

Detection of occluded coronary arteries in non-ST-elevation myocardial infarction (NSTEMI) patients with deep learning models and ReliefF-based weighted subspace SVM ensembles (RBWSSE) algorithm

Ozgen Safak¹, Mehmet Tolga Hekim¹, Tolga Çakmak¹, Fatih Demir², Yaman Akbulut³, Zehra Kadiroğlu⁴, Abdulkadir Sengür⁴ and Mehmet Ali Kobat⁵

¹ Clinics of Cardiology Department, Medicine Faculty, Balikesir University, Balikesir, Turkey

² Software Department, Engineering Faculty, Firat (Euphrates) University, Elazığ, Merkez, Turkey

³ Software Department, Technology Faculty, Firat University, Elazığ, Turkey, Firat (Euphrates) University, Elazığ, Turkey

⁴ Electrical-Electronic Department, Technology Faculty, Firat University, Elazığ, Turkey, Firat (Euphrates) University, Elazığ, Turkey

⁵ Clinics of Cardiology Department, Medicine Faculty, Firat University, Elazığ, Turkey, Firat (Euphrates) University, Elazığ, Turkey

ABSTRACT

Background/Objectives: Heart attacks are the leading cause of sudden death worldwide. Early diagnosis of the main coronary arteries is vital to prevent sudden death. While occluded coronary arteries are easy to detect from electrocardiogram (ECG) signals in ST-elevation myocardial infarction (STEMI), they are not in Non-ST-Elevation Myocardial Infarction (NSTEMI) cases. This is because ECG abnormalities in NSTEMI cases are visually indistinguishable to physicians. This study aims to develop a deep learning-based method that can directly detect occluded main coronary arteries in NSTEMI patients from 12-lead ECG data without performing coronary angiography (CAG).

Methods: In this study, 12-channel digital ECG signals of NSTEMI cases were collected by expert physicians and labelled by CAG processing. Thus, a unique dataset has been created in this field. In the proposed approach, the labelled signals are used to predict the occluded main coronary artery or arteries with deep learning-based models. A hybrid classification strategy has been developed.

Results: A classification accuracy of 73% was achieved with the Residual & Attention & Long Short-Term Memory (LSTM)-Convolution Neural Network (CNN) (RAL-CNN) model developed on the seven-class data set. With the classification strategy ReliefF-Based Weighted Subspace—Support Vector Machine (SVM)—Ensembles (RBWSSE), the classification performance was significantly increased (about 8%), and 81.3% classification accuracy was achieved. Classification accuracies obtained with popular pre-trained CNN models are also given. Although the classification results are not top-level, they serve as a baseline model for future studies. With newer models to be developed in the future, the classification performance will be further improved for this unique data set.

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Corresponding author

Fatih Demir, fatihdemir@firat.edu.tr

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INTRODUCTION

Cardiovascular diseases remain the leading cause of death worldwide, and rapid diagnosis of acute coronary syndromes (ACS) is critical for improving survival outcomes. Among these conditions, Non-ST-Elevation Myocardial Infarction (NSTEMI) represents a clinically challenging group because the standard electrocardiogram (ECG) does not show clear ST-segment elevations that typically guide intervention decisions in STEMI cases. While coronary angiography (CAG) remains the gold standard for identifying occluded coronary arteries, it is an invasive, costly, and sometimes risky procedure—particularly for elderly patients or those with comorbidities such as chronic kidney disease. Consequently, there is a growing clinical demand for non-invasive, automated methods capable of predicting which coronary arteries are occluded in NSTEMI patients directly from ECG signals ([Ayano et al., 2024](#); [Chen et al., 2024](#)).

Previous studies on ECG-based coronary artery disease detection have mostly focused on binary classification tasks (e.g., normal vs. abnormal or STEMI vs. non-STEMI) or used mixed datasets that include both STEMI and healthy subjects. However, no study has yet developed or validated a model capable of identifying the specific occluded main coronary artery (circumflex artery (Cx), left anterior descending (LAD), right coronary artery (RCA), or their combinations) in NSTEMI patients using 12-lead ECG data labeled by CAG. This gap limits clinicians' ability to make informed decisions regarding whether CAG is necessary or if medical treatment alone may suffice ([Gour et al., 2024](#); [Parveen et al., 2024](#)).

Therefore, the motivation of this research is to design a robust, interpretable, and non-invasive deep-learning framework that can predict the occluded coronary artery or arteries in NSTEMI patients using standard ECG data. To achieve this, we developed a hybrid deep-learning architecture named Residual & Attention & Long Short-Term Memory (LSTM)-Convolution Neural Network (CNN) (RAL-CNN) and a novel ensemble classification strategy called Relief-Based Weighted Subspace SVM Ensembles (RBWSSE). The combination of these methods aims to extract meaningful spatial-temporal features from ECG spectrograms and to enhance classification robustness through feature-weighted ensemble learning. The ultimate goal is to support clinical decision-making and reduce unnecessary CAG procedures in at-risk NSTEMI populations.

Motivation

ECG is the first diagnostic method in patients presenting to the emergency room with chest pain. After ECG, routine blood parameters and cardiac enzymes (troponin, creatinine kinase, creatinine kinase-MB) are ordered. If the patient reports chest pain in the form of pressure and radiating to the left arm, jaw and back, the ECG is first performed

to check whether there is a rise or depression in the ST segment of the P-QRS-T wave. If ST segment elevation is detected, the patient is considered to have an acute ST-elevation heart attack (STEMI) and undergoes an emergency coronary angiography (CAG) procedure ([Kuang et al., 2025](#)).

In case of a normal ST segment or ST segment depression on ECG, the patient's cardiac enzymes (especially troponin) are checked. If these values are above the normal range, the patient is diagnosed with non-ST elevation heart attack (NSTEMI) ([Puymirat et al., 2012](#)). One of the main coronary artery vessels CX, LAD, RCA or multiple combinations (CX+LAD, CX+RCA, LAD+RCA and CX+LAD+RCA) may be occluded in these patients.

Most patients with NSTEMI are aged 70 years or older ([Couper et al., 2018](#)). Moreover, the proportion of the world population aged 80 years and older is projected to triple in the next 20 years ([United Nations, 2019](#)). Increasing age is an important predictor of adverse events in patients with coronary artery disease, and older patients with acute coronary syndromes are at higher risk of short- and long-term adverse outcomes compared to younger patients ([Granger et al., 2003](#); [Avezum et al., 2005](#)). However, the rate of CAG decreases with age due to the risks of CAG. For NSTEMI patients 60 years of age or younger, the CABG procedure rate is 78% (22% at risk for CABG), while for NSTEMI patients 81 years of age or older, the CABG procedure rate is 38% (62% at risk for CABG) ([Rashid et al., 2019](#)).

Among patients with a diagnosis of NSTEMI, those with poor clinical status, impaired hemodynamic parameters, variability on the dynamic ECG, or severe chest pain that does not resolve are considered "high-risk patients," and urgent CAG is performed in these patients. Patients with normal hemodynamic parameters and a resolution of active chest pain undergo CAG within the first 12 h. Among NSTEMI patients who do not undergo urgent CAG, patients in the advanced age group, patients with high risk of bleeding, chronic kidney disease, patients who cannot undergo hemodialysis, pregnant women, cancer patients, and patients with heart failure are defined as the "high-risk group for CAG." Since the benefit-benefit ratio of CAG cannot be easily determined in these patients, performing this operation is a difficult decision for both the physician and the patient. At this stage, the risks of CAG can be discussed with the patient and his/her relatives and can be followed up with medication.

Knowing which coronary artery(s) are involved (occluded) before CABG may facilitate this difficult decision. Involvement of more than one coronary artery or the left anterior descending coronary artery (LAD) indicates a poor prognosis (disease course or prognosis). In this case, the risk to life is higher than the risk of CAG, and a decision may be made to perform CAG. In the case of predicted involvement in a single coronary artery (CX or RCA) excluding the LAD, the risk to the patient's life is not high, and if the patient is in the at-risk group for CAG, it will be possible to treat with medication ([Collet et al., 2020](#)). This study is aimed at patients in the at-risk group for CAG. Within the framework of the study, it is aimed to develop an algorithm that detects the involved coronary artery or arteries of NSTEMI patients and decides whether or not to perform CAG with deep learning-based approaches from the ECG images of these patients who have no visual abnormalities on the ECG graph as mentioned above. For this purpose, an

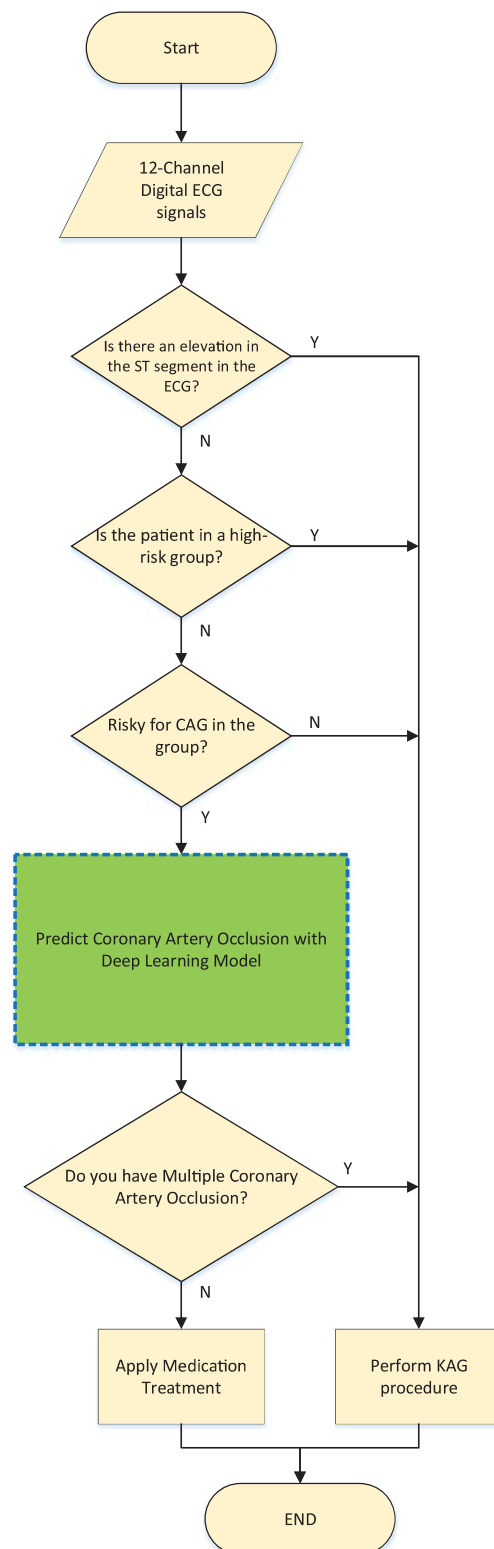


Figure 1 Image of a CAG labeled as CX+LAD occluded after CAG processing.

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explanatory flow diagram of the stages of the algorithm to be used in the study is given in Fig. 1.

Related works

The Convolutional Neural Network (CNN) model (AlexNet) in the 1000-class object recognition competition called ImageNet was popular after 2012. This success has increased the interest in deep learning models in the literature. High performance has been achieved especially in image recognition problems in the medical field. The biggest advantage of these models is that they can be easily applied to large data. In addition, deep learning models have eliminated the feature extraction requirement in traditional machine learning methods. Deep learning models, which provide superior performance, have naturally found applications in the automatic diagnosis of heart diseases.

