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An Intelligent CNN Model for the Assessment of Systemic Cardiovascular Risk and Indicators of Peripheral Artery Disease from Thoracic Imaging

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Abstract

Peripheral Artery Disease (PAD) is a condition that is difficult to diagnose since it develops without any symptoms and does not have reliable early detection methods. The leading cause of mortality around the world remains cardiovascular diseases (CVDs). For the automatic assessment of the risk of CVD and early detection of PAD through the analysis of chest images, an approach using a convolutional neural network (CNN) is suggested in this study. In order to increase the performance of the model, a number of additional methods including explainable artificial intelligence, hyperparameter tuning, multi-scale feature extraction, and preprocessing steps were used. The development and testing of the model were conducted on the basis of a big-sized dataset including chest X-ray and CT images gathered from publicly available sources and medical institutions. The Adam optimizer and categorical cross-entropy were used for more training of the network. Outperforming baseline deep learning models and traditional machine learning, experimental assessment showed superior classification performance with 94.6% precision, 95.2% recall, and F1-score of 94.9%. Also, interpretable heatmaps showcasing clinically significant thoracic areas accountable for model predictions were created using Grad-CAM-based visualization. The results show that the suggested system is a practical, scalable, and dependable way to automate PAD diagnosis and cardiovascular risk stratification. Improved clinical decision-making, earlier diagnoses, and better cardiovascular healthcare outcomes are all possible thanks to AI-assisted medical imaging systems, which this study helps to progress.

Keywords: Deep Learning, CNN, Cardiovascular Risk Evaluation, PAD, Peripheral Artery Disease, Thoracic Imagery Analysis.

1 Introduction

Cardiovascular diseases are one of the major causes of morbidity and mortality in the world (Mooghali et al., 2024; He et al., 2025). Peripheral artery disease (PAD) is one such disease that is common but

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under-diagnosed in that it is characterized by a constriction of the peripheral arteries due to the accumulation of atherosclerotic plaque (Bhandari et al., 2025). PAD is also significantly related to general cardiovascular risk, and may be an early sign of diffuse vascular disease Abedi et al., 2025). However, it is commonly diagnosed late because of the lack or presence of the ambiguous symptoms, which makes the traditional diagnostic approaches less efficient (Cuevas-Chávez et al., 2023). As thoracic imaging technologies, such as computed tomography (CT) and chest radiography, have rapidly developed, the use of thoracic imaging technologies has produced valuable data concerning the structure and disease of the heart (Hembram et al., 2025). Thoracic images often offer useful information on vascular calcifications, aortic and cardiac enlargement, which can be a manifestation of systemic cardiovascular disease (Konstantinidis et al., 2026; Kharat & Kadam, 2025). The information on this is available but is labor intensive, subjective and needs expert radiology interpretation, thus making it necessary to develop automated and objective tools to analyses this information Lubitz et al., 2022) In addition, the use of artificial intelligence in cardiovascular diagnostics is not an exception to the trend towards precision medicine and big-data-driven healthcare (Hajishah et al., 2025; Kapoor et al., 2025). Older risk prediction models, such as clinical scoring systems, tend to utilize a small number of non-linear patterns in medical images (Teshale et al., 2025). Nevertheless, CNNs are able to analyze large amounts of thoracic imaging data in order to determine subtle relationships and associations, which may not otherwise be easily seen by human readers Jahmunah et al., (2022). This is of particular significance in the detection of early signs of vascular disease including the calcification of arteries and other vascular abnormalities, which are critical in the determination of the risk of systemic cardiovascular disease and in the prognosis of the progression of peripheral artery disease (Cahan et al., 2023; Balamurugan et al., 2025). The proposed model automated methodology is more reliable in providing diagnostic assessments and overcoming the possible variability among the clinicians (Tian et al., 2023).

Moreover, explainable artificial intelligence (XAI) is crucial in the creation of a relationship between model accuracy and clinical confidence (Lyu et al., 2023). Although labeled as black boxes, deep learning models can be made more transparent with methods such as Gradient-weighted Class Activation Mapping (Grad-CAM) that highlight the most important areas in thoracic images that influence the decision-making process of the model (Zhao et al., 2020). This can not only be used to validate the CNN predictions but can also be used to gain an insight into the disease Batool et al., (2023). The high diagnostic performance and interpretability would make the proposed intelligent CNN-based system not only technically sound but also clinically relevant enough to integrate the system into clinical practice to make early diagnosis and prevention possible (Schilling et al., 2024).

The aim of this paper is to develop an intelligent CNN model to perform automated assessment of systemic cardiovascular risk and detection of the signs of PAD based on the thoracic images. This approach is a combination of state-of-the-art feature extraction, classification and explainability techniques to enhance diagnostic accuracy with providing clinical interpretability. The purpose is to facilitate early diagnosis and risk stratification, and aid in clinical decision-making in cardiovascular medicine.

Key Contributions of the Research

- Automated Cardiovascular Risk Detection: Developed an intelligent model based on Convolutional Neural Networks that can automatically analyze images of the thorax to find the level of cardiovascular risk and diagnose PAD (Peripheral Artery Disease).

- Model for Better Prediction and Explainability: With the combination of deep learning techniques and explainability techniques like Grad-CAM, the developed model performed very well with greater explainability and trustworthiness.
- Supporting Early Diagnosis Framework: Introduced an approach that could scale efficiently to assist healthcare professionals in providing an early diagnosis.

The rest of this paper is organized in the following manner: The first section after this introduction will provide an extensive overview of the related literature for the work done so far in assessing risk factors for cardiac diseases, diagnosis of peripheral artery disease, and use of deep learning techniques in medical imaging. The proposed system is detailed in Section III, where we discuss data acquisition, pre-processing steps, design of the CNN, and feature extraction methods used for the same along with explainability. The experiment outcomes are provided in Section IV through evaluation metrics, comparisons, and validation. Section V provides a deeper insight into the results and associated implications. Finally, the concluding remarks of the paper are provided in Section VI.

