Deep Learning-Driven Localization of Coronary Artery Stenosis Using Combined Electrocardiograms (ECGs) and Photoplethysmograph (PPG) Signal Analysis

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***Abstract*—The application of artificial intelligence (AI) to electrocardiograms (ECGs) and photoplethysmograph (PPG) for diagnosing significant coronary artery disease (CAD) is not well established. This study aimed to determine whether the combination of ECG and PPG signals could accurately identify the location of blocked coronary arteries in CAD patients. Simultaneous measurement of ECG and PPG signal data were collected from a Malaysian university hospital, including patients with confirmed significant CAD based on invasive coronary angiography. ECG and PPG datasets were concatenated to form a single dataset, thereby enhancing the information available for the training process. Experimental results demonstrate that the Convolutional Neural Networks (CNN) + Long Short-Term Memory (LSTM) + Attention (ATTN) mechanisms model significantly outperforms standalone CNN and CNN + LSTM models, achieving an accuracy of 98.12% and perfect Area Under the Curve (AUC) scores of 1.00 for the detection of blockages in the left anterior descending (LAD) artery, left circumflex (LCX) artery, and right coronary artery (RCA). The integration of LSTM layers captures temporal dependencies in the sequential data, while the attention mechanism selectively highlights the most relevant signal features. This study demonstrates that AI-enhanced models can effectively analyze simultaneous measurement of standard single-lead ECGs and PPG to predict the location of coronary artery blockages and could be a valuable screening tool for detecting coronary artery obstructions, potentially enabling their use in routine health checks and in identifying patients at high risk for future coronary events.**

Keywords*—Deep learning; CNN; LSTM; ATTN; simultaneous ECG and PPG; coronary artery disease

I. INTRODUCTION

CAD represents a substantial global burden on cardiovascular health [1]. Its impact extends to long-term mortality and morbidity all around the world. Existing studies have demonstrated that ischemic heart disease contributes to approximately 16% of total mortality [2]. Furthermore, epidemiological surveys underscore the escalating prevalence of CAD on a global scale. Nevertheless, the evaluation and diagnosis of CAD persistently hinge upon conventional clinical symptoms, signs, and relevant comorbidities.

It is crucial to determine the location of myocardial infarction and ischemia, as well as identify the specific coronary artery that is blocked and where the occlusion occurs. This information facilitates the diagnosis of ischemia and infarction and guides treatment decisions. For instance, administering nitroglycerin to relieve ischemic chest pain can lead to hemodynamic collapse in patients with right ventricular ischemia/infarction [3]. Therefore, recognizing ECG signs of right ventricular issues is essential. Clinicians, especially interventional cardiologists, benefit significantly from this knowledge, as it directly impacts the selection of coronary catheters.

A variety of non-invasive diagnostic modalities are at the disposal for the assessment of potential coronary artery obstructions in patients with CAD, encompassing stress ECG, and nuclear medicine imaging [4], [5]. Nonetheless, these methodologies are encumbered by several limitations: they are not readily accessible, necessitate the use of specialized apparatus, are laborious, and entail considerable expense. The performance of these tests are moderately suboptimal, ranging approximately between 75-90%, and the issue of radiation exposure cannot be overlooked. Moreover, stress-induced tests that require physical exertion from the patient may not be viable for those in a debilitated state. Hence, there is an imperative need for the development of an easily attainable, economical, and highly precise test for the prediction of ischemic localization.

ECG is recognized as a non-invasive diagnostic instrument that boasts several merits: it is straightforward to operate, consistent in results, broadly accessible, and cost-efficient relative to other diagnostic methods [6]. The ECG is capable of discerning significant CAD by manifesting particular alterations in the ECG patterns, such as deviations in the ST-segment, inversions of the T-wave, and the emergence of Q-waves [7]. Nonetheless, the precision in interpreting ECG data may be compromised by the presence of other medical conditions, including arrhythmias, cardiomyopathies, and bundle branch blocks.