[Acharya et al. \(2017b\)](#) created a CNN model with four convolutional layers and four maximum-pooling layers to detect heart attacks from ECG signals. They also used the wavelet transform function in the preprocessing stage to remove noise from ECG signals. The classification accuracy for noisy signals was 93.53%, while the classification accuracy for noise-free signals was 95.22%. [Yildirim, Plawiak Pawel and Tan & Acharya \(2018\)](#) used a one-dimensional CNN model to detect 17 different cardiac arrhythmia disorders. The 16-layer architecture composed of convolutional, maximum-pooling, lumped normalization, smoothing, and fully connected layers achieved 91.33% classification accuracy. [Phoemsuk & Abolghasemi \(2024\)](#) used 1D-CNN for CAD detection from ECG signals. The proposed method was tested on the MIMIC III and Fantasia datasets in the PysioNet database. The test performance on these datasets was 86% and 89%, respectively. [Seoni et al. \(2024\)](#) proposed an explainable artificial intelligence-based model for automatic detection of CAD. A technique called Spatial Uncertainty Estimator (SUE) is used to improve the prediction reliability of ECG signals. With the SUE technique, the overlap of Grad_CAM features in the spatial environment is calculated and score values are generated. The CNN-Bidirectional LSTM (BiLSTM) model was used for CAD detection from ECG signals. With this approach, 99.6% accuracy, 99.8% sensitivity, and 98.2% specificity values were obtained. [Hassan, Hussein & Hassan \(2023\)](#) used a deep neural network model with a pre-trained CNN architecture to extract features from ECG signals. The principal component analysis (PCA) technique is used to reduce the size of extracted features. The proposed method was tested on the Cleveland dataset, a publicly available dataset. The proposed approach achieved 93.3% classification accuracy for the test dataset. [Yildirim et al. \(2019\)](#) used hybrid deep learning models to detect coronary artery disease. The Deep Autoencoder (DOC) model was used for feature extraction. The LSTM model was used to classify the samples and a classification accuracy of over 99% was achieved. [Jafarian et al. \(2020\)](#) used one-dimensional and two-dimensional CNN models together to diagnose heart attack from ECG signals. The output of the one-dimensional CNN model was extracted as an attribute map image. These images were used in the two-dimensional CNN model for classification and a classification accuracy of 98.22% was achieved. [Baloglu et al. \(2019\)](#) worked with 12-channel ECG signals to detect acute heart attack. ECG signals from 12 channels were transmitted to a one-dimensional CNN model. The

one-dimensional CNN model is composed of a total of 10 layers (4 of which are convolutional). This model achieved a classification accuracy of 99%.

[Liu et al. \(2020\)](#) proposed a deep learning-based approach for automatic classification of NONSTEMI, STEMI and non-heart attack patients. The proposed approach consists of an 82-layer CNN (deep learning model) architecture. Attention strategy is also used in this architecture. For this study, ECG signals were collected from the emergency room of a hospital. The ECG signals were labeled by experts in the field of cardiology after the CAG procedure. In this study, 287 ECG signals are classified as NONSTEMI, 737 ECG signals are classified as STEMI and 1051 ECG signals are classified as Non-heart attack cases and ECG signals are digitally recorded by PHILIPS brand ECG device. Sensitivity and specificity were used as performance metrics, and the values of 98.4% and 96.9% were achieved, respectively. [Lee et al. \(2021\)](#) used machine learning based algorithms (SVM KNN and Logistic regression) to predict mortality rates of NONSTEMI and STEMI patients at 3 months and 12 months. They used patient demographic and clinical data to make these predictions. In the studies, it was determined that the 12-month mortality rates of NONSTEMI cases were higher and the 3-month and 12-month mortality rate predictions of NONSTEMI cases were based on the AUC (Area Under Curve) metric and values of 0.889 and 0.849 were obtained respectively.

[Gustafsson et al. \(2021\)](#) used ECG signals of patients who came to the emergency room of a hospital in Stockholm to automatically classify NONSTEMI, STEMI and non-heart attack patients with a deep learning-based approach. In the dataset, 3,993 ECG signals were classified as NONSTEMI, 1,340 ECG signals as STEMI and 6,978 ECG signals as healthy. Residual neural network (ResNet) (deep learning model) architecture with modified jump links was used as the method. The training and test dataset were separated by 70% and 30% respectively. The accuracy was 57% for the NONSTEMI class, 71% for the STEMI class and 75% for the healthy class. [Liu et al. \(2021\)](#) used an CNN model with an end-to-end learning strategy to automatically identify NONSTEMI and STEMI patients from 12-channel ECG signals. After performing CAG, 697 ECG signals were classified as STEMI and 354 ECG signals were classified as NONSTEMI. Sensitivity and specificity were used as performance metrics and reached 98% and 95%, respectively. [Khan et al. \(2020\)](#) used traditional machine learning techniques to identify four different classes of heart attacks from phonetic-cardiogram signals. Mel-Frequency Cepstral Coefficients technique was used to extract features. The Subspace Ensemble KNN algorithm was used as the classifier. The dataset was organized into STEMI (two classes: lower wall myocardial infarction (40 samples), acute myocardial infarction (24 samples)), healthy (499 samples) and NONSTEMI (82 samples) class labels. Accuracies were 76% for the lower wall myocardial infarction class, 68% for the lower wall myocardial infarction class, 98% for the healthy class label, and 91% for the NSTEMI class label.

In general, studies in the literature for NSTEMI cases have been conducted on datasets including STEMI and healthy classes. In addition, no studies were found to determine the CAG requirements of NSTEMI cases or to find the main coronary artery vessels of NSTEMI patients.

In the literature, there are also machine learning-based studies for finding occluded main coronary arteries. [Alizadehsani et al. \(2016\)](#) used statistical data to automatically detect LAD, CX and RCA main coronary artery occlusions using a machine learning based approach. The dataset includes patients' demographic data, ECG data information, laboratory and cardiac echo data. In the ECG data information, the ST segment elevation and depression status and the status of other segments were entered as present and absent. A total of 303 patients were sampled and 54 features were created for each patient. SVM algorithm was used for vessel occlusion prediction. LAD, CX and RCA coronary artery vessels were predicted with accuracies of 86.14%, 83.17% and 83.50% respectively. [Alizadehsani et al. \(2020\)](#) used the same dataset (Z-Alizadeh Sani dataset) used in the previous study. In this study, PCA and Gini Index techniques were used to select the most representative ones among 54 attributes. SVM algorithm was used in the classification stage. LAD, CX and RCA coronary artery vessels were predicted with an accuracy of 82.67%, 83.67% and 86.43% respectively. [Tao et al. \(2019\)](#) used a machine learning-based method to automatically classify major coronary artery vessels from magneto-cardiography (MCG) images. They extracted 164 features from MRI images. Time, frequency, and knowledge-based techniques were used to extract these features. In the classification phase, an ensemble classification strategy using SVM and XGBoost algorithms was preferred. 165 LAD, 85 CX, and 104 RCA coronary artery samples were predicted with accuracy rates of 0.74, 0.68 and 0.65 respectively. [Jahmunah et al. \(2021\)](#) used a deep learning-based approach to classify patients with coronary artery vascular disease, heart attack, congestive heart failure, and health. The ECG signals of patients were used as the data type. In this study, ECG signals were acquired from 92 healthy subjects, seven patients with coronary artery disease, 148 heart attack cases and patients with congestive heart failure. A patient was sampled many times and each ECG signal was divided into 2-s segments, resulting in approximately 150,000 samples. In the methodology stage, the ECG signals are pre-processed using Gabor filtering technique. Then they were classified with 1-D CNN. With this technique, 96.74% classification accuracy was obtained. [Butun et al. \(2020\)](#) used the 1-D CAPSNET (Capsule Network) model to distinguish coronary artery vascular disease labeled ECG signals from normal ECGs. ECG signals were divided into 2 s segments to obtain 80,000 normal ECG samples and 15,000 coronary artery disease labeled ECG samples. In this study, 99% classification accuracy was achieved. [Li et al. \(2021\)](#) utilized phonocardiogram (PCG) and ECG signals to distinguish those with coronary artery vascular disease from those without. In this approach, features were extracted from three different CNN models. Raw ECG and ECG signals were used to extract features from the first CNN model, spectrum images from ECG and ECG signals were used to extract features from the second CNN model, and Mel-Frequency Cepstrum Coefficients (MFCC) images from ECG and ECG signals were used to extract features from the third CNN model.

All extracted features were combined to form a feature set. Classification was performed in the sigmoid layer. As a result of the experimental studies, 96.51% accuracy, 99.37% sensitivity and 90.08% specificity performances were achieved. When the artificial intelligence-based studies on coronary vascular diseases are examined in general, it is seen

that studies have been conducted on two different types of data sets. In the first one, studies on signal-based data sets (ECG, PCG and MCG) consist of two classes on the presence and absence of coronary disease. In the other, a statistical dataset was used for single vessel occlusions of the LAD, CX and RCA coronary arteries. From this point of view, it is concluded that there is no similar or identical dataset and therefore no artificial intelligence-based study in the literature. In the literature, digital signals instead of ECG images have been used as input data in machine learning-based approaches. From these digital ECG data, studies have been conducted to diagnose heart diseases, irregular heartbeats, heart attacks, and coronary artery diseases that are directly related to heart diseases. While evaluating these studies, open data sets were used ([Goldberger et al., 2000](#); [Moody & Mark, 2001](#); [Oeff et al., 2012](#)).

CAG data provide the basis for other investigations that are now available in the literature. CAG images have been used to identify coronary artery occlusions and CAD using deep learning-based models. CAG images were used by [Jimenez-Partinen et al. \(2024\)](#) to generate an automated CAD model. For classification, many pre-trained CNN models, including DenseNet, MobileNet, NasNet, and ResNet, were employed. AUC and F-score were 98.1% and 92.7%, respectively. A modified Inception V3 model was employed by [Lee et al. \(2024\)](#) to identify CAD in CAG pictures. The model's performance was assessed using 7945 CAG pictures in total. The accuracy of CAD detection was 92.3%. A CNN model based on deep learning was used by [Wang et al. \(2024\)](#) to identify coronary artery stenosis from CAG pictures. This method produced performance values of 87.1% F-score, 85.4% sensitivity, and 88.9% accuracy. A hybrid depth learning technique was employed by [Li, Chen & Xu \(2024\)](#) to detect CAD from CAG images. The hybrid model made use of both recurrent and deep neural networks. A KNN classifier is used to improve the prediction outcomes of this model. This method produced an 87.82% F-score, 88.57% sensitivity, and 82.8% accuracy. CAG pictures were employed in a transformer-based model by [Peng et al. \(2024\)](#). As a result, their sensitivity for identifying coronary artery occlusions was 81.5%. The available literature studies closest to the topic used, along with gaps in the literature, are presented in [Table 1](#).

A review of the literature summarized above reveals that there is no study that uses machine learning techniques on ECG graphs to find the main coronary artery or arteries for NONSTEMI patients, make or help to find the occlusion of the main coronary artery or arteries, and make the decision for CAG. This provided additional motivation for the study that was intended to be developed.

Scientific contribution

Coronary artery disease is the leading cause of death worldwide, and the prognosis for patients with non-ST-elevation myocardial infarction (NSTEMI) is significantly influenced by the prompt and accurate identification of occluded main coronary arteries. In modern clinical practice, the ECG is the most important test for chest pain, but it doesn't do a good job of finding blocked arteries in NSTEMI. Coronary angiography (CAG) is the best way to find occlusion, but it is expensive, invasive, and risky, especially

Table 1 Literature summary and research gap.				
Study/Reference (2025)	Method/Model used	Dataset details	Reported Accuracy/ Performance	Research gap
Bishop & Meadley (2025)	AI models (Neural Networks, ANN, CNN) for out-of-hospital ECG analysis	Review, highlights studies using international ECG datasets	AI models show superior sensitivity, can identify occlusion earlier than clinicians	Prospective, multicenter validation still needed; clinical deployment in prehospital and rural scenarios; need for OMI-focused models
Riek et al. (2025)	ECG-SMART-NET (Temporal+Spatial CNN, ResNet-based)	Multisite real-world clinical dataset, 10,393 ECGs, 7,397 pts	AUC: 0.953; outperforms ResNet-18 and Random Forest for OMI	Many deep learning models are not benchmarked against prospective ECG +angiography at exact time; pathophysiological nuance (active vs reperfused occlusion)
Herman et al. (2025)	AI-powered ECG model validated vs angiography	Prospective multicenter registry, >700 ACS/ICA pts across Europe	First to evaluate AI detection of TIMI 0-1 culprit occlusion on ECG; (study design, outcomes pending)	Prospective database just launched; validation against clinical endpoints and workflow impact still ongoing
Ayano et al. (2024)	1D-CNN, BiLSTM, 2D-CNN combined	3 ECG datasets (multi-disease)	>90%	Generalized deep learning, less focus on specific coronary occlusion, lacks clinical deployment for NSTEMI-only settings.
Latifoğlu et al. (2024)	Transfer Learning (AlexNet, ResNet, VGG16), Majority Voting	Public ECG datasets	High (not specified)	Models tested on public datasets, not tailored to NSTEMI occlusion or direct clinical triage.
Baloglu et al. (2019)	Custom 1D-CNN (10 layers)	12-lead ECG (MI detection)	99.78%	Focused on MI overall, not occluded artery mapping. No prospective clinical impact data.
Khatri & Bansal (2024)	RGB image mapping + ResNet	ECG signals (MI/ CAD)	99.25% (MI)	Unique feature mapping but lacks external, diverse evaluation and NSTEMI occlusion specificity.
Hasbullah, Mohd Zahid & Mandala (2023)	1D-CNN + BiLSTM	PTB-XL ECG dataset	91%	Model lacks explainability, not evaluated for decision support or clinical workflow integration.
Yeh et al. (2025)	XGBoost (statistical features)	Clinical ECGs + demographics	Sensitivity 84%	Relies on additional demographic/stats, not direct ECG deep learning; not validated for occlusion mapping.
Jimenez-Partinen et al. (2024)	DenseNet, MobileNet, NasNet, ResNet (CAG images)	CAG images (CAD detection)	F-score 92.7%, AUC 98.1%	Relies on post-CAG imaging, not applicable to “no-CAG” NSTEMI group; not real-time from ECG.
Wang et al. (2024)	Deep CNN (CAG images)	CAG images (stenosis detection)	Accuracy 88.9%	Not focused on NSTEMI, requires invasive imaging.
Lee et al. (2024)	Inception V3 (CAG images)	7945 CAG images	Accuracy 92.3%	Needs CAG, not applicable to primary ECG-based triage.

for older people, people with other health problems, or people who are at high risk of bleeding. In low-risk situations, it is often not readily accessible or warranted. Non-invasive, quick, and trustworthy decision support is more important than ever as the world’s population ages and the percentage of NSTEMI patients who are more likely to experience procedural complications rises quickly.