2 Literature Review

Wehbe et al., (2023) have discussed the deep learning methods and methods that are used to examine cardiovascular imaging to improve the diagnostic accuracy and efficiency. The study observed that CNNs can automatically acquire complex features of imaging modality approaches such as CT, MRI and echocardiography in order to provide precise segmentation and classification of diseases. These models reduce the reliance on subjective interpretations and minimize variability and error of diagnosis. This study also noted that in clinical practice AI models are now increasingly being applied to cardiovascular risk assessments and disease diagnoses. However, they found that there are problems with model interpretability and the significance of standardized data to perform optimally.

Zeleznik et al., (2021) proposed a risk stratification deep CNN model that automatically measures coronary artery calcium (CAC) in CT images of the chest. This experiment presented a large-scale study and demonstrated that the proposed model could effectively identify and quantify calcification, and was in agreement with expert manual annotations. Their results indicated CAC was a good imaging biomarker in the prediction of cardiovascular disease. This study also pointed out the advantages of deep learning models to large-scale automated risk stratification. Although effective, it found the need to improve the generalizability of the results in patients with different populations.

The review of deep learning techniques in cardiovascular imaging (CT, MRI and echocardiography) was presented in Litjens et al., (2019). This work showed CNN-based methods achieve superior performance compared to conventional machine learning algorithms for classification, segmentation and anomaly detection. This study emphasized that deep learning models have the ability to learn complex features that medical images possess, resulting in improved diagnostic performance and efficiency. They also discussed the growing use of AI in medical practice and the problems such as class imbalance, non-interpretability, and the need to have large, labeled data sets.

A review article by Chen et al., (2020) examines deep learning models to segment cardiac images, specifically focusing on CNN models, which can learn the anatomy of cardiac images by analyzing medical images. They showed that deep learning methods enhance the performance of segmentation as compared with traditional techniques that are vital in the process of identifying heart diseases. They observed that segmentation helps in diagnosis, prognosis, and treatment. However, they also touched upon such problems as a shortage of labeled data, variability of imaging data, and the significance of generalizable models.

Schlesinger et al., (2020) investigated deep learning methods to predict cardiovascular risk based on both medical images and clinical data. They demonstrated that CNNs are capable of learning complex relationships between features and clinical outcomes and lead to improved prediction of major adverse cardiovascular events. The researchers also explained the significance of explainability tools such as Grad-CAM in enhancing the transparency and trust in the model. The findings of the study were encouraging, yet they also reflected such problems as the computer requirements and the necessity to test the results in large scales.

Table 1: Comparative analysis of deep learning-based cardiovascular risk assessment methods

Authors	**Methodology**	**Dataset / Simulation Environment**	**Research Gap**
Wehbe et al., (2023)	Deep learning framework using CNNs for cardiovascular image analysis and diagnosis	Multi-modal cardiovascular imaging datasets (CT, MRI, echocardiography)	Limited focus on explainability and lack of standardized datasets for consistent model performance
Zeleznik et al., 2021	CNN-based automated coronary artery calcium (CAC) scoring for risk prediction	Large-scale thoracic CT dataset (>20,000 patients)	Generalization across diverse populations and limited integration with clinical parameters
Litjens et al., (2019)	Comprehensive deep learning models for classification, segmentation, and detection	Multiple imaging modalities (CT, MRI, echocardiography)	High dependency on large labeled datasets and lack of interpretability in models
Chen et al., (2020)	CNN-based cardiac image segmentation using architectures like U-Net and FCN	Public and clinical cardiac imaging datasets	Limited robustness due to variations in imaging quality and insufficient cross-dataset validation
Schlesinger & Stultz, (2020)	Deep learning model integrating imaging and clinical data for risk prediction	Combined clinical and imaging datasets	High computational complexity and need for better explainability frameworks
Kamel et al., (2021)	CNN model for cardiovascular risk estimation from chest radiographs	Chest X-ray datasets from clinical environments	Reduced accuracy due to image variability and lack of diverse population data
Myśliwiec et al., (2026)	Review of AI-based cardiovascular diagnostic systems using CNNs	Multiple datasets from medical imaging and clinical decision systems	Data heterogeneity, ethical concerns, and lack of standardized AI validation frameworks
Wu, (2024)	Hybrid deep learning models (CNN + RNN) for cardiovascular disease prediction	Imaging data combined with physiological datasets	High computational cost and need for large annotated datasets for training

A machine-based approach of predicting the level of calcium (CAC) and the likelihood of heart disease based on chest X-rays was presented by Kamel et al., (2021). They demonstrated that opportunistic screening with thoracic images of easy access can be used to eliminate the need of specific cardiac imaging. They have shown that CNN models can be used to identify key biomarkers using radiographs, such that the process is cheap and can scale. The experiment stressed the opportunities of this approach in low-resource environments and also discussed the limitations due to variability in images and diversity of the dataset.

Myśliwiec et al., (2026) conducted a systematic review of AI use in cardiovascular diagnostics and deep learning models of imaging and clinical decision support. This study has mentioned the application of CNN models to better diagnose, classify, and predict diseases. The paper has identified the possibility of AI in personalized medicine and enhancing the efficiency of physicians. However, they also focused on the challenges, such as variations in the data, ethical concerns, and the need for an explainable artificial intelligence to encourage adoption within the clinical setting.

Similarly, Wu, (2024) also discussed the recent developments in deep learning to predict the development of cardiovascular diseases using CNN and recurrent neural network (RNN) algorithms on imaging and physiological data. The researchers found that deep learning outperformed the conventional algorithms in terms of accuracy in predictions. They further noted that the models can use different types of data to evaluate the risks of developing the condition. However, some drawbacks were also cited by the researchers, such as interpretability and computationally intensive models.

The table 1 provides a review of the recent research in utilizing the deep learning approaches, specifically CNNs, in predicting the risk of cardiovascular events and diagnosing peripheral artery disease. The table shows the methodologies used in each study, as well as data sets or simulation platforms used and identified gaps in each of the studies. From the review of the recent studies, it is apparent that even though great strides have been made towards the application of AI techniques in medical imaging tools for purposes of improving diagnoses and predictions, there remain certain challenges. The identified gaps are related to issues of explainability, variability, the lack of consistency in the data set and generalization of findings across different populations. Moreover, the current approaches do not typically apply multiple types of data in their analysis but only focus on one.