PPG is a non-invasive method utilized to detect variations in blood volume by employing an infrared light sensor positioned on the skin's surface. Beyond its conventional use in heart rate monitoring and pulse oximetry, PPG has garnered attention for its potential in detecting CAD. One of the key methodologies in PPG analysis for CAD detection is Pulse Wave Analysis (PWA). PWA evaluates the PPG waveform to assess arterial stiffness, a hallmark of CAD. The presence of plaque in the arteries can alter the waveform's shape, specifically causing a delay in the pulse wave transit time [8]. In addition, ECG and PPG signals can be combined to enable the assessment of cardiac conditions through heart rate variability (HRV) analysis [9].

Artificial intelligence (AI), particularly through deep learning CNN, has been deployed in diverse disease models [10], [11], [12]. CNNs excel in learning from voluminous datasets, autonomously identifying salient features from data, whether one-dimensional (e.g., signals) or two-dimensional (e.g., images). Recurrent neural network (RNN) architectures such as LSTM is extensively utilized in domains like natural language processing, and analysis of sequential data. As adjunct classifiers to a CNN framework, they fulfill distinct roles in augmenting classification precision. The LSTM architecture, in particular, is proficient in detecting temporal correlations within sequential data [13]. Within deep learning paradigms, attention mechanisms (ATTN) empower models to concentrate on pertinent segments of input data, sidelining the less critical parts. This technique is invaluable in sequential data tasks, where the significance of context and element interrelations fluctuates. Utilizing ATTN, the most informative attributes of an ECG signal can be unearthed across various network layers [14] aiding in functions like classification or regression. In healthcare diagnostics, signal and image data are pivotal. The AI-augmented ECG (AI ECG) algorithm, leveraging deep learning, deciphers significant patterns in ECG data [15]. The effectiveness of deep learning models, particularly a hybrid CNN-LSTM architecture, in enhancing the accuracy of PPG signal analysis for detecting and delineating waveforms was proven by [16]. A deep neural network (DNN) utilizing a multilayer perceptron architecture, enhanced with regularization and dropout techniques, has been employed to enhance the accuracy and reliability of CAD diagnosis and prognosis using clinical data [17]. Prior research has validated its utility in diagnosing heart diseases. Yet, its potential in pinpointing ischemic localizations is a domain yet to be investigated.

The motivation for the study is centered on the need for a more efficient, accessible, and accurate method for diagnosing coronary artery disease (CAD) by identifying the location of arterial blockages. Current diagnostic tools like stress ECG and nuclear medicine imaging, while useful, have limitations including moderate accuracy (75-90%), high costs, and reliance on specialized equipment. Moreover, they may not be viable for patients with debilitating conditions.

ECGs) and PPGs are non-invasive and cost-effective methods, but their full potential in diagnosing CAD is underexplored. By combining ECG and PPG signals and utilizing advanced AI models (CNN + LSTM + Attention mechanisms), this study aims to improve the accuracy of CAD diagnosis, particularly in predicting the location of coronary artery blockages. This approach could lead to a more accessible and precise screening tool for CAD, reducing the need for invasive methods like coronary angiography.

II. Related Work

In a study by Tao et al. [18], an automatic system was developed to detect and localize ischemic heart disease (IHD) using magnetocardiography (MCG) data and machine learning techniques. The authors employed MCG recordings from 227 patients with diagnosed coronary stenosis and 347 healthy controls, using coronary angiography (CAG) as the gold standard for diagnosis. They extracted 164 features from the MCG signals, divided them into time-domain, frequency-domain, and information theory categories, and tested several machine learning classifiers, including k-nearest neighbors (KNN), decision tree (DT), support vector machine (SVM), and XGBoost. The XGBoost classifier was used to localize ischemic regions, achieving an accuracy of 0.74 for LAD, 0.68 for LCX, and 0.65 for RCA.

Huang et al. [19] developed and evaluated a deep learning model using CNN to identify significant CAD from standard 12-lead ECG. The study utilized six pre-trained CNN models (VGG16, ResNet50V2, InceptionV3, InceptionResNetV2, Xception, and DenseNet) for feature extraction, ultimately finding that the InceptionV3 model without a dense layer provided the best performance. The model classified patients into four groups: normal (no CAD), and those with obstructions in the LAD, LCX, and RCA. The dataset included ECGs from 2,303 patients with angiography-proven significant CAD and 1,053 control patients without CAD. The AI model demonstrated a macro-average area under the ROC curve (AUC) of 0.869 for CAD detection, with individual AUCs of 0.885 for LAD, 0.776 for RCA, 0.816 for LCX, and 1.0 for non-CAD (normal) cases.