It is not possible for physicians to visually distinguish which coronary artery(s) are occluded in patients with NONSTEMI features on ECG radiographs. In addition, as mentioned earlier, the details in the ST segment of the ECG of such patients are too small to be recognized visually. The major challenge in detecting occluded coronary arteries in NSTEMI patients from ECG signals arises from the absence of distinctive visual patterns such as ST-segment elevation, which are typically used to identify ischemic regions in STEMI cases. In NSTEMI, the morphological changes in the ECG are subtle, non-specific, and often obscured by noise, comorbid conditions, or age-related signal variations. These factors make manual or visual interpretation insufficient for determining which main coronary artery (LAD, RCA, or CX) is occluded. Therefore, it becomes mandatory to perform the CAG procedure in NONSTEMI cases.

In this project, we target patients with NONSTEMI who do not have high-risk status and are in the at-risk group for CAG. It is aimed at determining which coronary artery(s) (CX, LAD, RCA) of these patients are occluded with deep learning approaches using 12-channel ECG signals and to develop a method to decide whether to perform CAG or drug treatment. With the implementation of this study, it has been and will be possible to achieve the following results:

- A unique data set has been created for researchers to benefit from. The size of this dataset will continue to be increased.
- When the occluded coronary artery(s) is detected by the algorithm and the decision for CAG is made early, the patient's prognosis will be favorable.
- When the algorithm concludes that there is no need for CAG, it will lead to the decision of drug therapy in patients where the risks of CAG will be high, so that the patient's prognosis will not worsen due to CAG. It is also envisaged that the medical workload in the cardiology clinic will be reduced.
- With this method to be developed, unnecessary patient referrals will also be reduced in health centers that do not have CAG equipment for patients who are determined to not need CAG.
- Within the scope of the project, an important data set will also be obtained by labeling and evaluating ECG graphs (labels indicating which coronary artery(s) are involved in ECGs). With the dissemination of the dataset, an important infrastructure will be created for other researchers who will work in this field.
- Experimental studies have been conducted with scratch trained CNN and pre-trained CNN models. These studies are baseline studies and will serve as a reference for other studies.
- Classification performance has been significantly increased with a hybrid classification strategy.

The following practical clinical needs and gaps serve as the driving forces behind this study:

- Safe, non-invasive triage: A decision support system that enables physicians to safely identify which patients, particularly in high-risk groups, can be treated with medication and which require immediate CAG is desperately needed.
- Unmet data and algorithmic challenge: No large, labeled, multi-class dataset of 12-lead ECG records from NSTEMI patients with arterially confirmed occlusion status has been made available by any study to date.
- Potential of AI/deep learning: Machine learning, and deep learning techniques in particular, have the potential to extract significant patterns from minute changes in ECG signals that are not visible to the naked eye. However, their use in predicting precise artery occlusion (as opposed to just MI detection) is new and mainly untested.

This study makes several noteworthy contributions:

- Creation of a unique, expert-labeled dataset: A multi-class digital 12-lead ECG dataset of NSTEMI patients, with each record labeled for specific main coronary artery occlusion status by post-CAG diagnosis, has been constructed. This dataset fills a major gap in the literature and will be shared to promote further research in this field.
- Algorithmic innovation: A novel deep learning model (RAL-CNN, integrating Residual, Attention, and LSTM modules), combined with the ReliefF-Based Weighted Subspace SVM Ensembles (RBWSSE) classification strategy, is proposed to tackle the 7-class occlusion prediction problem. Spectrogram-based preprocessing and 3D channel arrangement enhance model accuracy by exploiting both temporal and spatial ECG data features.
- High clinical relevance: Using non-invasive ECG signals alone, the suggested method assists in identifying occluded arteries in NSTEMI patients, not only their presence but also their precise location and combination. Particularly in vulnerable populations, this could give clinicians critical, useful information to help them tailor risk/benefit assessments of CAG vs. medical management.
- Performance advancement and baseline establishment: Rigorous ablation and comparison experiments demonstrate significant improvement over classic CNN and recent pre-trained models. The best classification accuracy (81.3%) is achieved with the proposed RBWSSE strategy, establishing a new reference point for research using this unique dataset.
- Reduction of unnecessary procedures and resource burden: By safely triaging patients who may be managed without CAG, the method can reduce patient risk, hospital workload, and health system costs—particularly in facilities lacking immediate access to invasive diagnostics.

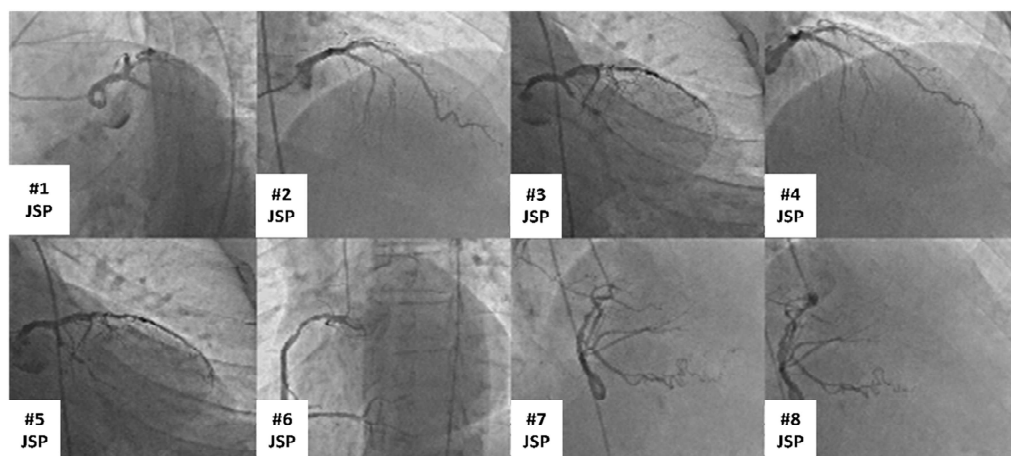


Figure 2 Image of a CAG labeled as CX+LAD occluded after CAG processing.

Full-size DOI: 10.7717/peerj-cs.3576/fig-2

DATASET

The data set was collected by cardiologists at Firat University. While selecting the patients for the creation of the data set, the first filtering was made among the patients who came to the emergency department of Firat University with suspicion of heart attack. Then ECGs of these patients were analyzed. Among these ECGs, those in the STEMI patient group were eliminated, and only those in the NSTEMI group (provided that they were of legal age) were included in the study by obtaining Written Informed Consent. From these patients, ECGs were performed between 1 and 10 according to the number of labels of the occluded main coronary artery. If there were few ECG data in the labeling of the occluded main coronary artery, more than one ECG was performed, and if there were many ECG data, 1 ECG was performed. All patients underwent 1 CAG (coronary angiography) procedure to determine the occluded coronary label.

A total of 12-channel digital ECG devices were used for data collection. The data were saved in XML format with a sampling frequency of 500 Hz and 1 KHz. The main coronary artery occlusions in the dataset were labeled as CX, RCA, and LAD. Multiple main coronary artery occlusions were labeled as CX+LAD, RCA+LAD, RCA+CX, and RCA+CX+LAD. For correct labeling, cardiologists performed CAG for each ECG acquisition.

Figure 2 shows a CAG image labeled as CX+LAD occluded after CAG procedure. In this way, a total of 907 12-channel digital ECG signals were recorded and labeled. The dataset contains 125 ECG signals from the CX class, 135 from the RCA class, 252 from the LAD class, 113 from the CX+LAD class, 104 from the RCA+LAD class, 56 from the RCA+CX class and 122 from the RCA+CX+LAD class. A detailed 12-channel ECG signal representation for the CX occluded main coronary artery is shown in Fig. 3. An example of a sample digital ECG signal from each class is shown in Fig. 4.

Table 2 provides descriptive information about the dataset. It shows which data augmentation technique was applied to each class on a per-class basis. These data augmentation techniques were used only on the training dataset, and the prediction results

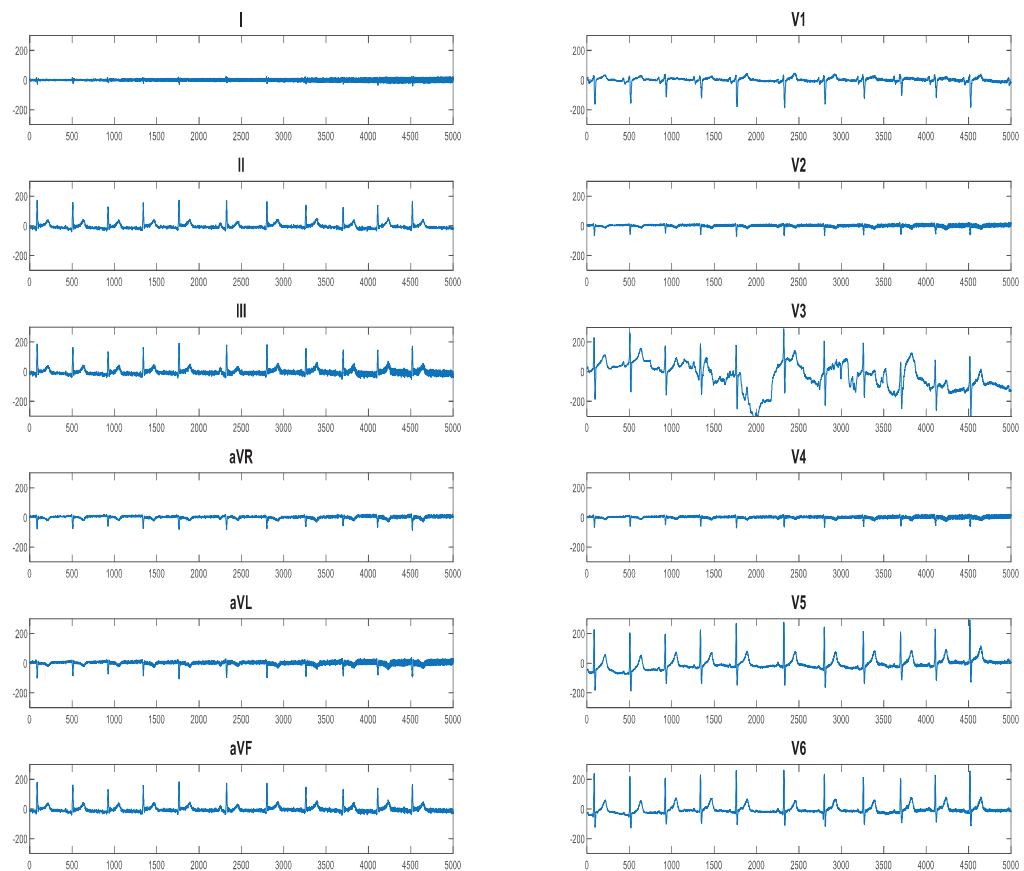


Figure 3 A detailed 12-channel ECG signal representation for the CX occluded main coronary artery. [Full-size !\[\]\(fcc3264021d438d9732560e78099f674_img.jpg\) DOI: 10.7717/peerj-cs.3576/fig-3](https://doi.org/10.7717/peerj-cs.3576/fig-3)

were not reflected in the validation data. The dataset used in this study consists of seven classes, including single, double, and triple main coronary artery occlusions. As shown in [Table 2](#), the dataset is a multi-class classification problem. Since the number of ECG samples per class was not uniformly distributed, a hybrid balancing strategy was adopted. In particular, class-weight adjustments were used during model training to lessen bias towards the majority (LAD) class, and data duplication and random oversampling were used to balance minority classes. During 10-fold cross-validation, this hybrid strategy successfully increased convergence and stabilised performance across all classes.