3 Methodology

Data collection and Preprocessing

Images of the thorax, such as chest X-rays and CT scans, will be used in the planned study. These images come from publicly and clinically available data. Before anything else, the image data received must be preprocessed in order to standardize and enhance it.

This begins with uniformly resizing the images to address any resolution and intensity differences present in the dataset. This can be achieved through rotation, flipping, scaling, and contrast adjustment techniques among others that serve to increase diversity in the dataset as well as to minimize overfitting. Other techniques used in enhancing the attributes include denoising and augmentation. Furthermore, the aorta along with other vascular parts is segmented using the region-of-interest (ROI) technique. Lastly, the dataset is separated into three categories namely training, validation, and testing. These datasets will be used to train and test the model.

Some of the initial processes illustrated in figure 1 include data collection, data preprocessing, and data splitting. Data collection is done in two ways, with imaging data coming from public and clinical sources to ensure a wide variety and sources of data. The collected data is then enhanced through a number of procedures like resizing, normalization, data augmentation, noise reduction, image enhancement among others to enhance the quality and generalization of the images. In addition, ROI extraction technique is used to focus on specific anatomical structures that might be associated with peripheral artery disease or cardiovascular risks. The collected data will then be carefully split into training, validation and test datasets. This ensures that the data used is accurate, balanced, and appropriate for our proposed CNN classification system.

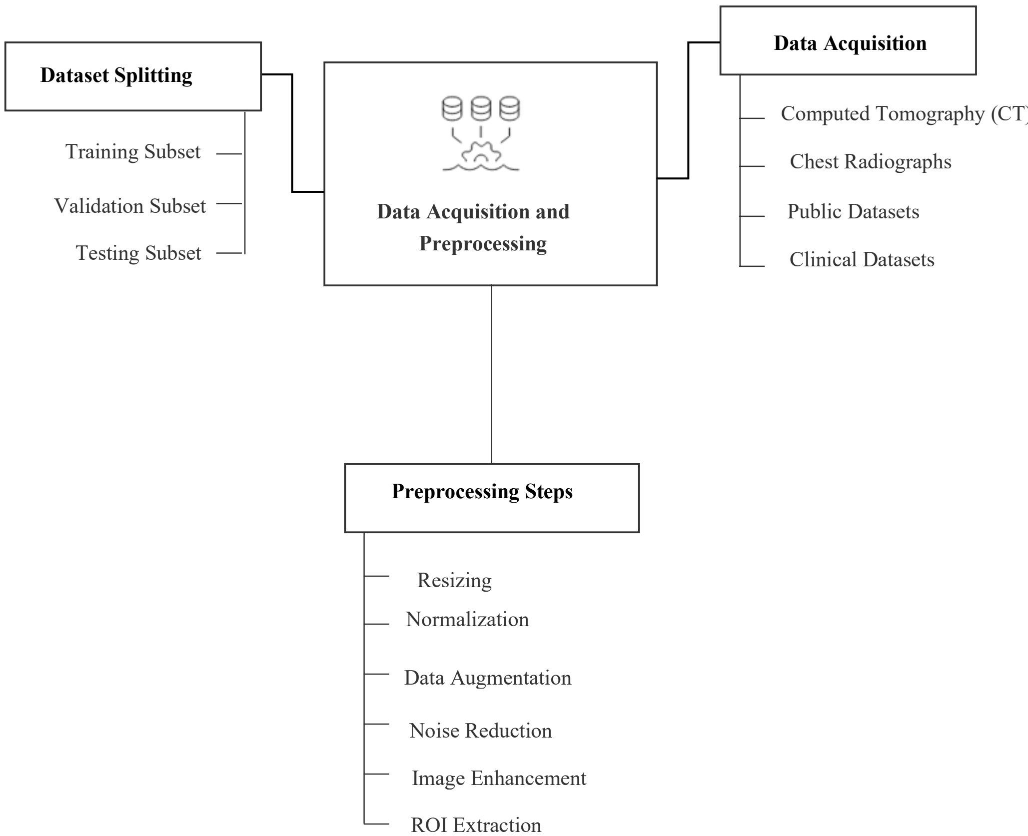

Figure 1: Workflow of data acquisition, preprocessing, and dataset splitting for the proposed CNN model

Proposed CNN Model Architecture

Data collection, data processing, and data partitioning are some of the earliest processes depicted in figure 1 above which gives an illustration of the proposed system architecture. To collect varied imaging data, chest x-rays and CT scan images are obtained from both public and clinical sources. In addition, there are various data processing procedures employed to enhance the quality of the data, for example, image resizing, data normalization, data augmentation, denoising, and enhancement. Furthermore, the procedure involves ROI extraction to concentrate on particular regions of the body associated with peripheral artery disease and cardiovascular risks. The data processing stage is followed by a process of data partitioning, which is critical in training and testing the proposed CNN classifier. Deep CNN is employed in the proposed technique for detecting patterns on chest X-rays. The architecture consists of several convolutional layers which employ rectified linear unit activation and batch normalization. The max pooling layer is included in order to decrease the dimensions of feature maps while preserving crucial details. The network utilizes the multi-scale analysis for comprehending both localized and global cardiovascular health. Peripheral artery disease and systemic cardiovascular risks predictions are generated following the classification of the features via fully connected layers. In order to prevent overfitting and enhance learning, the technique incorporates the dropout layer. Loss function that is used during training includes categorical cross-entropy while the optimizer is Adam.