The paper by Roopa and Harish [20] proposes a novel approach using the Information Fuzzy Network (IFN) to analyze ECG signals for identifying and localizing thrombus in culprit arteries. The method involves preprocessing ECG signals using a Savitzky-Golay filter, followed by feature extraction through the Stockwell Transform for point detection, Nearest-Neighbor Interpolation for time interval measurement, and peak amplitude assessment. The classification process differentiates between ischemic and non-ischemic signals, identifies the culprit artery, and pinpoints the thrombus location. The study used ECG datasets from the MIT Physionet databank, including Long-Term ST, Spontaneous Ventricular Tachyarrhythmia, and T-Wave Alternans Challenge databases, providing a comprehensive range of cases. For the LAD artery, ST elevation in lead V3 greater than in V1 suggests an LAD blockage, with further localization determined by elevations in other leads, such as aVF, L2, and L3 indicating a proximal block to the major septal artery. The LCX is identified by ST elevation in L2, L3, and aVF with L2 greater than L3, while the RCA is identified by ST elevation in L2, L3, and aVF with L3 greater than L2 and a higher V1 elevation than V3. The proposed method achieved a classification accuracy of 92.3%, with 87.5% sensitivity and 100% specificity.

The previous studies on CAD detection and localization, such as those by Tao et al., Huang et al., and Roopa and Harish, primarily focused on single modalities (MCG or ECG) and did not explore the combined potential of ECG and PPG signals. Moreover, while machine learning techniques and conventional CNNs were employed, more advanced AI models like LSTM and attention mechanisms have not been fully investigated, limiting the ability to capture complex temporal and spatial features. Additionally, the precision in localizing specific coronary arteries remains moderate, and none of these studies explored the diagnostic potential of PPG signals, leaving a gap in fully leveraging its capabilities for CAD detection. Lastly, the existing research lacks generalizability across diverse and multimodal datasets, potentially limiting the robustness and accuracy of CAD diagnosis. This study aims to address these gaps by integrating ECG and PPG signals, enhanced by advanced AI models (CNN, LSTM, and attention mechanisms), to achieve more accurate and comprehensive CAD detection and localization.

III. Materials and Methods

A. Study Population

This paper analyzes the dataset of a study conducted on patients with angiography-proven significant CAD. All study participants have given their written consent and the study is approved by the Research Ethics Committee of Universiti Kebangsaan Malaysia (UKMPPI/111/8/JEP-2020-806). These patients underwent elective invasive coronary angiography at the Hospital Chanselor Tuanku Mukhriz (HCTM) Malaysia. The criteria for inclusion were severe stenosis (>70%) based on quantitative coronary angiography assessment. All participants enrolled in the study fell within the age range of 20 to 65 years, as the aim was to specifically target individuals without any prior history of CAD. All patients were monitored by their cardiology physicians in outpatient clinics.

B. Data Collection

The algorithm for patients' simultaneous ECG and PPG data recording is shown in Fig. 1. A cohort comprising 60 patients diagnosed with significant CAD via angiography was assembled, and a comprehensive dataset of 7156 simultaneous single-lead ECGs and PPG was amassed for analysis. Subsequently, based on the findings from the patients' angiography reports, they were categorized into three distinct groups: those exhibiting stenosis in the left anterior descending artery (LAD), left circumflex artery (LCX), and right coronary artery (RCA).

Within this cohort, the LAD group consisted of 27 patients, yielding 3884 simultaneous single beat ECG and PPG records, the LCX group comprised 16 patients, corresponding to 1565 simultaneous single beat ECG and PPG records, and the RCA groups encompassed 17 patients, accounting for 1707 simultaneous single beat ECG and PPG records. Fig. 2 shows samples of simultaneous single beat ECG and PPG signals for each class LAD, LCX, and RCA from the dataset.