PROPOSED METHODOLOGY

The overall structure of the proposed framework is illustrated in [Fig. 5](#). The approach is designed around three main methodological phases: dataset preparation, spectrogram-based signal representation, and hybrid deep learning modeling. The core rationale of the proposed pipeline is to extract complementary spatial, spectral, and temporal information from multi-lead ECG signals to achieve robust and interpretable classification. As explained in ‘Dataset’, raw 12-lead ECG recordings were gathered and labeled in the first stage using approved diagnostic standards. All information was gathered



Figure 4 An example of a sample digital ECG signal from each class.

Full-size  DOI: 10.7717/peerj-cs.3576/fig-4

Table 2 Dataset information.				
Class label	Coronary artery combination	Number of samples	Type	Balancing technique applied
CX	Circumflex artery occlusion	125	Single	Oversampling <i>via</i> data duplication & augmentation
RCA	Right coronary artery occlusion	135	Single	Oversampling <i>via</i> data duplication & augmentation
LAD	Left anterior descending artery occlusion	252	Single	No balancing required
CX+LAD	Double artery occlusion	113	Multi	Class-weight adjustment during training
RCA+LAD	Double artery occlusion	104	Multi	Class-weight adjustment during training
RCA+CX	Double artery occlusion	56	Multi	Oversampling (minority class)
RCA+CX+LAD	Triple artery occlusion	122	Multi	Oversampling (minority class)
Total	—	907 ECG records	7-class (multi-class)	Hybrid balancing (oversampling + class-weighting)

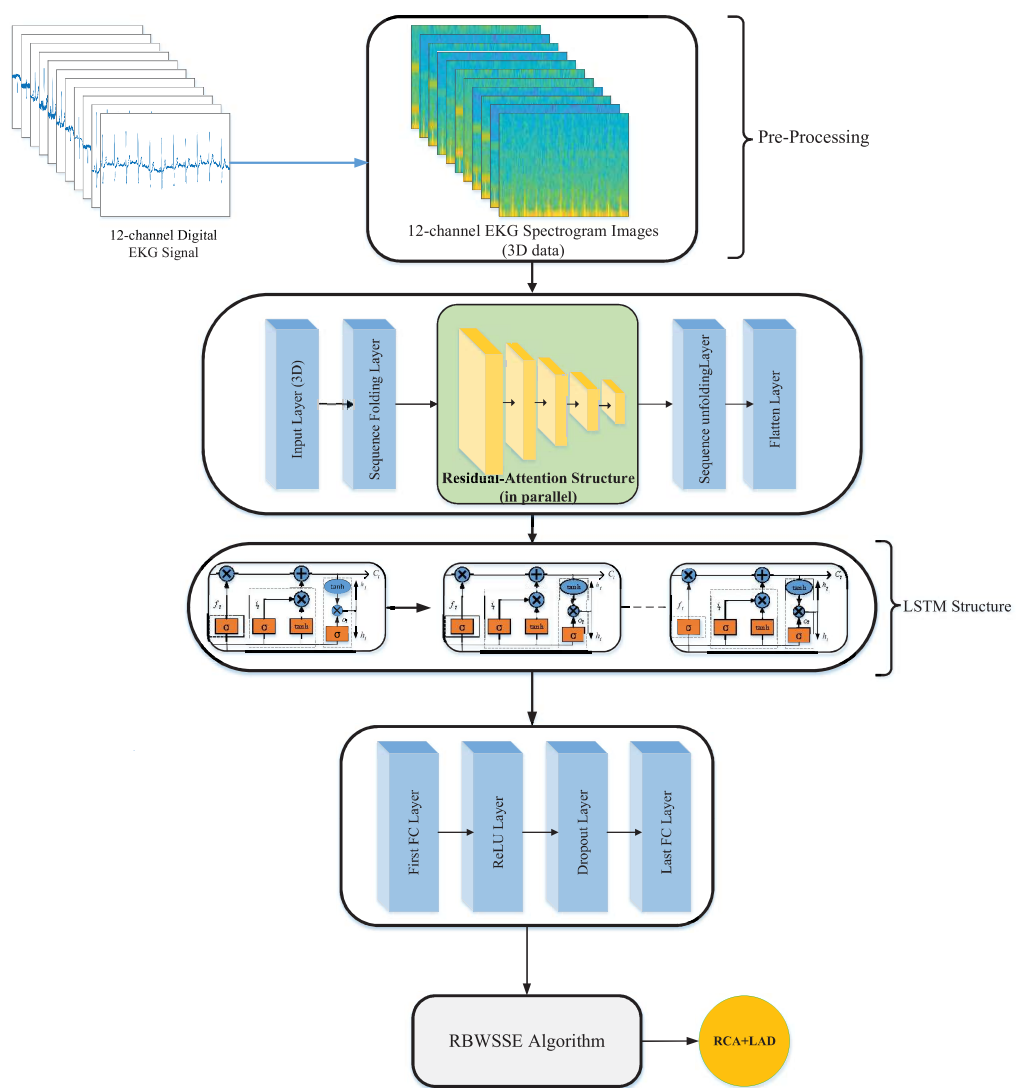


Figure 5 Proposed approach framework.
Full-size DOI: 10.7717/peerj-cs.3576/fig-5

in compliance with the Declaration of Helsinki and authorized by the Ethics Committee of Firat University (protocol code 10301, dated September 1, 2022).

After this stage, the 12-channel digital ECG data stored in XML format is read in the MATLAB program. In the second stage, spectrogram images of the digital ECG data were obtained for each channel. There are several advantages of using spectrogram images in the analysis of electrocardiogram (ECG) signals.

- Spectrograms facilitate the application of signal processing techniques. The spectrogram allows visualization of both the time and frequency components of the signal simultaneously. This is particularly useful for detecting transient events in ECG signals (for example, sudden arrhythmias).
- Spectrograms provide rich features for machine learning and artificial intelligence algorithms. Various features, such as frequency, time, and intensity, can be extracted from ECG signals and used in classification and prediction models.
- The spectrogram allows to the analysis of the frequency components of the signal. The frequency components of different waves (P, QRS, T) in ECG signals can provide important information about cardiac conditions.

Additionally, 12-channel ECG spectrogram images are arranged to be trained in a 3D structure. This contributes to a higher accuracy of the CNN-based model. Evaluating different channels together with convolutional filters provides more contextual information and reduces false positive/negative rates.

In the third phase of this study, a deep learning model called Residual&Attention&LSTM-CNN (RAL-CNN) was designed. A representative representation of this model is given in Fig. 6. There are a total of 81 layers in this structure. As can be seen in Fig. 6, Attention and Residual structures were designed in parallel with the trained strategy. This parallel structure improves the classification performance. The features from the Residual and Attention structures are combined in the layer named add42. The discriminative information from these two layers is further enhanced by the LSTM structure's ability to retain strong feature representations in memory. After being transferred to the fully connected layer named fc4, the class prediction values are generated according to the probability scores in the softmax classifier. Table A2 gives the block and layer information of the RAL-CNN model.

The Attention structure contains a total of nine layers and a total of three convolutional, 1 maximum pooling, 1 ReLU and 1 sigmoid activation functions are used. approach is explained in the following paragraph. First, attention mechanisms enhance the model's ability to recognize and focus on important features. Traditional CNNs extract features by shifting the input with fixed-size filters. This method treats the entire image or data equally, ignoring important information in specific regions. However, the attention mechanism allows the model to distribute attention by emphasizing that certain regions or attributes may be more important than others. This allows the model to learn more precise and meaningful attributes. In addition, attention mechanisms allow the model to be more efficient in the learning process. Especially when working with large and complex datasets, focusing on important information leads to a more efficient use of computational

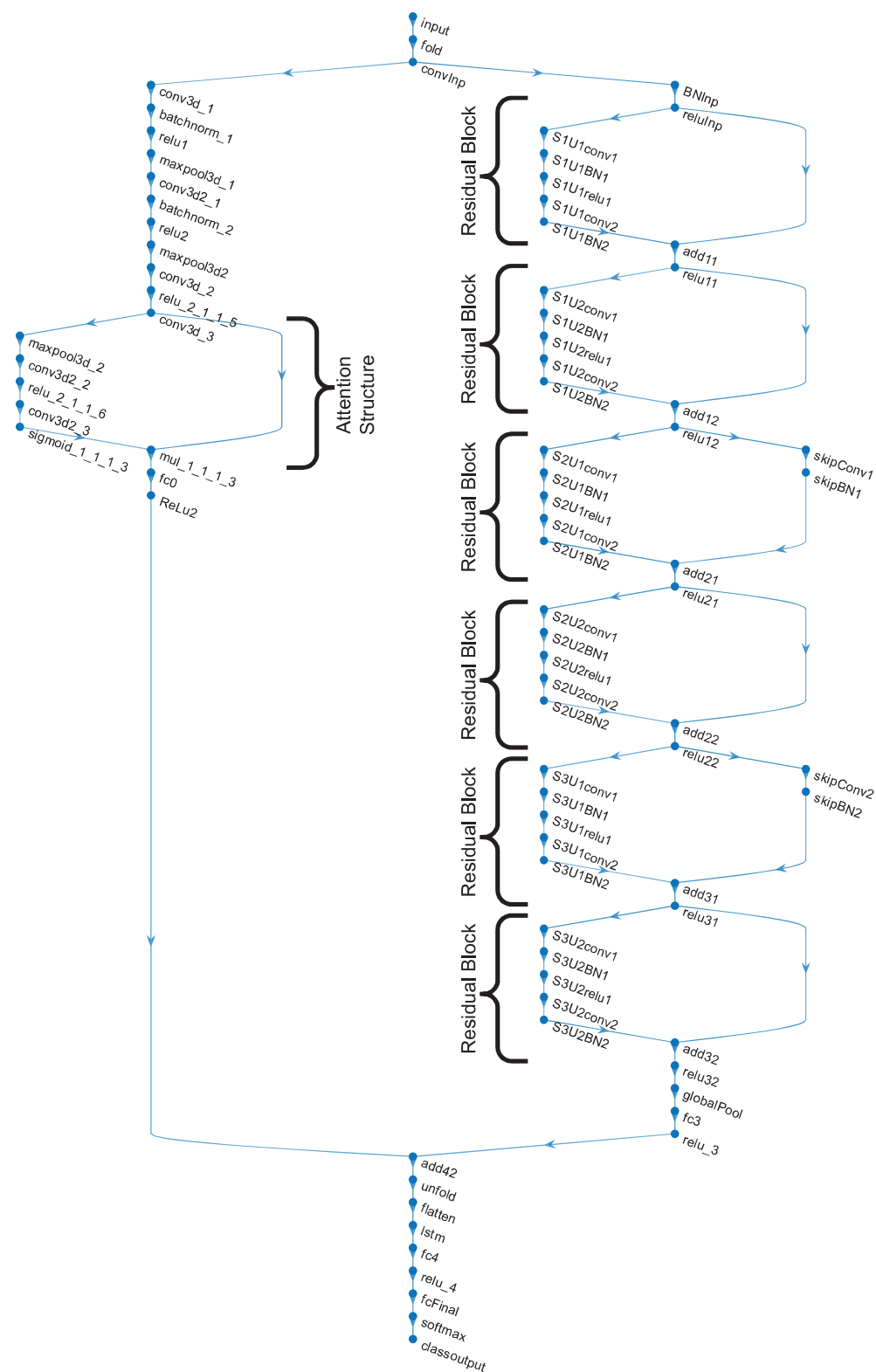


Figure 6 RAL-CNN architecture.

Full-size DOI: 10.7717/peerj-cs.3576/fig-6

resources. This both speeds up the training process and improves the overall performance of the model. Furthermore, attention mechanisms can help the model perform better on different and unseen data by increasing its generalization ability. Another important advantage of the Attention structure is that it improves the interpretability of the model. Traditional CNNs are often considered a “black box” in terms of understanding how they arrive at their outputs. Attention mechanisms make the model’s decision-making process more transparent by showing which features or regions are given more attention. This increases the reliability and acceptability of the model, especially in critical areas such as medical image analysis. In conclusion, the use of Attention structure in CNN models offers significant advantages in terms of both performance improvements and model interpretability. These mechanisms contribute to making the models more efficient, accurate and reliable, leading to more successful and reliable results in various application areas.