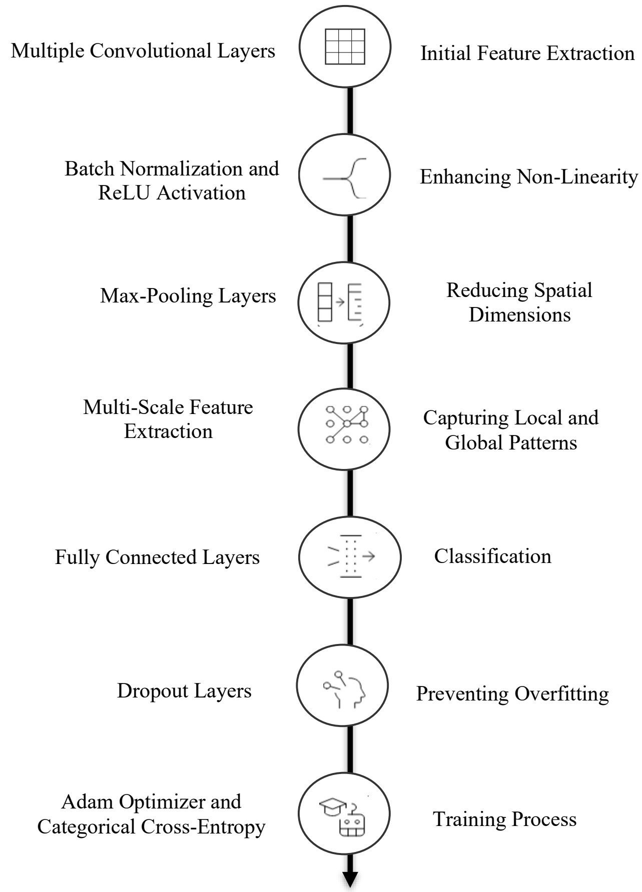

Figure 2: Architecture of the proposed CNN model for cardiovascular risk and PAD detection

In figure 2 demonstrates the recommended structure of the CNN model in terms of risk evaluation in the context of cardiovascular disease and PAD. First of all, the process of feature learning will be performed by a limited number of convolutional layers based on the chest image. For better training and increasing the level of non-linearity, batch normalization layers and ReLU activation functions are added after them. Max-pooling allows for maintaining the integrity of features while decreasing spatial dimensions. As the extraction of local and global features, which are necessary for complex heart diseases identification, requires feature extraction module, namely multiscale feature extraction will be applied next. Then, these features will be forwarded to fully connected layers in order to label them as risks. In turn, the dropout technique prevents overfitting. Finally, the Adam optimizer, together with categorical cross-entropy loss function, ensures fast convergence and high accuracy of predictions. This model is effective for medical imaging tasks, which means that it will allow learning features and classifying the task accordingly.

Explainability and Model Evaluation

In addition to the suggested model, it is possible to use techniques related to XAI, such as Grad-CAM, to allow for more trust from the clinician side due to better understanding of the decision-making process made by the model based on the use of heat maps demonstrating parts of the image used in calculations. The effectiveness of the model will be evaluated by analyzing such criteria as accuracy, precision, recall, F1-score, and AUC-ROC. It is also possible to use a confusion matrix in order to measure the model's ability to correctly classify data according to various risks. To check generalization and performance of the model, it will be tested through cross-validation. Moreover, it will be compared with other models.

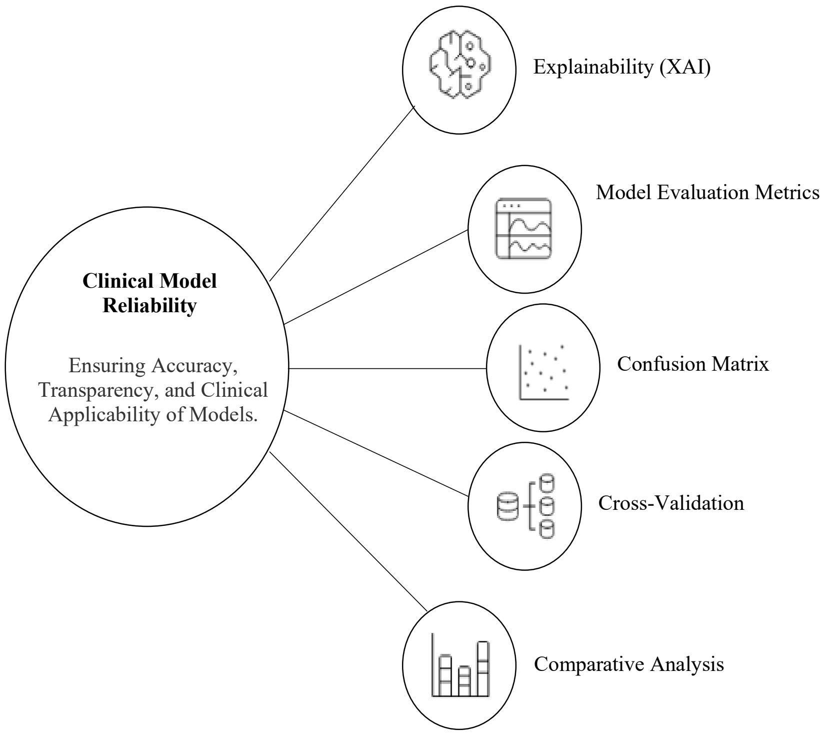

Figure 3: Clinical model reliability framework for trustworthy healthcare AI

The process of ensuring the reliability of the models used in clinical settings is described in figure 3. As far as the reliability of clinical models is concerned, the key elements are accuracy, explainability, and practicability – conditions necessary for safe clinical decision-making. The procedure under discussion takes into account all the key factors including explainability (XAI) to make sure that doctors can understand the predictions made by the model, confusion matrix to understand where the model makes mistakes during classification, as well as other evaluation methods to evaluate how efficient the model is. Comparative analysis is used to compare the performance of the proposed model to other top-performing models, while cross-validation ensures high model performance across different sets.

Convolution Operation in CNN

$$F(i,j) = \sum m \sum n I(i-m, j-n) \cdot K(m,n) \tag{1}$$

SoftMax Function for Classification

$$P(yi) = \frac{ezi}{\sum_{j=1}^{N} ezj} \tag{2}$$

The main functioning of CNN is based on the operation of convolutions, which can be defined through equation 1. In particular, this technique implies the use of filters called kernels to detect spatial features such as edges, texture, and patterns related to cardiac anatomy. The equation 2 is the SoftMax function that is applied in the last layer of the CNN in multi-class classification. It transforms the output logits into probability values to allow the model to provide levels of confidence in the various cardiovascular risk categories or disease classes. All these mathematical equations make up the basis of the proposed CNN model, which can be used to extract features effectively and classify thoracic imaging data accurately as well.