The data utilized in this study, obtained from the hospital, consisted of simultaneous ECG and PPG time series data collected from patients diagnosed with CAD. This dataset comprised standard single-lead ECG (lead II) signals generated by the MAX86150EVS ECG/PPG module, characterized by a measurement frequency of 400 Hz and a measurement duration of 10 minutes. Prior to commencing the training process, the dataset underwent filtering and segmentation procedures to get the best quality of single beat signals and to augment the number of samples, thereby introducing subsamples for each original sample. As a result, a total of 7165 samples were obtained, each representing a complete cycle of the simultaneous ECG and PPG signal and comprised of 187 data points. These time series data in terms of their shape and size will be utilized for subsequent training of our deep learning models.

C. Dataset Preparation and Preprocessing

Prior to inputting the data into the deep learning model, the ECG and PPG datasets were concatenated to form a single dataset. This integration aims to provide a more comprehensive set of information during the training process, which is hypothesized to enhance the model's performance. Fig. 3 presents examples of concatenated ECG and PPG signals corresponding to each class, specifically LAD, LCX, and RCA. In our experimental setup, the dataset underwent division into two distinct subsets: a training set and a test set. Specifically, 80% of the dataset was allocated to the training and validation process. Validation is done during training utilizing 20% of the training data. The remaining 20% of the original dataset constituted the test set. It is noteworthy to mention that an imbalance in data distribution among the groups was observed.

Previous research has indicated that such imbalances can introduce biases during model training [19]. Consequently, to mitigate this issue, we adopted a down-sampling approach, and randomly removed data so that all the classes have the same number of samples. Fig. 4 shows a bar chart for class distribution before and after the data balancing process.

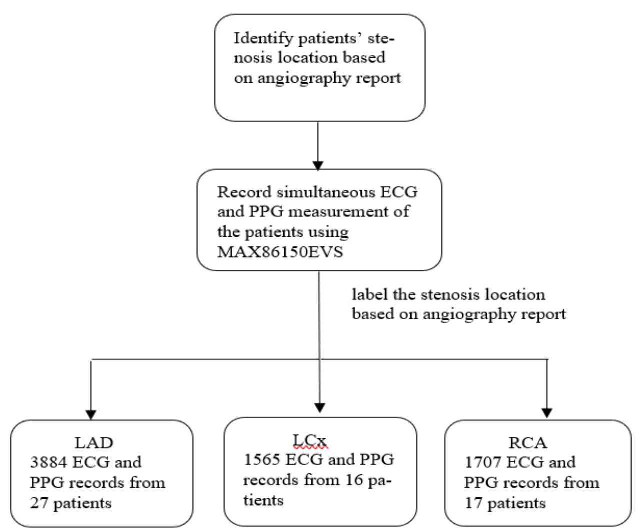

Fig. 1. Data collection protocol.

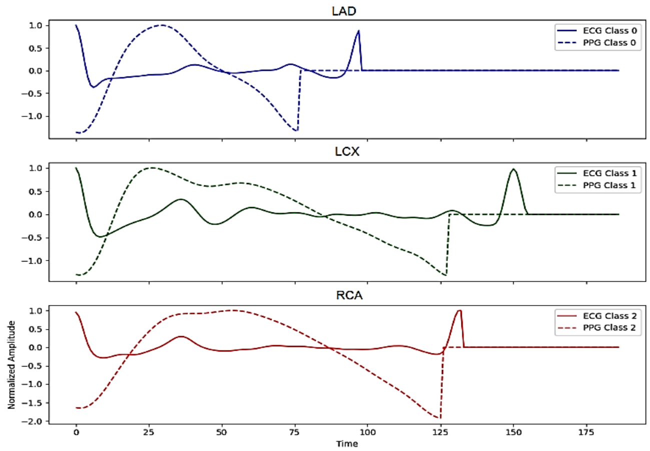

Fig. 2. Normalized simultaneous ECG and PPG measurement samples for patient having blockage at LAD, LCX, RCA.

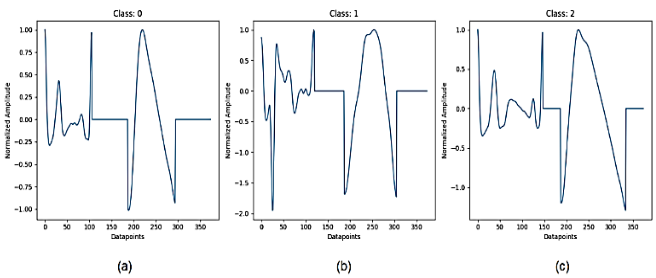

Fig. 3. Concatenated ECG and PPG samples for patient having blockage at (a) LAD, (b) LCX, (c) RCA.