Residual structure contains a total of six blocks. Each block contains two convolutional, one ReLU and two Batch Normalization (BN) layers. The reason for using the residual structure in the proposed model is given in the following paragraph. Basically, residual structures facilitate the learning of weights by adding direct connections between layers in deep neural networks. By adding the output of one layer to the input of the next layer, these connections reduce information loss and gradient fading in the deeper layers of the network. This makes it possible to train deeper networks and improves the accuracy of the model. In addition to improving the performance of the model, residual structures speed up training and make it more efficient. They also improve the generalization ability of the model and reduce the risk of overfitting. This approach, especially used in architectures such as ResNet, plays an important role in the success of modern deep learning models.

The LSTM structure is set to have 100 cells. The sequence folding and sequence unfolding layers in the RAL-CNN model were added to train the LSTM model and CNN-based models together. Using CNN-based models with LSTM structure has the following advantages. LSTMs effectively learn long-term dependencies and relationships over time in time series data, while CNNs extract spatial features in images and other high-dimensional data. The combination of these two constructs captures both the temporal and spatial dependencies of the data, extracting richer and more meaningful features, and often offering higher accuracy and performance than pure LSTM or pure CNN models. Then, 100 features were extracted from the first fully connected layer of the RAL-CNN model. These extracted features were classified with the developed ReliefF Based Weighted Subspace SVM Ensembles (RBWSSE) algorithm. The RBWSSE algorithm has increased its performance by incorporating more powerful features into the classification phase.

The recordings were standardized to equal lengths to ensure signal consistency across channels. This preprocessing step was crucial to maintain uniform data dimensions for subsequent time–frequency analysis and deep model training. In this phase, the digital 12-channel ECG signals were transformed into spectrogram images to represent the time-varying frequency characteristics of cardiac activity. The rationale for using spectrograms lies in their ability to reveal transient frequency changes and morphological

variations that are not easily observable in raw time-series data. Such representations provide richer information for machine learning models by preserving both the temporal sequence and spectral energy distribution of ECG waveforms. Windowed short-time analysis, which balances time and frequency resolution to emphasize the dynamic patterns connected to cardiac events, was used to create each spectrogram. The model was then able to learn spatial relationships and dependencies between various cardiac viewpoints by organizing the 12 spectrograms that corresponded to the ECG leads into a 3D multi-channel structure. This method lowers false detections and enhances overall diagnostic performance by assisting the network in capturing inter-lead correlations. The last phase is devoted to creating the Residual & Attention & LSTM-CNN (RAL-CNN) architecture, which is intended to concurrently capture temporal, contextual, and spatial dependencies in the spectrogram representations. This hybrid structure has three justifications:

- By preventing information loss and facilitating effective gradient flow in deep architectures, residual connections allow the model to learn increasingly intricate hierarchical features.
- In order to improve interpretability and model focus on diagnostically relevant areas while boosting generalization to unseen data, attention mechanisms dynamically highlight the most informative regions of the spectrograms.
- Static CNNs might miss long-term relationships between cardiac cycles, but LSTM units allow the network to preserve temporal dependencies across feature maps.

The only task of RAL-CNN is to extract features. The RAL-CNN model does not have the task of weighting the features. The features extracted by the Residual and Attention branches are combined to integrate global and local information before being processed by the LSTM module. The fused representation is then classified using fully connected layers followed by a softmax function to produce probability-based predictions. Using the ReliefF-Based Weighted Subspace SVM Ensembles (RBWSSE) method, which improves class separability through adaptive weighting and ensemble-based decision fusion, the most discriminative features from the final fully connected layer are further optimized in the final classification stage.

All things considered, this methodological design offers a unified deep learning pipeline that raises classification accuracy while simultaneously improving interpretability, efficiency, and robustness. This guarantees that the model's predictions match clinically significant ECG patterns.

The proposed RAL-CNN model differs from conventional CNN approaches by jointly integrating residual, attention, and LSTM modules within a single framework. This hybridization allows simultaneous extraction of spatial, temporal, and context-aware features from ECG spectrograms. Furthermore, the extracted deep features are classified by the newly designed RBWSSE algorithm, which combines feature weighting, subspace diversity, and ensemble decision fusion. This dual-stage architecture forms the novel

contribution of this study, providing both robustness and explainability in detecting occluded main coronary arteries in NSTEMI cases.

METHODOLOGY TECHNIQUES

Pre-processing

The use of spectrogram images in the analysis of ECG (electrocardiography) data offers significant advantages over conventional techniques. Spectrograms provide a more comprehensive and intelligible representation of ECG signal variations by combining time and frequency dimensions. This dual-dimensional approach is particularly beneficial for diagnosing irregular heart rhythms and complex cardiac conditions ([Hannun et al., 2019](#)). By allowing for the examination of both time and frequency data on a single graph, spectrograms enable doctors and researchers to identify anomalies more quickly and accurately. Furthermore, spectrogram analysis can detect subtle anomalies that traditional time-wave analysis may miss, as it visually displays the signal's power spectrum and highlights power differences at specific frequencies. Consequently, spectrograms derived from ECGs are indispensable for accurate diagnosis and analysis ([Acharya et al., 2017a](#)).

A spectrogram is a convenient way to convert the input signal into color images. In addition, spectrogram images describe the variation in time and frequency with respect to the intensity of the input signal in the quantized regions and thus best characterize the signal in the time and frequency domain ([Chaurasiya, 2020](#)).

The Short Time Fourier Transform (STFT) is used to generate spectrogram images. The STFT represents the frequency content of the signal at a moment in time for a given window. Thus, a signal can be visualized as a 2D function of time and frequency. Given a signal 'x', the STFT and spectrogram are calculated as follows. [Equation \(1\)](#) represents the STFT used to obtain the time-frequency representation of ECG signals. [Equation \(2\)](#) defines the spectrogram, which shows the power spectrum of the ECG signal over time and frequency.

$$F(n, \omega) = \sum_{-\infty}^{\infty} x(i)w(n-i)e^{-j\omega n}. \quad (1)$$

$$Spektrogram = |F(n, \omega)|^2. \quad (2)$$

Digital 12-lead ECG recordings were used in the experimental study's initial phase. All 12 leads were sequentially concatenated to create a two-dimensional input matrix of size $12 \times 5,000$, ensuring synchronized temporal alignment across channels. Each ECG signal had 5,000 samples. To reduce baseline wander and high-frequency noise while maintaining clinically significant waveform morphology, the raw signals were filtered using a 4th-order Butterworth band-pass filter (0.5–40 Hz) before generating the spectrogram. The STFT was then used to convert the preprocessed ECG segments into time-frequency representations. With a window size of 100 samples, a sampling frequency of 1 kHz, 50% overlap, and an FFT length of 1,000 points, a Hamming window was used. The magnitude of each STFT output was converted to the decibel scale using $S(n, \omega) = 10\log_{10}(|F(n, \omega)|^2)$, resulting in spectrograms that accurately captured the

temporal-spectral dynamics of cardiac activity. These spectrograms were normalized to the range [0, 1], resized to 224×224 pixels, and subsequently used as image-based inputs for the convolutional neural network models.

Deep techniques

One method that imitates cognitive attention is attention structure. The attention structure highlights the salient features of the incoming data while removing the remainder.

Gradient descent and optimization are techniques used to determine which aspects of the data are more significant than others (Yeung & Lam, 2022).

Figure 7 depicts the attention module that was employed in this investigation. The output feature map (y_i) of the i_{th} layer is shown by " x_i " in Fig. 7, and " g_i " is a gating signal vector that determines the focus region for each pixel by being gathered from a coarser scale (Niu, Zhong & Yu, 2021). Equation (3) is used to calculate the output using element-wise multiplication. This equation calculates the attention coefficients that determine the importance of each feature map region. Equation (4) represents the attended feature map obtained by weighting the input feature map with the attention coefficients.

$$y_i = \alpha_i \times x_i \quad (3)$$

$$\alpha_i = \sigma \left(\delta^T \left(a_x^T x_i + a_g^T g_i + b_1 \right) + b_2 \right) \quad (4)$$

where " b_1 " and " b_2 " are bias terms and " a " is the linear transformation using the $1 \times 1 \times 1$ dimensional convolution operator, respectively. The attention module's weights are randomly initialized and fine-tuned during the deep architecture's end-to-end training process.

Residual structure is a technique developed to solve a number of problems that arise in the training of deep neural networks (especially Convolutional Neural Networks-CNNs). It was introduced in 2015 by He et al. (2016) and popularized by a network architecture called ResNet. The Residual framework is based on the concept of "residual learning" and its main goal is to make training deep networks easier and more efficient. Residual structures provide important advantages to CNN models, as follows:

- Residual connections reduce the problem of vanishing gradients and allow for faster and more stable training of deep networks.
- Residual structures make it possible to train deep networks with multiple layers (e.g., more than 100).
- Residual networks have the capacity to generalize better due to deeper and more complex structures.

A residual block consists of two main components. The first is the main transformation using standard CNN layers (convolution, batch normalization, and ReLU activation). The other is the skip connection, which allows the input data to be added directly to the output of the block. The mathematical representation of the residual block is given in Eq. (5). This equation expresses the residual block output as the sum of the transformed features and the original input.

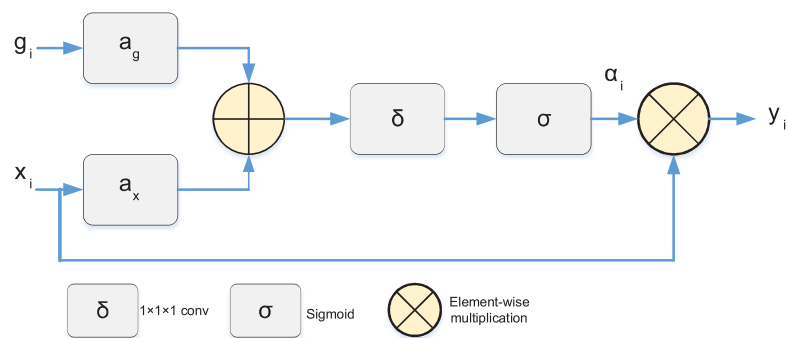


Figure 7 Attention block structure.

Full-size DOI: 10.7717/peerj-cs.3576/fig-7

$$y = F(x, \{W_i\}) + x \quad (5)$$

where x is the block input, $F(x, \{W_i\})$ is the main transformation involving 3 or 4 convolutional layers, and y is the block output.

The fundamental component of the CNN is the convolutional layer. Features are extracted from the input image using this layer. Little matrices called convolutional filters are shifted over the input image (shift operation). Every filter performs a dot product on a particular input image area. Feature maps: A feature map is produced when filters are applied to an input image. This map indicates whether features—such as corners and edges—are present or absent.

Non-linear activation functions like ReLU are typically applied after convolutional layers. If the input is positive, ReLU leaves it alone; if it is negative, it sets it to zero. This gives the model more nonlinearity and improves feature representation.

The input feature map's size is decreased by the usage of pooling layers. Two primary categories of pooling exist. The maximum pooling takes the greatest value inside a specified region (such as a 2×2 window). This minimizes the size and highlights the most important aspects. The entire feature map is averaged by global average pooling. As a result, each feature map generates a single number, and this layer is typically used before the fully connected layers.

Following the normalizing of the data in each mini-batch, batch normalization (BN) employs a scaling and shifting procedure. This increases training speed and stability. The normalization process in the BN layer is done as shown in Eq. (6). This equation performs batch normalization using the mean and variance of each mini-batch to stabilize training.

$$x = \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}} \quad (6)$$

where μ and σ stand for the mini-batch's mean and variance, respectively. A little value called ϵ is added to provide numerical stability.

In multi-class classification problems, the activation function softmax is frequently employed as the last layer. Every class is given a probability value, and the aggregate of these values is 1. Softmax activation function calculation is given in Eq. (7). This equation

defines the softmax function, which converts logits into normalized class probability values.

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \quad (7)$$

where z_i is the class output for the i_{th} instance, of the model.