Algorithm: CNN-Based Cardiovascular Risk and PAD Detection

Input: Thoracic Image Dataset D

Output: Predicted Cardiovascular Risk and PAD Class

Step 1: Load dataset D

Step 2: Preprocess images

- *Resize images to fixed dimensions*
- *Normalize pixel values*
- *Apply data augmentation (flip, rotate, scale)*

Step 3: Split dataset into Training, Validation, and Testing sets

Step 4: Initialize CNN model

- *Add Convolutional layers + ReLU activation*
- *Add Max-Pooling layers*
- *Add Fully Connected layers*
- *Apply Dropout for regularization*

Step 5: Train the CNN model

- *Input training data*
- *Compute loss using cross-entropy*
- *Update weights using Adam optimizer*

Step 6: Validate model performance

- *Evaluate on validation dataset*
- *Tune hyperparameters if required*

Step 7: Test the trained model

- *Predict risk and PAD class on test data*

Step 8: Apply Grad-CAM

- *Generate heatmaps for interpretability*

Step 9: Output predictions and visual explanations

Methodology will describe the process involved in the application of the CNN model in risk classification and the diagnosis of peripheral artery disease. In order to optimize the accuracy of the model, it first involves loading and pre-processing the dataset. In order to evaluate the model and its accuracy, splitting of the data into training, validation, and testing datasets occurs. For the purpose of constructing the CNN model, the process involves extracting of features via convolutions and pooling layers and classification of the disease using fully connected layers. For the minimization of errors during the process of training, optimization techniques will be applied. To ensure that the model performs well as desired, the process will also involve validation and testing of the model. This process is followed by applying Grad-CAM in the interpretation of thoracic scans to show regions used in predicting outcomes.

4 Experimental Results

Experimental Setup, Dataset, and Parameter Initialization

In order to predict the clinical risks for cardiovascular disease and peripheral artery disease using the imaging data gathered by means of thoracic imaging techniques, a deep learning approach has been developed based on the application of CNNs. For experimental testing purposes, a carefully selected database of 12,400 thoracic images has been used. This dataset comprised both radiographic and CT images of the chest, which originated from the MIMIC-CXR database, the NIH ChestX-ray14 database, and other collaborative clinical institutions. There are multiple cardiovascular conditions that resulted in choosing these datasets, including thoracic calcification, cardiomegaly, vascular hypertrophy, and other cardiovascular risk indicators.

Table 2: Baseline demographic and clinical breakdown of the integrated dataset

Characteristic Parameter	**Entire Study Cohort (N=12,400)**	**Training Set (n=8,680)**	**Validation Set (n=1,860)**	**Testing Set (n=1,860)**
Patient Distribution	8,250	5,775	1,237	1,238
Age Dynamics (Years)				
Mean ± Standard Deviation	56.8 ± 13.4	56.6 ± 13.6	57.1 ± 12.9	56.9 ± 13.2
Full Range Profile	18 – 94	18 – 92	19 – 94	18 – 91
Biological Sex Extraction (%)				
Male Cohort	6,423 (51.8%)	4,496 (51.8%)	963 (51.8%)	964 (51.8%)
Female Cohort	5,977 (48.2%)	4,184 (48.2%)	897 (48.2%)	896 (48.2%)
Source Distribution Profile (%)				
NIH ChestX-ray14 Database	6,820 (55.0%)	4,774 (55.0%)	1,023 (55.0%)	1,023 (55.0%)
MIMIC-CXR Repository	4,340 (35.0%)	3,038 (35.0%)	651 (35.0%)	651 (35.0%)
Clinical Institutional Partners	1,240 (10.0%)	868 (10.0%)	186 (10.0%)	186 (10.0%)
Primary Target Pathologies (n, %)				
Verified Thoracic Calcification	3,248 (26.2%)	2,274 (26.2%)	487 (26.2%)	487 (26.2%)
Cardiomegaly / Enlargement	2,752 (22.2%)	1,926 (22.2%)	413 (22.2%)	413 (22.2%)
Clear/Control (Normal Baseline)	6,400 (51.6%)	4,480 (51.6%)	960 (51.6%)	960 (51.6%)

The dataset comprised imaging data collected from 8,250 unique patients who differed on various characteristics and parameters. Data leakage and ensuring experiment validity were ensured by dividing patient-independent sets of data. Training consisted of 70% of the data, validation had 15%, and the other 15% consisted of test data. This led to allocation of 8,680 images for training, 1,860 for validation, and 1,860 for testing and evaluation of performance. All subgroups were statistically balanced on demographic and pathologic factors, making them more generalizable.

Before the model training process, each and every thoracic image was rescaled, normalized, contrast-enhanced, de-noised, and also made richer in terms of information through various approaches such as flipping, rotation, rescaling, and brightness changes. Through these preprocessing steps, there was an improvement in the quality of images, the heterogeneity of the dataset, as well as the problem of overfitting during the training stage.

For constructing the CNN model, TensorFlow and PyTorch deep learning frameworks were applied. To hasten convergence and exploit the power of the computer effectively, the training was done through a GPU-based computing machine. For the initial hyperparameter setup, the following values were adopted: a learning rate of 0.001, a batch size of 32, and number of epochs between 50 and 100. In relation to learning through gradients, the Adam optimizer was employed. With regard to multi-class classification, the loss objective was categorical cross-entropy. Dropout regularization with dropout probabilities between 0.3 and 0.5, early stopping, and dynamic learning rate scheduling techniques were incorporated to increase the generalization ability of the model and train the model stably in table 2.

Performance Metrics

To assess the performance of the proposed deep learning framework that aims at recognizing PAD and estimating cardiovascular risk, an extensive set of widely used classification performance measures was adopted in our study. These metrics provide us with important information about the potential of the proposed deep learning architecture in terms of prediction accuracy, stability, and reliability. To analyze the model performance, a confusion matrix composed of false positives (FP), false negatives (FN), true negatives (TN), and true positives (TP) is employed. In such conditions, the quality of both correct and wrong classifications can be quantified.