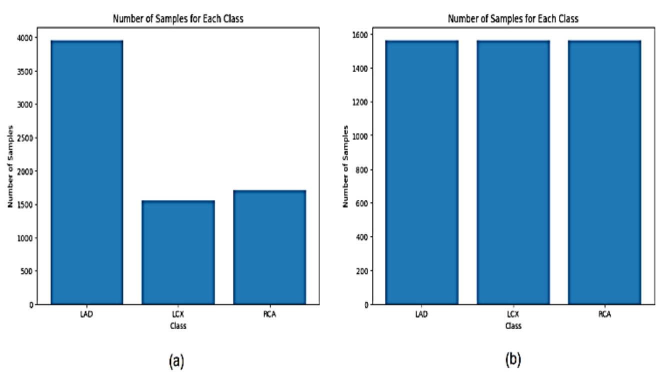

Fig. 4. (a) Imbalanced dataset before data balancing process, (b) Balanced dataset after data balancing process.

D. Model Build-up

In the construction of our deep learning models, we incorporated CNN, LSTM networks, and ATTN along with their respective parameters, resulting in promising outcomes from the integration of all three models. The process of identifying the optimal model involved three key phases.

Initially, we developed a model solely employing 1D CNN. Following the extraction of features by the CNN from the single-lead ECG signals, these features under-went flattening through Max Pooling. Max pooling, a pooling operation technique, extracts the maximum value within each region of the feature map covered by the filter. As a result, the output of the max-pooling layer is a feature map that retains the most prominent features from the preceding feature map. Subsequently, an intermediate dense layer with Rectified Linear Unit (ReLU) activation function was introduced, followed by an additional dense layer with a size of three, representing the three categories of LAD, LCX, and RCA as the output layer. This dense layer employed the Softmax activation function. The performance of this model was then evaluated.

In the second phase, we incorporated an LSTM layer into the existing model and assessed its performance. Finally, in the last phase, we augmented the previous CNN + LSTM model with an ATTN layer and evaluated its performance. The architectural representation of the model is depicted in Fig. 5 after data balancing process.

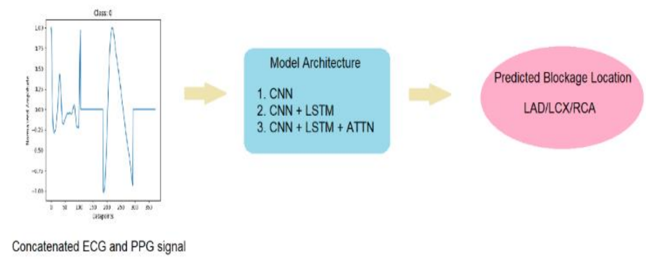

Fig. 5. Architecture for coronary artery blockage localization prediction model.

E. Training Process

The training platform utilized in this study is Google Colaboratory (Colab), which operates within a high-RAM GPU environment. Colab serves as a cloud computing platform supporting Python 3.8 and the TensorFlow package, widely employed for constructing and training deep learning models. As a Google resource, Colab seamlessly integrates with Google Drive, allowing users to access files within Colab by uploading datasets to their personal Google Drives. For model development, we leveraged the Keras application programming interface (API) to construct CNN, LSTM, and ATTN models. Keras not only simplifies the construction of deep learning models but also provides a rich set of APIs and functions, including callbacks, optimizers, metrics, losses, and more, enhancing the versatility and efficiency of model development.

F. Evaluation Metrics

The principal objective of this investigation centered on evaluating the capacity of AI-enhanced ECGs to localize coronary artery blockages utilizing standard single-lead ECG recordings obtained at baseline. The performance of this methodology was evaluated through various assessment metrics, including the area under the curve (AUC) of the receiver operating characteristic (ROC) curve, and accuracy. These metrics were computed by averaging the results of five repetitions of training and are reported along with the mean, standard deviation, and 95% confidence interval. The evaluation process also involved the utilization of a confusion matrix, which defined four crucial terms: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). These terms were instrumental in computing the aforementioned metrics. Accuracy, represented by Eq. (1), assesses the models' classification proficiency by quantifying the proportion of accurately classified samples out of the total samples. Precision, expressed in Eq. (2), indicates the percentage of correctly predicted positive results among all predicted positive samples. Recall, detailed in Eq. (3), represents the proportion of correctly classified positive samples out of all actual positive samples.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

