

An Ensemble Deep Learning Framework for Coronary Heart Disease Detection Using Coronary Angiography Images

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ARTICLE INFO	ABSTRACT
Published Online: 29 April 2026	Coronary heart disease (CHD) is one of the most common causes of death and a significant health issue of concern globally. Recent cardiovascular epidemiological studies indicate that the worldwide cardiovascular diseases cause about 17.9 million deaths every year, with coronary heart disease constituting the biggest share of these mortalities. Timely coronary artery abnormalities identification is thus important in enhancing patient outcomes and minimizing mortality. Over the past years, AI and deep learning technologies have made great strides in enhancements to automated medical diagnosis systems, especially in medical imaging applications. Although the deep learning models have been successful in classifying images, individual deep neural network structures tend to lack the ability to be generalised when trained on heterogeneous medical data due to overfitting, model bias, and poorer generalisation. Ensemble learning has become an attractive method to enhance classification accuracy through multiple models and enhance their complementary advantages. This paper presents a deep learning method that uses the ensemble of images to detect coronary heart disease on coronary angiography images. The architecture is a combination of multiple convolutional neural networks models namely ResNet50, VGG16, and EfficientNetB0 to identify and extract meaningful features of the images. Their personal forecasts are then pooled by a majority voting process in order to come up with the ultimate classification output. Evaluation metrics used in assessing the model will include accuracy, sensitivity, specificity, and precision as well as, the area under the ROC curve (ROC-AUC). The suggested solution is likely to provide superior diagnostic accuracy and general performance, in contrast to the conventional single-model solutions. The framework proposed will help cardiologists in the early diagnosis and clinical decision-making to enhance care delivery.
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KEYWORDS: Coronary Heart Disease, Convolutional Neural Network, Deep Learning, Ensemble, Framework	

1. INTRODUCTION

Cardiovascular diseases are some of the most significant Worldwide health issues, and one of the most popular and fatal ones is coronary heart disease (CHD). CHD occurs when arteries in the heart become narrow or blocked by a plaque of atherosclerotic material, thereby reducing the blood supply to the heart muscle (Tang et al., 2023).

Early diagnosis of coronary artery stenosis is critical in minimizing the risk of developing severe complications like myocardial infarction, heart failure and sudden cardiac death.

Traditional diagnostic techniques of CHD are electrocardiography (ECG), echocardiography, and coronary angiography. The best of these is considered to be coronary angiography, as it provides images of the coronary arteries in high resolution and detail (Roth et al., 2020).

Nevertheless, the process of studying angiographic images manually is highly skillful and liable to the presence of inconsistencies and human error. As medical imaging data continues to increase, artificial intelligence has been

embraced more to facilitate automated diagnosis and clinical decision-making (Topol, 2019).

Prior machine learning–based methods considered structured clinical information in order to predict cardiovascular risk. These approaches usually rely on engineered features handcrafted and might have difficulty capturing the nonlinear and nonlinear nature of medical images (Sharma & Verbeke, 2020).

However, deep learning methods (particularly convolutional neural networks (CNNs)) have been a particularly successful approach to image classification, as they learn hierarchical features directly on raw data (Alzubaidi et al., 2023).

Single CNN models may also have issues of overfitting, noise sensitivity, and lack of generalization to new data, despite their strengths. Ensemble learning can help to solve these problems by having several models to increase accuracy and robustness (Sagi and Rokach, 2018).

Based on this, the current paper suggests an ensemble deep-learning model that combines several CNNs to enhance the process of identifying coronary heart disease in coronary angiography images.

2. LITERATURE REVIEW

The latest advancements in artificial intelligence (AI) have greatly enhanced the efficiency of automated medical diagnosis systems, particularly in cardiovascular diseases diagnosis. The use of machine learning (ML) methods, including logistic regression, decision trees, support vector machines (SVM), and random forests, has been a common method to predict heart diseases because of their reliability and interpretability (Abdul et al., 2023; Ahmed et al., 2023). The approaches are sufficiently well-adapted to structured clinical data, and often present very strong baseline performance in predictive medical tasks. However, conventional ML models highly rely on manually crafted features, and thus, they need domain knowledge and may not be sufficient to reflect the complex trends in high-dimensional data, particularly in medical imaging (Alzubaidi et al., 2021).