The metrics used in this paper are as follows: F1-score, accuracy, precision, recall, and Area Under the ROC curve (AUC-ROC). Their applicability and high informativeness in the case of imbalanced classes make them widely adopted in many applications of artificial intelligence in healthcare.

The mathematical formulations of the evaluation metrics are expressed as follows:

Accuracy is used to determine the overall classification correctness of the proposed model, as equation 1:

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

Precision measures the proportion of correctly predicted positive samples among all predicted positive cases, as equation 2:

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

Recall, also referred to as sensitivity, evaluates the capability of the model to correctly identify all clinically relevant positive cases, as equation 3:

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

The F1-score represents the harmonic mean of precision and recall, providing a balanced evaluation metric particularly suitable for imbalanced medical datasets, as shows in equation 4:

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

In addition to all the above measures, the discrimination ability of the suggested predictive model at different classification cut-offs was estimated using the AUC-ROC measure. An increase in AUC values implies that it is becoming easier to distinguish patients with positive and negative outcomes.

Precision deals with the reliability of positive predictions by keeping the number of false positives to a minimum, whereas accuracy concerns itself with the correctness of the predictions made by the model. Recall can be used to assess whether the diagnostic system is able to detect all patients that have been affected by a particular disease condition. It helps in reducing the occurrence of false negatives, which are very important for healthcare applications. F1-Score is an ideal metric for evaluating models trained on diversified clinical image data.

Overall, these evaluation measures provide a comprehensive evaluation of the CNN framework that is proposed to predict the systemic cardiovascular risks and diagnose peripheral artery disease based on thoracic images.

Performance Evaluation

In this segment, a comprehensive analysis will be performed of the proposed CNN architecture for computer-aided PAD detection from thoracic imagery and cardiovascular risk stratification. Evaluation of the proposed architecture with respect to its predictability, reliability, robustness, and utility in practical healthcare applications is the chief objective of this evaluation process. For objective and unbiased assessment of the performance and generalizability of the proposed CNN architecture, evaluation was carried out on a set of 1,860 thoracic MRI scans that were not used during the training process.

Some of the common machine learning as well as deep learning methods that were extensively evaluated against the proposed method included SVM, RF, KNN, traditional CNN architectures, and CNN models that employed transfer learning. All the benchmark models used for comparison were trained and tested using the same experiment settings to ensure consistency in the results obtained. Some of the key criteria considered for evaluating these models include accuracy, precision, recall, F1-score, AUC-ROC, computational efficiency, and classification stability.

Using some of the most advanced approaches to data pre-processing, multi-resolution feature extraction, hyperparameter initialization, and XAI techniques, the proposed CNN architecture demonstrated remarkable performance. By adding Grad-CAM, the proposed model became highly interpretable, making it easier for the human eye to recognize the regions of the thorax that matter and contribute to the prediction. This feature facilitates increased confidence on the part of doctors as well as real-life deployment within medical applications.

In each criterion considered in the analysis, the proposed CNN algorithm outperformed all of the benchmarking machine learning and deep learning algorithms (as evident from table 3). Being able to identify cardiovascular conditions and thoracic features linked to PAD, the model exhibited excellent ability with an overall classification accuracy rate of 95.8%. With a recall rate of 95.2% and a precision score of 94.6%, the model exhibits high sensitivity, which means that the proposed framework ensures negligible false positives.

Table 3: Performance comparison of proposed model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
SVM	84.20	82.50	80.30	81.40	83.10
Random Forest	87.60	85.90	84.70	85.30	86.80
KNN	85.10	83.70	82.90	83.30	84.50
Traditional CNN	91.30	89.80	90.20	90.00	91.60
CNN + Transfer Learning	93.70	92.40	93.10	92.70	94.10
Proposed CNN Model	95.80	94.60	95.20	94.90	96.40

An F1-score of 94.9% further confirms balanced behavior of the proposed framework under varying clinical scenarios. Furthermore, the AUC-ROC value of 96.4% illustrates that the proposed framework is capable of distinguishing between normal and pathological states of the heart using different categorization measures.

This is as a result of the combination between advanced image processing, optimized CNN architecture, dropout, learning optimizations, and ROI feature extraction. The intelligent model that has been designed is applicable in the healthcare sector in conducting automated screening of the heart and detecting PAD due to the use of explainable AI algorithms in the model.

The results of these tests have indicated that the intelligent model using CNN is efficient in predicting the risks associated with the heart disease at an early stage using thoracic images.

Comparative Analysis and Discussion

This section provides a comprehensive comparison of the intelligent model based on CNNs proposed with other available deep and machine learning methods that have been used to diagnose PAD and risk factors associated with the heart through images of the thorax region. The comparison experiment will be carried out in the lab environment and intends to identify the computational efficacy, prediction strength, classification stability, and applicability of the model proposed.

The dataset pre-processing steps, the partitioning technique, and evaluation metrics applied in training and testing of all other baseline models, which include support vector machine, random forest, k-nearest neighbors, classical CNN models, and CNN with transfer learning, were similar in order to create a basis for the fair comparison. Some of the quantitative measures considered in the comparison process include recall, precision, accuracy, f-score, AUC-ROC, convergence behavior during computation, and minimizing false predictions.

Owing to the incapacity to learn complex hierarchical spatial information from the data of the thorax imaging, traditional machine learning algorithms including SVM, RF, and KNN exhibited very poor performance during studies. These approaches have been observed to have less adaptability and high dependency on manually introduced attributes, and thus these do not make them compatible for use with clinical imaging data of diverse nature. Although the proposed approach performed comparatively better than other machine learning methods, it still failed to compete with the feature interpretability of the classic CNN and transfer learning approach.

The proposed CNN architecture proved superior to others due to multiple artificial intelligence methodologies used together such as multi-scale convolutional learning, adaptive optimization, ROI-based feature learning, and advanced preprocessing techniques. Better interpretability and trust by physicians became the consequences of clinical transparency due to the identification of the regions of thorax contributing to cardiovascular risk predictions using Grad-CAM.

