose and examine coronary artery stenosis (CAS) using ECG and PPG signals, further aided by deep learning algorithms. The comparison between three models—CNN, CNN-LSTM, and CNN-LSTM-ATTN—verifies that the effects of applying progressive AI structures upon CAS localization are prominent. The results demonstrate that both ECG and PPG signals are informative individually; however, when combined and processed through the CNN-LSTM-ATTN model, the highest classification accuracy of 98.12% and AUC scores of 1.00 were achieved for stenosis in LAD, LCX, and RCA.

These findings underscore the necessity of fusing multiple physiological signals to enhance CAS localization predictability and highlight the effectiveness of the CNN-LSTM-ATTN model in capturing spatial and temporal characteristics of multiple physiological signals while selectively attending to essential features. This approach shows great potential for non-invasive diagnosis of coronary artery diseases and the localization of obstructive lesions, which current clinical imaging techniques may inadequately address.

However, the study is not without limitations. The dataset used was relatively small, with data collected from a single hospital, which may limit the generalizability of the findings. Additionally, the study focused solely on single-lead ECG and PPG signals, excluding the potential benefits of multi-lead configurations or other physiological signals. Future research should explore larger, more diverse datasets and investigate the integration of additional modalities to further validate and enhance the proposed method. Moreover, real-time clinical implementation remains a challenge that warrants further development to ensure the practicality and reliability of the approach in routine healthcare settings.

In conclusion, while the proposed method demonstrates promising results for non-invasive CAS diagnostics, addressing these limitations will be crucial for broader adoption and impact in clinical practice.

Acknowledgment

The authors gratefully acknowledge the financial support provided by the Ministry of Higher Education Malaysia through the Trans-disciplinary Research Grant Scheme (TRGS/1/2019/UKM/01/4/3).

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