Deep learning (DL) has emerged as an effective method to overcome these issues, and features are learned automatically with raw data. In particular, it was discovered that the convolutional neural networks (CNNs) are incredibly effective to identify the hierarchical feature representations without manually designing features (Kim et al., 2021). This skill is, in particular, essential in medical imaging, where variations in the image characteristics can result in significant shifts in diagnosis. As a result, CNNs have found widespread applications in tumor detection, retinal diseases classification, cardiovascular analysis (Abimannan et al., 2023).

VGGNet, ResNet, and EfficientNet CNNs have gained popularity in medical imaging classification thanks to their depth and generalisability across a wide range of datasets

(Tan, M., & Le, 2019). CNNs rely on the basic process of convolution that allows one to extract spatial features by performing learnable filters over input images. This operation helps to identify edges, textures and complex structures that are critical to proper diagnosis. The deeper the network, the more abstract and discriminative features CNNs are able to capture, boosting classification performance.

One of the advances in the field of deep learning was the introduction of residual learning in the ResNet architecture that tackles the issue of degradation seen in very deep networks. Residual connections enable models to learn identity mappings to enhance gradient flow during training and empowers the construction of much deeper networks without performance loss (Tjoa and Guan, 2021)(Wang et al., 2021). It is a broadly adopted innovation in medical imaging applications where more detailed architectures are frequently needed to capture more complex disease patterns.

Although the convolutional neural networks (CNNs) have impressive performance, even single-model networks can have the issue of overfitting, sensitivity to noise, and instability, particularly when scholars work with small or unbalanced medical data (Mohammed and Kora, 2023). Such difficulties may inhibit their effective generalization in clinical practice settings. Ensemble learning techniques have become more and more popular in order to overcome these limitations. Ensemble methods can be used to improve the performance of the predictions of various models, minimize the variance, and enhance the overall robustness (Li et al., 2021).

Several ensemble methods, such as bagging, boosting, and stacking, have been effectively applied in medical practice such as prediction of heart diseases. Importantly, the stacking and majority voting have shown excellent performance on the basis of complementary advantages of various deep learning models (Sun et al., 2024). Ensemble systems can also be significantly more accurate and better generalize than an individual model; through the combination of many learners, this property can be particularly valuable in high-stakes settings, such as cardiovascular disease diagnosis.

To conclude, although conventional machine-based learning techniques have a sound foundation in predicting heart disease, deep learning, and particularly CNNs have a better output by extracting features automatically. These models can be enhanced with ensemble learning and thus it is a promising method of developing accurate, robust, and scalable medical diagnostic systems.

3. PROPOSED METHODOLOGY

The proposed model will be developed and evaluated in six main stages:

Phase 1: Data Acquisition and Preprocessing

The data that will be used in this research will consist of echocardiography, angiographic, and computed tomography (CT) heart images that are found in the Kaggle repository.

Each image was preprocessed, such as normalizing pixel intensity values to [0, 1] with a standard normalization method to make them consistent and enhance model convergence. In particular, the research makes use of the Coronary Angiogram Stenosis Dataset that includes a total of 15,330 annotated medical images of two classes, i.e., coronary heart disease (CHD) and normal cases. All the pictures are of the same resolution 512×512 pixels, which makes them compatible with deep learning structures. To train the model and evaluate its performance, the dataset was divided into training (75%), validation (10%), and test (15) subsets and image intensities were normalised to [0,1] using equation (1).

$$I_{\text{norm}} = \frac{I - I_{\min}}{I_{\max} - I_{\min}} \quad (1)$$

I denote the original value, $I_{\min}$ is the minimum value in the dataset, $I_{\max}$ is the maximum value in the dataset and I_{norm} = normalised (scaled) value.