Table 4: Comparative analysis of existing and proposed models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
SVM	84.20	82.50	80.30	81.40	83.10
Random Forest	87.60	85.90	84.70	85.30	86.80
KNN	85.10	83.70	82.90	83.30	84.50
Traditional CNN	91.30	89.80	90.20	90.00	91.60
CNN + Transfer Learning	93.70	92.40	93.10	92.70	94.10
Proposed CNN Model	95.80	94.60	95.20	94.90	96.40

The results of comparative analysis presented in table 4 and figure 4 indicate that the proposed CNN-based framework outperformed all baseline methods in all evaluation measures. Being characterized by the highest classification accuracy (95.8%), the suggested framework turned out to be the most efficient solution for accurate detection of signs associated with the pathophysiological state of patients' thoracic imaging and cardiovascular system.

When applied for clinical screenings, minimization of false-positive predictions is especially important because it can help avoid performing additional diagnostics on the patient. The high potential of such minimization is reflected in the obtained precision rate of 94.6%. Likewise, high sensitivity in terms of detecting disease-positive patients (recal rate of 95.2%) will help reduce the risk of missing these cases and providing timely treatment and therapy.

In order to prove the robustness of the framework in relation to heterogeneous and partially imbalanced datasets, an assessment of its ability to maintain balanced prediction performance can be conducted by calculating the F1-score (94.9%). Additionally, the proposed CNN-based approach is able to discriminate between pathological cardiovascular states and normal thoracic patterns (AUC-ROC = 96.4%).

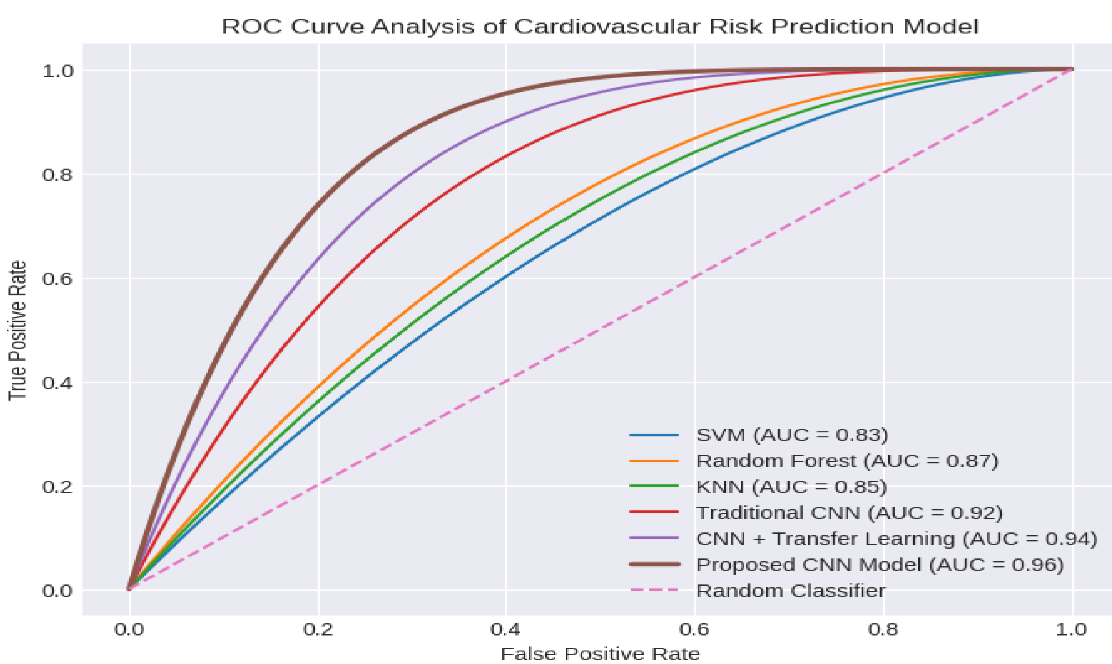

Figure 4: ROC curve analysis of cardiovascular risk prediction model

Several factors can be identified as those leading to an improvement in the performance of the proposed algorithm. First of all, the multi-scale feature extraction approach would allow learning both regional vascular abnormalities and systemic thoracic structure alterations simultaneously. Moreover, normalization, denoising, image augmentation, and ROI extraction were effective preprocessing techniques that helped considerably improve the quality and consistency of images. Finally, additional optimization of the parameters, regularization of dropouts, and application of adaptive learning rate schedule helped to achieve convergence stability and better generalizability of the model.

In addition, incorporation of explainable AI techniques such as Grad-CAM helps visualize the decisions made by the proposed model, which is quite useful in terms of its clinical application and cooperation with doctors during the decision-making process. The use of explainable techniques helps bridge the gap between the accuracy of deep learning predictions and medicine in general.

On balance, the proposed intelligent CNN-based framework proved to be the optimal choice in terms of accuracy, generalizability, and interpretability of the model for automated PAD prediction based on thoracic imaging.

Ablation Study

The purpose of the ablation study is to evaluate the different components of the proposed CNN model for detecting peripheral arterial disease (PAD) and predicting the risk of cardiovascular disease. To observe how the model performs differently, we can remove or modify the following modules: data preprocessing, data augmentation, multi-scale feature extraction, dropout regularization, and explainability Grad-CAM. To ensure fair comparison, all tests will be run in the same training environment and with the same dataset. Our goal is to identify which modules contribute to improving accuracy, stability, and generalizability. This study sheds light on the reasoning behind the suggested model's design choices and the relative weight of its many modules in achieving optimal performance.