RBWSSE algorithm

The RBWSSE algorithm was developed to increase the classification performance. The representative representation of the RBWSSE algorithm is given in Fig. 8 and its pseudocode is shown in Fig. 9. In the first stage of the algorithm, the importance weights of the features in the feature set are calculated with the ReliefF algorithm. The ReliefF algorithm is preferred because it has high performance and low computational cost. In the next stage, the feature set is ranked from the features with the highest weight to the lowest according to the weights calculated with the ReliefF algorithm (Kira & Rendell, 1992; Tuncer, Dogan & Acharya, 2020). Then the feature set is divided into subspace feature sets. Prediction scores are produced with SVM classifiers on the subspace feature sets. These prediction scores are transferred to a matrix and weighted. The first subspace feature set is ranked in a way that it has the highest weight in the matrix, while the last subspace set is ranked in a way that it has the lowest weight. For example, in a matrix with ten subspaces, the first subspace is weighted 10 times more than the last subspace. In the last stage, the majority voting technique is applied to this matrix. Thus, feature importance weights are effective in the high classification stage. In addition, features with low importance weights are not completely removed from the classification process. The reason for this is that they contribute to the decision process in cases where the decision stage is critical. For this algorithm, 5 subspaces are sufficient for feature sets with 100 to 500 features, 10 for feature sets with 500 to 5,000 features, and 20 for more. More subspaces may increase the computational cost. This may cause problems for time-critical tasks. Since 1,000 features were used in the study, the number of subspaces was selected as 10.

The proposed RBWSSE method operates in two sequential stages. In the first stage, the ReliefF algorithm evaluates the importance of each feature extracted from the final fully connected layer of the RAL-CNN model. ReliefF assigns a relevance score to every feature based on its ability to distinguish between neighboring samples of different classes while maintaining consistency within the same class. These scores quantify each feature's discriminative strength and are normalized to form a feature-weight vector. In the second stage, these normalized weights are used to guide the Subspace SVM ensemble construction. The RBWSSE algorithm uses a probability-driven subspace selection mechanism, where features with higher ReliefF weights have a higher chance of being included in individual base classifiers, as opposed to training SVMs on randomly chosen subspaces. By concentrating on a more informative subset of the feature space, each SVM enhances classification stability and lessens sensitivity to redundant or noisy variables. A weighted majority voting system is used to determine the final prediction, with each SVM's

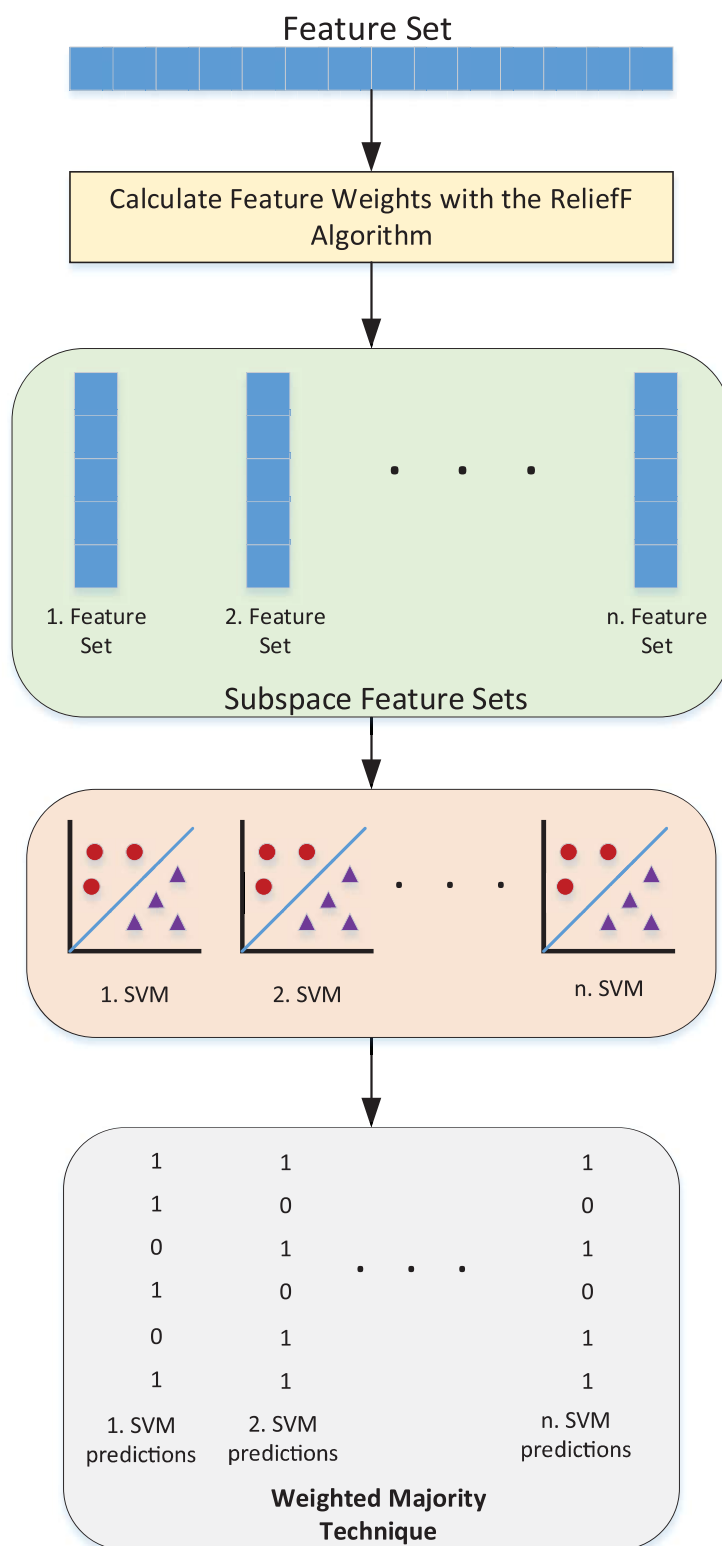


Figure 8 Representation of the RBWSSE algorithm. [Full-size !\[\]\(fcc3264021d438d9732560e78099f674_img.jpg\) DOI: 10.7717/peerj-cs.3576/fig-8](https://doi.org/10.7717/peerj-cs.3576/fig-8)

Algorithm 1. Pseudocode of the RBWSSE algorithm

Input:

- Feature set $F = \{f_1, f_2, \dots, f_n\}$
- Training dataset D with labels Y
- Number of subspaces k

Output:

- Final class prediction (ensemble decision)

```

1. // Step 1: Feature weighting using ReliefF
2.  $W \leftarrow \text{ReliefF}(F, D, Y)$  // Compute importance weights for each feature
3. // Step 2: Sort features by weight (descending order)
4.  $F_{\text{sorted}} \leftarrow \text{Sort}(F, \text{key}=W, \text{order}=\text{descending})$ 
5. // Step 3: Divide sorted features into  $k$  subspaces
6. Subspaces  $\leftarrow$  Divide  $F_{\text{sorted}}$  into  $k$  equal (or nearly equal) parts
   // Subspaces =  $\{S_1, S_2, \dots, S_k\}$  where  $S_1$  has the highest ranked features
7. // Step 4: Initialize prediction matrix  $P$ 
8.  $P \leftarrow$  empty matrix of size  $(|D| \times k)$ 
9. // Step 5: Train SVMs and collect predictions
10. for  $i$  from 1 to  $k$  do
11.   Train SVM $i$  on subspace  $S_i$  using  $D[:, S_i]$ 
12.    $P[:, i] \leftarrow \text{Predict}(\text{SVM}_i, D[:, S_i])$  // Class labels predicted
13. // Step 6: Assign weights to subspaces
14. Weights  $\leftarrow [w_1, w_2, \dots, w_k]$  where  $w_1 > w_2 > \dots > w_k$ 
   // Example:  $w_i = (k - i + 1) / \sum_{j=1}^k \{k\}(j)$ 
15. // Step 7: Weighted majority voting
16. Final_Predictions  $\leftarrow$  empty list
17. for each instance  $j$  from 1 to  $|D|$  do
18.   votes  $\leftarrow$  empty dictionary
19.   for  $i$  from 1 to  $k$  do
20.     label  $\leftarrow P[j, i]$ 
21.     votes[label]  $\leftarrow$  votes.get(label, 0) + Weights[i]
22.   final_label  $\leftarrow \text{argmax}(\text{votes})$  // Label with highest weighted vote
23.   Final_Predictions.append(final_label)
24. return Final_Predictions

```

Figure 9 Pseudocode of the RBWSSE algorithm.

Full-size  DOI: 10.7717/peerj-cs.3576/fig-9

contribution being proportionate to the total significance of the features it employs. This integration enables the ensemble to balance diversity and accuracy—ReliefF ensures that relevant features dominate the learning process, while subspace SVMs preserve classifier diversity and prevent overfitting. The detailed workflow of the RBWSSE approach and its algorithmic flowchart have now been added to the revised manuscript to facilitate full reproducibility.

Performance metrics

Accuracy is chosen as the main criterion to measure the performance performance of the proposed approach. Sensitivity, precision, specificity, and F-score are also evaluated. The true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values in the confusion matrix are used to calculate these criteria. The accuracy criterion is calculated as shown in Eq. (8). Equation (8) computes the accuracy metric, representing the overall correct classification rate of the model.

$$Accuracy (acc) = \frac{TP + TN}{TP + FP + TN + FN}. \quad (8)$$

In cases where there is an imbalance between classes, accuracy may be deceptive. For instance, a high accuracy could be attained but the model's performance might not be all that good if 95% of the data are in one class and the model reliably predicts this class. For this reason, the use of other metrics is included in the study.

The precision of a model is the percentage of actual positive instances that the model predicts to belong to the positive class. It displays the proportion of accurate positive forecasts. In cases where false positives are expensive, precision is particularly crucial. Precision (PRE) is calculated as in Eq. (9). Equation (9) calculates precision, showing the proportion of correctly predicted positive samples among all positive predictions.

$$Precision (PRE) = \frac{TP}{TP + FP}. \quad (9)$$

The model's sensitivity or recall indicates how well it finds genuine positives. It speaks to the number of true positives that are accurately forecasted. Particularly in cases when false negatives are expensive, sensitivity is crucial. Sensitivity (SEN) is calculated as in Eq. (10). Equation (10) defines sensitivity (recall), indicating how effectively the model identifies true positive cases.

$$Sensitivity (SEN) = \frac{TP}{TP + FN}. \quad (10)$$

Specificity demonstrates how well the model recognizes cases that fall into the negative category. It conveys the number of genuine negatives that are accurately predicted. When there are a lot of false positives, specificity is helpful. Specificity (SPE) is calculated as in Eq. (11). Equation (11) represents specificity, which measures the model's ability to correctly identify true negative cases.

$$Specificity (SPE) = \frac{TN}{TN + FP}. \quad (11)$$

The F-score provides a single performance measure by balancing precision and sensitivity through their harmonic mean. It is especially helpful when striking a balance between sensitivity and precision is needed. When class distributions are uneven, the F1-score might be helpful as it provides an overview of the model's overall performance. F-score is calculated as in Eq. (12). Equation (12) defines the F-score as the harmonic mean of precision and sensitivity for balanced performance evaluation.

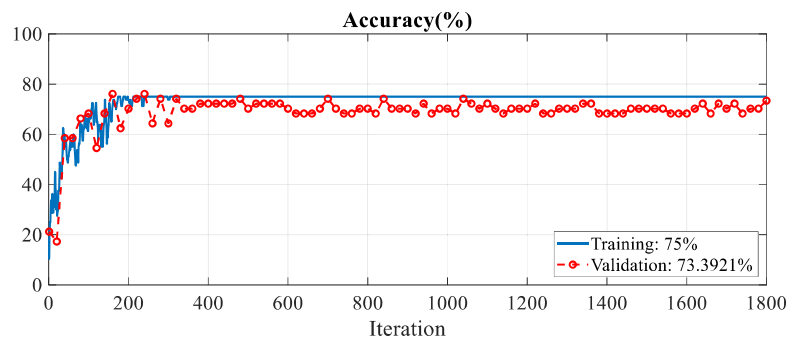


Figure 10 Accuracy change graphs of the RAL-CNN model for training and validation.

Full-size DOI: 10.7717/peerj-cs.3576/fig-10

$$F\text{-score} = 2 \times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}}. \quad (12)$$

EXPERIMENTAL STUDIES

All coding of the study was performed in MATLAB (2022b) environment installed on windows 11 operating system. The applications were implemented on desktop hardware with i9 13,900 KF intel processor, 64 GB DDR5 memory and NVIDIA RTX 4090 24 GB graphics card.