ROC curve elucidates the fluctuation between the true positive rate (TPR), often termed sensitivity, and the false positive rate (FPR), also known as 1-specificity, over a spectrum of decision thresholds. By modulating the threshold from 0 to 1, a sequence of TPR and FPR coordinates is generated. The ROC curve, plotted with FPR on the X-axis and TPR on the Y-axis, graphically represents the dynamic between specificity and sensitivity in test results. The area under the curve (AUC) signifies the proportion of the area beneath the ROC curve relative to the total possible area. The computation of AUC allows for the ROC curve's quantification, thus enabling the comparative evaluation of model efficacy. The AUC demarcates the model's discriminative capacity into four tiers: (1) AUC < 0.5 (no discrimination), (2) 0.7 ⩽ AUC < 0.8 (acceptable discrimination), (3) 0.8 ⩽ AUC < 0.9 (excellent discrimination), and (4) 0.9 ⩽ AUC ⩽ 1.0 (exceptional discrimination).

ROC-AUC analysis is leveraged in a multitude of fields, including radiology, biology, and, more recently, machine learning and data mining. Within the medical sector, it is prevalently utilized for disease diagnostics, epidemiology, empirical medical research, and radiological methods. The ROC curve's primary advantage is its ability to provide a lucid and direct visual representation of a diagnostic method's clinical precision.

IV. Results and Discussion

To optimize the model architecture, the simultaneous ECG and PPG dataset was utilized to evaluate three distinct model layers. The model demonstrating the highest accuracy was selected as the optimal architecture. The experimental results are presented in Table I. Table I presents the evaluation metrics of three different models utilized in the study: CNN, CNN + LSTM, and CNN + LSTM + ATTN. The performance of these models was assessed based on their accuracy and area under the curve (AUC) values for predicting blockages in three coronary arteries: the left anterior descending (LAD) artery, left circumflex (LCX) artery, and right coronary artery (RCA). Use letters for table footnotes. The corresponding ROC curve and confusion matrix are shown in Fig. 6.

As shown in Table I, The CNN model achieved an accuracy of 94.69%. When the LSTM layer was integrated with the CNN model, the accuracy slightly decreased to 92.47%. However, the introduction of the attention mechanism alongside the CNN and LSTM layers led to a significant improvement, with the CNN + LSTM + ATTN model achieving an accuracy of 98.12%.

TABLE I. EVALUATION METRICS OF THREE DIFFERENT MODELS USED IN THIS STUDY

Model	Accuracy	AUC		
		LAD	***LCX***	***RCA***
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 the detection of LAD blockages, the CNN model obtained an AUC of 0.96. The addition of the LSTM layer increased the AUC to 0.98, demonstrating the model's enhanced ability to capture temporal dependencies in the data. The incorporation of the attention mechanism further elevated the performance, with the CNN + LSTM + ATTN model reaching the maximum AUC of 1.00, indicating perfect classification.

In the case of LCX blockages, the CNN model achieved an AUC of 0.97. The CNN + LSTM model improved this metric to 0.99, showing a robust enhancement due to the LSTM layer. The CNN + LSTM + ATTN model again achieved the highest AUC of 1.00, reflecting its superior ability to focus on the most relevant features of the ECG and PPG signals for accurate detection.

For RCA blockages, the CNN model also achieved an AUC of 0.97. The CNN + LSTM model maintained a high AUC of 0.98, confirming the beneficial impact of temporal feature extraction. The CNN + LSTM + ATTN model reached a perfect AUC of 1.00, further validating the effectiveness of the attention mechanism in improving the model's discriminative power.

The comparative analysis reveals that the integration of LSTM and attention mechanisms into the CNN model substantially enhances its performance. The CNN + LSTM + ATTN model consistently outperforms both the standalone CNN and the CNN + LSTM models across all metrics. The inclusion of the LSTM layer helps capture temporal dependencies inherent in the sequential ECG and PPG data, thereby improving the model's ability to differentiate between classes. Furthermore, the attention mechanism selectively emphasizes the most relevant parts of the signals, thereby enhancing the model's focus and leading to more accurate classification.