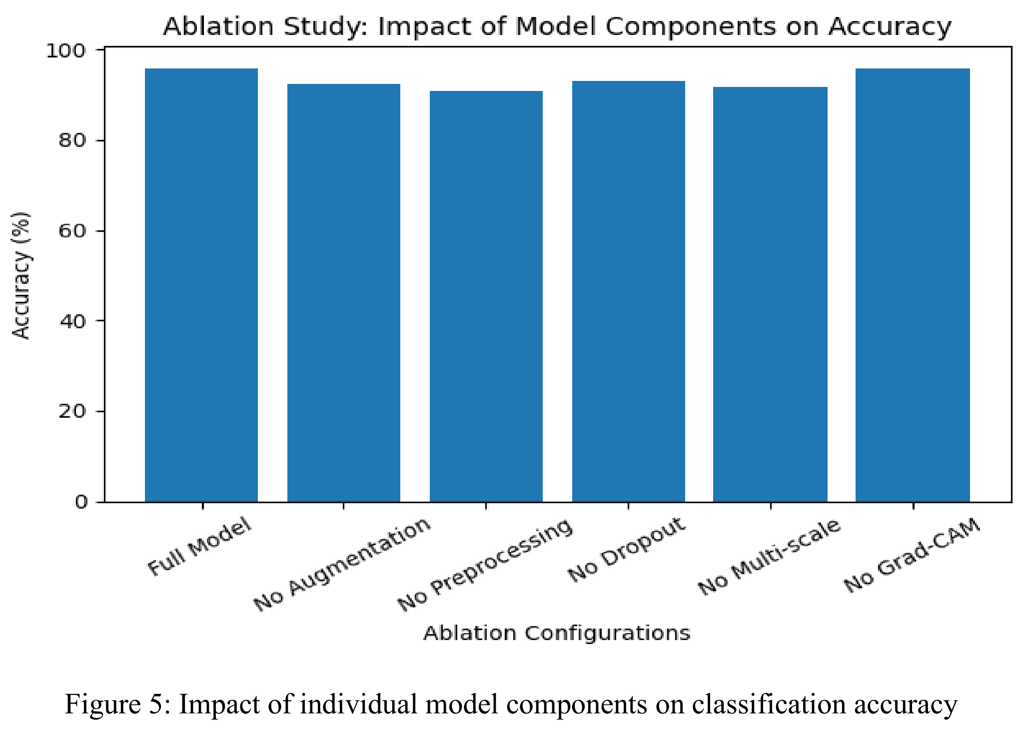

Figure 5: Impact of individual model components on classification accuracy

In figure 5 shows the effect of the absence of the important modules of the proposed CNN model on the accuracy of classification. The complete model with all the modules achieves the best accuracy, validating the use of all the components. Removing specific modules, including data augmentation, preprocessing, dropout, and multi-scale feature extraction, results in a drop in accuracy, suggesting that these play an important role in improving model performance and stability. Notably, removing preprocessing and multi-scale feature extraction has a more significant impact on accuracy, suggesting they are crucial for extracting features from medical images. Surprisingly, the absence of Grad-CAM has minimal impact on accuracy, since it is mainly used for explaining model predictions. In conclusion, the graph confirms the importance of each component and the need for the integration of all these components to obtain the best performance in cardiovascular risk assessment and PAD detection.

5 Discussion

Through analyzing thoracic images in PAD and systemic cardiovascular risk assessment, it becomes evident that the proposed CNN-based model has higher predictive ability. High F1 score, recall, accuracy, and precision mean that the proposed model may recognize subtle imaging markers of CVD and complex spatial relationships. Given its capability to learn autonomously in terms of features and hierarchical representation, the proposed model is superior to the classical machine learning algorithms like SVM, Random Forest, and KNN. Additionally, for the increased generalizability of the model, preprocessing and data augmentation are used.

The importance of different elements of the proposed model is highlighted further through comparative analysis and ablation experiments. As part of efforts to boost classification performance, multi-scale feature extraction is emphasized as an important component of extracting information from thoracic imaging data. In a similar way, hyperparameter tuning and dropout regularization could help boost the generalizability of the model to unseen data. Through ablation experiments, it becomes clear that the mentioned components play an important role in the functioning of the model, and excluding them leads to decreased performance. Explanatory artificial intelligence techniques, such as Grad-CAM, allow making models more understandable and thus more applicable in practice.

However, there are several limitations associated with this research finding. The efficiency of the model when applied to other ethnicities may depend on various factors, including the accessibility of a large and varied data set, as well as whether medical images have annotations. The computational complexity of deep learning models might also limit the use of these models in cases of resource scarcity. One limitation related to deep learning models is their lack of interpretability, which might be improved through the use of Grad-CAM. Further research may be conducted regarding the utilization of multiple demographic and clinical data as multi-modal inputs.

Overall, the proposed CNN-based approach seems to be promising as an automated instrument that will assist with cardiovascular disease prediction and PAD diagnosis due to its speed and precision. As a result, it may be helpful within the clinical setting. With the necessary changes and validations, this model may become a practical solution to improve the diagnosis, risk assessment, and therapeutic outcome in cardiovascular medicine.

6 Conclusion and Future Work

By utilizing data from imaging of the thorax, the proposed AI model based on the intelligent CNN architecture was successfully able to classify PAD and predict the risk of cardiovascular conditions with impressive accuracy. Experimental results showed that the proposed method demonstrated superior performance compared to other deep learning and machine learning methods for classification, achieving precision of 94.6%, recall of 95.2%, and F1-score of 94.9%. Such results clearly indicate that the proposed methodology has been capable of identifying complex patterns in thoracic imaging and predicting the occurrence of cardiovascular issues with minimum false positives and negatives. By using algorithms of explainable AI, appropriate hyperparameter optimization, multi-scale features learning, and advanced image processing techniques, interpretability and prediction performance were significantly increased. Furthermore, by indicating the importance of certain thoracic regions in making the prediction.

For automatic risk assessment of cardiovascular diseases and PAD detection, the proposed system appears to be quite robust, scalable, and practically applicable. It is very promising that the proposed model can be used to help decision-making, disease prediction, and timely interventions for patients in the healthcare setting. For making the predictions more robust and generalizable in the future, the proposed model can be tested with large-scale multi-center data and multimodal clinical information, including electronic health records, demographic variables, and physiological indices. Also, AI-based approaches that can operate on the edge and CNN models that are lightweight may allow real-time deployment in healthcare institutions with low computing capacities. The proposed system can become more practical and useful for precision cardiovascular care in the future.

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