In the first phase of the experimental studies, digital 12-channel ECG signals in XML format were read in MATLAB. The 12 signals were stacked one after the other to create a two-dimensional input data structure. Since the length of each channel is 5,000, raw input data of size $12 \times 5,000$ was created. In the next step, spectrogram images were created for each channel. Hamming windowing was used to generate spectrogram images. window size was set to 100, sampling frequency to 1 KHz, overlap size to 50, and FFT length to 1,000.

For training the RAL-CNN model, the training options in the following sentences were selected. These option parameters were adjusted by fine-tuning the parameters through trial and error. The initial learning rate was set to 0.001, mini-batch size 64, epoch value 100 and validation frequency 50. When stored with activations of the RAL-CNN model, the model size is 158 KB. This size is quite small compared to popular models (in the order of MB) such as AlexNet, VGGNet, and MobileNet. Furthermore, the largest processing power in the RBWSSE algorithm is used by the ReliefF algorithm. This is also a low-cost forward-thinking algorithm. Therefore, the proposed methodology is a lightweight model. 10-fold cross-validation was used as the training evaluation method. Figures 10 and 11 show the training and validation changes for accuracy and loss factors respectively.

As can be seen in Fig. 10, the training and validation values for the accuracy criterion are 75% and 73.39%, respectively. As can be seen in Fig. 11, the training and validation values for the loss criterion are 0.1 and 0.348, respectively. The confusion matrix values of the RAL-CNN model according to 10-fold cross-validation values are given in Fig. 12.

The results obtained from the confusion matrix of the RAL-CNN model and other performance metric values by class are given in Table 3. As can be seen from Table 3, the

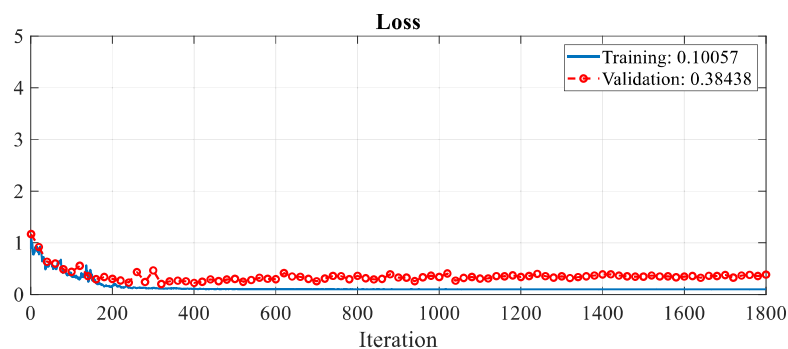


Figure 11 Loss change graphs of the RAL-CNN model for training and validation.

Full-size [DOI: 10.7717/peerj-cs.3576/fig-11](https://doi.org/10.7717/peerj-cs.3576/fig-11)

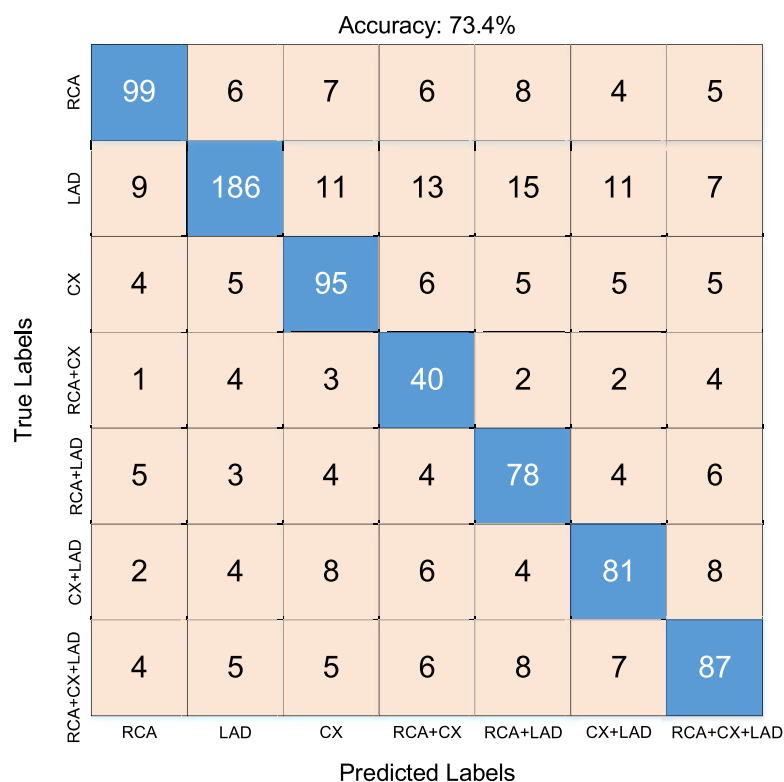


Figure 12 Confusion matrix results of the propose approach.

Full-size [DOI: 10.7717/peerj-cs.3576/fig-12](https://doi.org/10.7717/peerj-cs.3576/fig-12)

best sensitivity (SEN) value was 0.73 for the RCA class. The best specificity (SPE) value was 0.96 for the RCA class. The best precision (PRE) value was 0.87 for the LAD class. The best F-score value was obtained at 0.8 for the LAD class.

The worst SEN value was 0.71 for the RCA+CX and RCA+CX+LAD classes. The worst SPE value was 0.93 for the RCA+LAD class. The worst PRE value was 0.49 for the RCA+CX class. The worst F-score value was obtained at 0.58 for the RCA+CX class.

Table 3 Results obtained from the confusion matrix of the RAL-CNN model and other performance metrics by class.

Class	SEN	SPE	PRE	F-score
RCA	0.73	0.96	0.80	0.76
LAD	0.74	0.95	0.87	0.80
CX	0.76	0.94	0.71	0.74
RCA+CX	0.71	0.94	0.49	0.58
RCA+LAD	0.75	0.93	0.65	0.70
CX+LAD	0.72	0.95	0.71	0.71
RCA+CX+LAD	0.71	0.94	0.71	0.71

The differences between the best value and the worst value for SEN, SPE, PRE and F-score criteria were 0.05, 0.03, 0.38 and 0.22, respectively.

DISCUSSIONS

This section is organized around an ablation study to demonstrate the efficiencies of the RAL-CNN model and the RBWSSE algorithm. In the first experiment of the ablation study, training-validation was performed with the same layer structure and training parameters without attention, residual and LSTM structures. A classification accuracy of 65.3% was achieved with this CNN model. The A-CNN model performed as poorly as the RAL-CNN model with 8.1% accuracy. In the second experiment of the ablation study, training-validation was performed with the same layer structure and training parameters without residual and LSTM structures. With this Attention-CNN (A-CNN) model, 66.6% classification accuracy was achieved. The A-CNN model performed as poorly as the RAL-CNN model with 6.8% accuracy. In the third experiment of the ablation study, training-validation was performed with the same layer structure and training parameters without attention and LSTM structures. This Residual-CNN (R-CNN) model achieved 66.6% classification accuracy. The R-CNN model performed worse than the RAL-CNN model with 5.9% accuracy. In the fourth experiment of the ablation study, training-validation was performed with the same layer structure and training parameters, only without the residual structure. This A-CNN+LSTM model achieved 68.2% classification accuracy. The R-CNN model performed worse than the RAL-CNN model with 5.2% accuracy. In the fifth experiment of the ablation study, training-validation was performed with the same layer structure and training parameters, only without the attention structure. This R-CNN+LSTM model achieved 69.6% classification accuracy. The R-CNN model performed worse than the RAL-CNN model with 3.8% accuracy. In the sixth experiment of the ablation study, training-validation was performed with the same layer structure and training parameters, only without the LSTM structure. This RA-CNN model achieved 70.5% classification accuracy. The R-CNN model performed worse than the RAL-CNN model with an accuracy of 2.9%. In order to improve the classification performance of the RAL-CNN model, features were extracted from the last connected layer and classified in the SVM algorithm. With this structure, the classification accuracy was obtained as 74.8%. The classification performance increased by approximately 1.5%

compared to the RAL-CNN model. In the proposed approach, features were extracted from the RAL-CNN model and the classification process was performed with the RBWSSE algorithm. With this algorithm, the classification performance increased by 6.5% compared to the approach used by the SVM classifier and a classification accuracy of 81.3% was obtained. The confusion matrix results obtained as a result of the eight experimental studies are given in Fig. 13. SEN, SPE, PRE, and F-score values calculated using these confusion matrix values are given in Table 4.

The metric values for the CNN model used in the experimental study are given in Table 4A. The best SEN value was 0.68 for the LAD and CX classes, while the worst SEN value was 0.59 for the RCA+CX+LAD class. The best SEN value of the CNN model was 0.05 lower than the proposed RAL-CNN, while the worst SEN value was 0.12 lower. The best SPE value was 0.94 for the RCA class while the worst SPE value was 0.90 for the RCA+CX+LAD class. The best SPE value of the CNN model was 0.02 lower than the proposed RAL-CNN value, while the worst SPE value was 0.04 lower. The best PRE value was 0.83 for the LAD class while the worst SEN value was 0.41 for the RCA+CX class. The best PRE value of the CNN model was 0.04 lower than the proposed RAL-CNN value, while the worst PRE value was 0.08 lower. The best F-score value was 0.75 for the LAD class while the worst SEN value was 0.50 for the RCA+CX class. The best F-score value of the CNN model was 0.05 lower than the proposed RAL-CNN value, while the worst F-score value was 0.08 lower.

The metric values for the A-CNN model used in the experimental study are given in Table 4B. The best SEN value is 0.71 for the LAD class, while the worst SEN value is 0.61 for the RCA+CX+LAD class. The best SEN value of the CNN model was 0.02 lower while the worst SEN value was 0.1 lower than the proposed RAL-CNN value. The best SPE value was 0.95 for the RCA class, while the worst SPE value was 0.91 for the RCA+CX+LAD class. The best SPE value of the CNN model was 0.01 lower than the proposed RAL-CNN value, while the worst SPE value was 0.02 lower. The best PRE value was 0.83 for the LAD class while the worst PRE value was 0.43 for the RCA+CX class. The best PRE value of the CNN model was 0.04 lower than the proposed RAL-CNN value, while the worst PRE value was 0.06 lower. The best F-score value was 0.77 for the LAD class, while the worst F-score value was 0.51 for the RCA+CX class. The best F-score of the CNN model was 0.03 lower than the proposed RAL-CNN, while the worst F-score was 0.07 lower.

The metric values for the RA-CNN model used in the experimental study are given in Table 4F. The best SEN value is 0.73 for the LAD class, while the worst SEN value is 0.65 for the CX+LAD class. The best SEN value of the CNN model was the same, while the worst SEN value was 0.06 lower than the proposed RAL-CNN value. The best SPE value was 0.95 for the RCA class, while the worst SPE value was 0.92 for the RCA+CX+LAD class. The best SPE value of the CNN model was 0.01 lower than the proposed RAL-CNN value, while the worst SPE value was 0.01 lower. The best PRE value was 0.85 for the LAD class, while the worst PRE value was 0.46 for the RCA+CX class. The best PRE value of the CNN model was 0.02 lower than the proposed RAL-CNN value, while the worst PRE value was 0.02 lower. The best F-score value was 0.79 for the LAD class, while the worst F-score