The significant improvements in both accuracy and AUC, particularly the perfect AUC scores achieved by the CNN + LSTM + ATTN model, underscore its exceptional potential for precise detection of coronary artery blockages. This suggests that the combined approach not only leverages the strengths of each component but also synergistically enhances the overall model performance, making it a promising tool for the diagnosis of coronary artery disease using ECG and PPG signals.

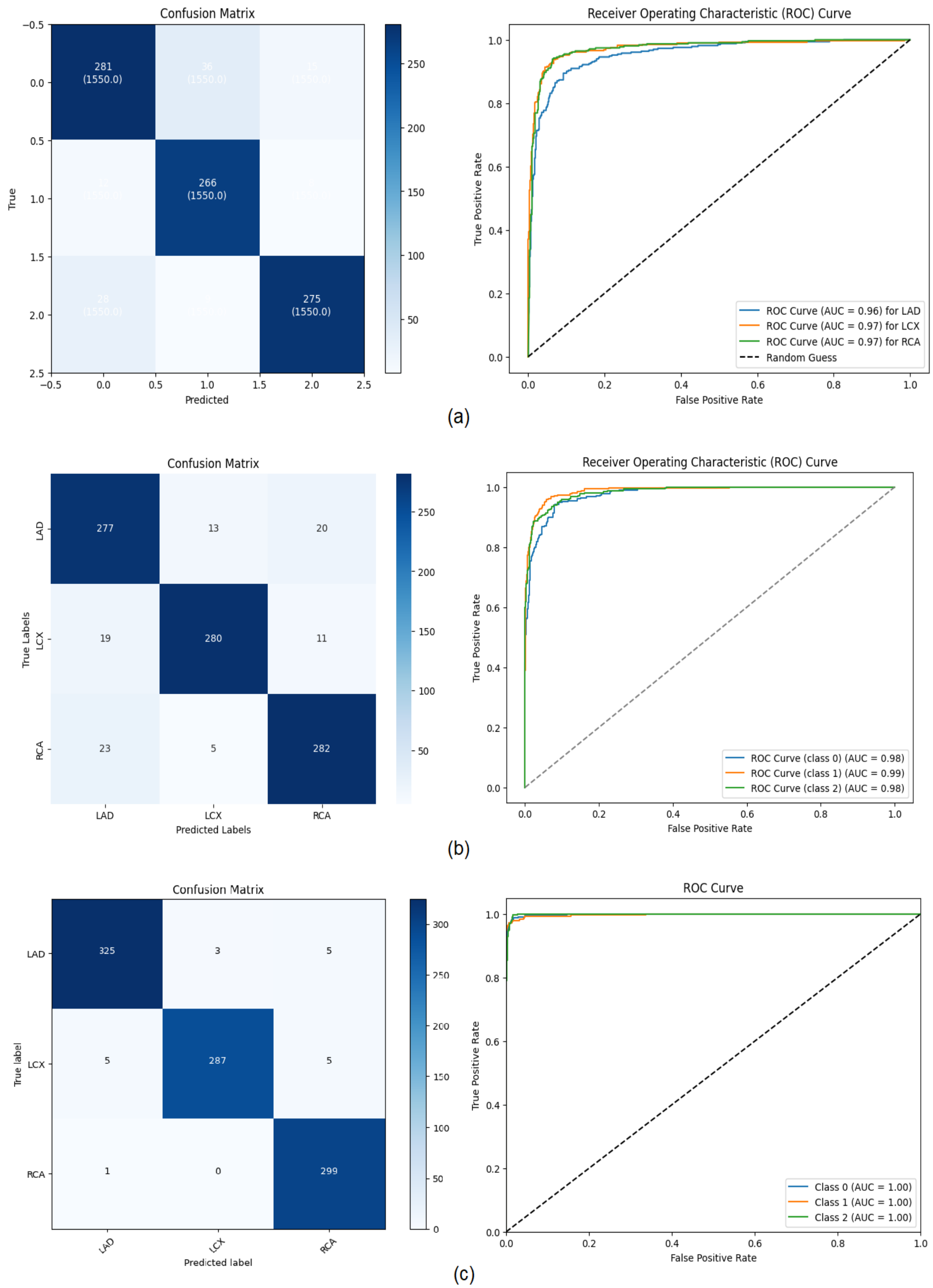

Fig. 6. Confusion matrix and ROC curve of (a) CNN model, (b) CNN + LSTM model, (c) CNN + LSTM + ATTN model.