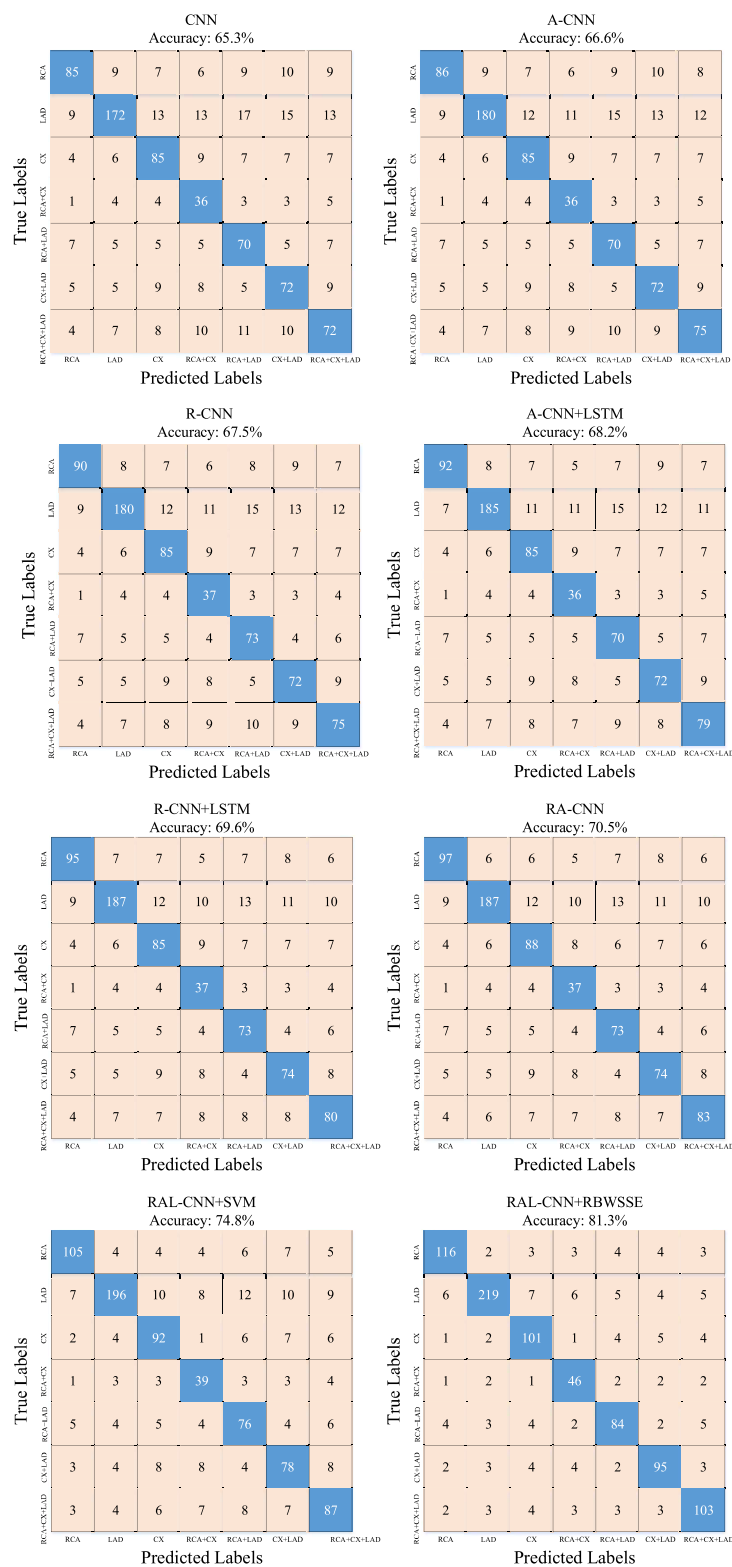


Figure 13 Confusion matrices for ablation studies. Full-size DOI: 10.7717/peerj-cs.3576/fig-13

Table 4 Results of the confusion matrices in Figure 12 and SEN, SPE, PRE and F-score results by class.

Class	SEN	SPE	PRE	F-Score
CNN (A)				
RCA	0.63	0.94	0.74	0.68
LAD	0.68	0.92	0.83	0.75
CX	0.68	0.92	0.65	0.66
RCA+CX	0.64	0.92	0.41	0.5
RCA+LAD	0.67	0.91	0.57	0.62
CX+LAD	0.64	0.91	0.59	0.61
RCA+CX+LAD	0.59	0.9	0.59	0.59
A-CNN (B)				
RCA	0.64	0.95	0.74	0.69
LAD	0.71	0.92	0.83	0.77
CX	0.68	0.92	0.65	0.67
RCA+CX	0.64	0.92	0.43	0.51
RCA+LAD	0.67	0.92	0.59	0.63
CX+LAD	0.64	0.92	0.61	0.62
RCA+CX+LAD	0.61	0.91	0.61	0.61
R-CNN (C)				
RCA	0.67	0.95	0.75	0.71
LAD	0.71	0.93	0.84	0.77
CX	0.68	0.92	0.65	0.67
RCA+CX	0.66	0.92	0.44	0.53
RCA+LAD	0.7	0.92	0.6	0.65
CX+LAD	0.64	0.92	0.62	0.63
RCA+CX+LAD	0.61	0.91	0.63	0.62
A-CNN+LSTM (D)				
RCA	0.68	0.95	0.77	0.72
LAD	0.73	0.93	0.84	0.78
CX	0.68	0.92	0.66	0.67
RCA+CX	0.64	0.93	0.44	0.53
RCA+LAD	0.67	0.92	0.6	0.64
CX+LAD	0.63	0.93	0.62	0.63
RCA+CX+LAD	0.65	0.91	0.63	0.64
R-CNN+LSTM (E)				
RCA	0.7	0.95	0.76	0.73
LAD	0.73	0.93	0.85	0.79
CX	0.68	0.93	0.66	0.67
RCA+CX	0.66	0.93	0.46	0.54
RCA+LAD	0.7	0.93	0.63	0.67
CX+LAD	0.65	0.93	0.64	0.65
RCA+CX+LAD	0.66	0.92	0.66	0.66

Table 4 (continued)

Class	SEN	SPE	PRE	F-Score
RA-CNN (F)				
RCA	0.72	0.95	0.76	0.74
LAD	0.73	0.93	0.85	0.79
CX	0.7	0.93	0.67	0.69
RCA+CX	0.66	0.93	0.47	0.55
RCA+LAD	0.7	0.93	0.64	0.67
CX+LAD	0.65	0.93	0.65	0.65
RCA+CX+LAD	0.68	0.92	0.67	0.68
RAL-CNN+SVM (G)				
RCA	0.78	0.97	0.83	0.81
LAD	0.78	0.97	0.9	0.83
CX	0.78	0.95	0.72	0.75
RCA+CX	0.7	0.96	0.55	0.61
RCA+LAD	0.73	0.95	0.66	0.7
CX+LAD	0.69	0.92	0.67	0.68
RCA+CX+LAD	0.71	0.95	0.7	0.7
RAL-CNN+RBWSSE (H)				
RCA	0.86	0.98	0.84	0.85
LAD	0.87	0.97	0.87	0.87
CX	0.86	0.97	0.77	0.81
RCA+CX	0.82	0.98	0.75	0.79
RCA+LAD	0.81	0.97	0.86	0.83
CX+LAD	0.77	0.98	0.83	0.8
RCA+CX+LAD	0.84	0.98	0.84	0.84

value was 0.55 for the RCA+CX class. The best F-score of the CNN model was 0.01 lower than the proposed RAL-CNN, while the worst F-score was 0.03 lower.

Tables 4G and 4H metrics are given to see the level of performance improvement provided by the RBWSSE algorithm over the SVM algorithm. In Table 4G, features were extracted from the fully connected layer of the RAL-CNN model trained from scratch and the classification process was performed with the SVM algorithm. In the sensitivity metric, better performance (0.78) was obtained in the single occluded main coronary arteries. In the specificity metric, a performance above 0.95 was obtained in all classes except CX+LAD. In the precision metric, the performance decreased between approximately 0.2–0.35 compared to the single occluded main coronary arteries. Considerable performances were obtained in Table 4H with the proposed approach strategy and in Table 4G with the SVM classifier strategy. In the sensitivity metric, an improvement of at least 8% was achieved according to the classes. In the specificity metric, the performance was 0.97 and 0.98 in all classes. In the precision metric, the performance in the multiple occluded main coronary arteries was increased by at least 14%. In the F-score metric, the performance increased in all classes and the performance was 0.8 and above except for the RCA+CX class (0.79).

The improvement in classification performance from 73% to 81.3% can be attributed to the complementary strengths of the RAL-CNN model and the RBWSSE ensemble strategy. The RAL-CNN network effectively extracts hierarchical spatial-temporal features from 12-lead ECG spectrograms. However, in multiclass NSTEMI cases—especially when multiple arteries are occluded—some discriminative features become suppressed or redundant within the deep layers.

By using ReliefF-based weighting to highlight the most informative deep features and lessen the impact of less pertinent or noisy ones, the suggested RBWSSE algorithm addresses this problem. Additionally, the ensemble is made more diverse by splitting the weighted features into several subspaces and training separate SVM classifiers on each subset, which enhances generalization and lessens overfitting. The complementary choices made by these subspace classifiers are then combined by the weighted majority-voting mechanism to produce a final prediction that is more reliable and stable.

In conclusion, the RBWSSE algorithm combines feature selection, ensemble diversity, and weighted decision fusion to improve the discriminative power of the RAL-CNN features, which accounts for the observed 8% performance improvement.

The experimental results show that the proposed RAL-CNN+RBWSSE model achieves a certain level of success on multi-channel ECG data, but its performance is still at the threshold for a high-level classification model. Despite this, the model is able to capture key differences between classes and can significantly distinguish spectral and temporal changes in ECG signals. This demonstrates that the current model structure provides a foundation for expansion and improvement.

One of the most important reasons for the limited current accuracy and sensitivity values is the limited size and diversity of the dataset. The small number of examples, particularly of rare cardiac conditions, has led to the model's inability to adequately generalize these patterns. Therefore, in future studies, enriching the dataset in terms of sample size, patient profile diversity, and signal quality will significantly improve the model's performance.

Furthermore, studies with larger datasets will provide the opportunity to test the robustness of the proposed RAL-CNN+RBWSSE architecture against different patient groups, signals obtained from different devices, and noise levels. Thus, this study not only demonstrates the performance of the current model but also provides a basic framework that can serve as a reference for future research.

In conclusion, the proposed model demonstrates reasonable success in its current limited dataset; however, it has the potential to produce more robust, generalizable, and clinically meaningful results as the data size and diversity increase.

CONCLUSIONS

The main goal of the study is to predict the blocked main coronary arteries of heart attack cases in the NSTEMI group from 12-channel ECG data without performing coronary angiography (CAG). Thus, it is aimed at reducing both the work intensity and operational risks of unnecessary CAG procedures. In this context, a very valuable data set has been created in the field of health. Deep learning-based studies were conducted with the

collected data set. These studies are aimed at providing a baseline model for other researchers who will use this dataset. For this purpose, the proposed approach (RAL-CNN) was evaluated on the collected dataset. With this model, 73.4% classification accuracy was achieved. In addition, a detailed ablation study was performed to show the contribution of attention, residual, and LSTM structures in the RAL-CNN model. With the developed RBWSSE algorithm, the classification accuracy was improved up to 81.3%. Each study that surpasses the classification performance of the baseline RAL-CNN model will contribute to the use and dissemination of the dataset. Moreover, different versions of the dataset will be reported, and different data will be collected yearly.

The key contribution of this research is the development of a multi-class deep learning framework capable of identifying not only the presence but also the location of coronary artery occlusions, as validated by coronary angiography labels. This capability provides valuable support for clinical decision-making and could potentially reduce unnecessary invasive procedures. The results demonstrate that combining deep spatial-temporal feature extraction (*via* RAL-CNN) with ensemble-based feature weighting (*via* RBWSSE) significantly enhances diagnostic reliability.

Although the proposed RAL-CNN+RBWSSE framework achieved satisfactory performance in ECG classification, it has several limitations. Generalization to larger populations or different acquisition settings may be limited by the dataset's small size and lack of diversity. Class imbalance and overfitting risks cannot be completely eliminated, even with the use of balancing and regularization techniques. Because of the hybrid structure's increased computational complexity, it must be optimised for embedded or real-time applications. Furthermore, only one dataset was used for validation; external multi-center validation is required to verify clinical applicability. Future efforts to increase data diversity, computational effectiveness, and model generalizability will be guided by these constraints. The major limitation of this study is that the number of patients in the NSTEMI group was not evenly distributed according to the main coronary artery classes. To overcome this limitation, multiple ECG data were obtained from patients in the NSTEMI group in classes with few data. Future work will focus on expanding the dataset, applying advanced hyperparameter optimization, and validating the model in real-time ECG monitoring systems to support clinical adoption further.

ADDITIONAL INFORMATION AND DECLARATIONS

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Competing Interests

The authors declare that they have no competing interests.

Author Contributions

- Ozgen Safak conceived and designed the experiments, performed the experiments, analyzed the data, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Mehmet Tolga Hekim conceived and designed the experiments, performed the experiments, analyzed the data, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Tolga Çakmak conceived and designed the experiments, performed the experiments, analyzed the data, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Fatih Demir conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Yaman Akbulut conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Zehra Kadiroğlu conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Abdulkadir Sengür conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Mehmet Ali Kobat conceived and designed the experiments, performed the experiments, analyzed the data, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.

Data Availability

The following information was supplied regarding data availability:

The raw data is available in the [Supplemental Files](#).

Supplemental Information

Supplemental information for this article can be found online at <http://dx.doi.org/10.7717/peerj-cs.3576#supplemental-information>.

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