Table II shows the model performance comparison of the best model obtained in this study with previous works by Tao et al., 2018 [18], Huang et al., 2022 [19], and Roopa and Harish, 2019 [20] in terms of their accuracy and AUC since these studies are closely related to the proposed work.

The results in Table II highlight the superiority of the proposed model, which utilizes combined simultaneous single-lead ECG and PPG signals with a CNN + LSTM + ATTN architecture, in predicting and localizing coronary artery blockages compared to previous studies.

TABLE II. PERFORMANCE COMPARISON WITH PREVIOUS WORKS

Author, Year	Data	AI Model	Acc.(%)	AUC		
				LAD	*LCX*	*RCA*
Tao et al., 2018 [18]	MCG	XGBoost	NA	0.74	0.68	0.65
Huang et al., 2022 [19]	12 lead ECG	InceptionV3		0.89	0.82	0.78
Roopa and Harish, 2019 [20]	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

The proposed model achieved an overall accuracy of 98.12%, surpassing the performance of prior studies. In terms of Area Under the Curve (AUC) metrics for different coronary arteries, the model reached perfect scores (AUC = 1.00) for the left anterior descending (LAD), left circumflex (LCX), and right coronary artery (RCA). These results significantly outperform other models, as shown in the comparison.

Tao et al. [18] use magnetocardiography (MCG) data and an XGBoost model, this study reported lower AUC values of 0.74 (LAD), 0.68 (LCX), and 0.65 (RCA). Huang et al. [19] applied a deep learning model (InceptionV3) on 12-lead ECG data, achieving AUCs of 0.89 (LAD), 0.82 (LCX), and 0.78 (RCA). Roopa and Harish [20] employed an Information Fuzzy Network (IFN) model using 12-lead ECG data with a reported accuracy of 92.3%.

The significant improvement in both accuracy and AUC values of the proposed model can be attributed to the integration of ECG and PPG signals, coupled with the advanced AI architecture combining CNN, LSTM, and attention mechanisms. The LSTM layers effectively capture temporal dependencies in sequential data, while the attention mechanism enhances feature extraction, leading to more precise localization of coronary artery blockages.

These results indicate that the proposed model represents a substantial advancement in the non-invasive diagnosis and localization of coronary artery disease, providing a more accurate and reliable approach compared to existing methods. This makes it a promising tool for future clinical applications in CAD detection.

V. CONCLUSION

In this study, a novel approach for diagnosing the location of coronary artery blockages in CAD patients by utilizing a combination of ECG and PPG signals was presented. The proposed model integrated Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Attention (ATTN) mechanisms to enhance the accuracy and robustness of CAD detection.

The experimental results demonstrated that the CNN + LSTM + ATTN model significantly outperformed the standalone CNN and CNN + LSTM models. Specifically, an accuracy of 98.12% and perfect Area Under the Curve (AUC) scores of 1.00 for detecting blockages in the left anterior descending (LAD) artery, left circumflex (LCX) artery, and right coronary artery (RCA) were achieved by the CNN + LSTM + ATTN model. The superior performance of the attention mechanism in selectively emphasizing the most relevant parts of the ECG and PPG signals, thereby improving the model's discriminative power, was underscored by these results.

The integration of the LSTM layer was found to further contribute to the model's ability to capture temporal dependencies inherent in the sequential ECG and PPG data, enhancing its capacity to differentiate between different classes of coronary artery blockages. The significant improvements in both accuracy and AUC scores highlighted the exceptional potential of the CNN + LSTM + ATTN model for precise detection of CAD.

In conclusion, the combined approach not only leveraged the strengths of each component but also synergistically enhanced the overall model performance, making it a promising tool for the diagnosis of coronary artery disease using ECG and PPG signals. Future work will focus on further validating the model with larger and more diverse datasets, as well as exploring its applicability in real-world clinical settings.

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