Phase 2: Deep Learning Model Design

Convolutional neural network (CNN) deep learning models of VGG-16, ResNet-50, and

EfficientNet-B0 will be employed to develop the coronary heart disease prediction model. (a) ResNet-50 is selected because its residual connections enable stable training of deeper networks, reducing vanishing gradient issues and improving representation learning in complex medical imaging problems: The residual mapping equation is shown in equations (2) and (3).

$$\begin{aligned} F(x, W) &= W_2 \sigma(W_1 x) \\ y &= \sigma(F(x, W) + x) \end{aligned} \quad (2)$$

x denote the

Input, Weights: W , Activation: σ , Residual: $F(x, W)$, Connection: $x + F(x, W)$, Output: $\sigma(x + F(x, W))$ and W_1, W_2 : Weight matrices. Layer-wise residual propagation shown in equation (4).

$$y_l = F(y_{l-1}, W_l) + y_{l-1} \quad (4)$$

y_l is the layer l output, y_{l-1} : prev. output, W_l : weights, $F(y_{l-1}, W_l)$: residual (+ y_{l-1}).

(b) VGG-16 is included for its strong feature extraction capabilities in medical image classification tasks, where its deep stack of convolutional layers has been shown to capture discriminative patterns in clinical imaging: The convolution operation is defined as in equation (5).

$$y_l = \sigma(W_l * y_{l-1} + b_l) \quad (5)$$

y_{l-1} : Input map to the l^{th} layer, W_l : kernel weights at layer l , $*$: Convolution operation, b_l : Bias term, $\sigma(\cdot)$: Non-linear activation function (ReLU) and y_l : Output map of layer l .

(c) EfficientNet-B0 is incorporated as an efficient yet accurate baseline architecture that achieves competitive performance through compound scaling of network depth, width, and input resolution: adopts equations (6,7, and 8) where: d : depth, w : width, r : resolution, α : depth coeff., β :

width coeff., γ : resolution scaling. coeff., and ϕ : compound scaling.

$$d = \alpha^\phi \quad (6)$$

$$w = \beta^\phi \quad (7)$$

$$r = \gamma^\phi \quad (8)$$

Phase 3: Model Optimisation

All models will be trained using equation (9). Cross-Entropy Loss function.

$$L = - \sum_{i=1}^N y_i \log(\hat{y}_i) \quad (9)$$

where L : Total loss, N : Number of classes, y_i : True label for class i , (usually 0 or 1), $\hat{y}_i$: Predicted probability for class i from the model, $\log(\cdot)$: Natural logarithm function, $\sum$: Summation over all classes, and $-$: Negative sign to ensure loss is positive.

Phase 4: Ensemble Model Development

A majority-voting ensemble (equation (10)) will be applied to improve the model accuracy.

$$\begin{aligned} \hat{y}_{\text{ensemble}} = \arg \max_{c \in \{0,1\}} & \left(\frac{1}{3} \sum_{m=1}^3 P_m(c | x) + \sum_{m=1}^M 1(\arg \max P_m(x) = c) + \right. \\ & \left. \sum_{m=1}^M w_m P_m(c | x) \right) \end{aligned} \quad (10)$$

$\hat{y}_{\text{ensemble}}$: is the final predicted class, and $\arg \max$ selects the class $c \in \{0,1\}$ (0: no disease, 1: disease) with the highest score. Here, x is the input, m indexes the base models, and M is the total number of models. $P_m(c | x)$ is the probability from the model m . The terms represent average prediction, majority voting, and weighted probability aggregation, respectively.

Phase 5: Model Evaluation Metrics

The results of the proposed system will be evaluated and analysed using standard metrics: accuracy, sensitivity (recall), specificity, precision, negative predictive value, F1-score, and area under the ROC curve (AUC-ROC).

Phase 6: Robustness and Sensitivity Analysis

Gaussian noise, Gaussian blur, brightness or contrast adjustment, and geometric rotation will be applied as sensitivity analysis parameters to assess model robustness to noise, detail loss, intensity changes, and spatial transformations. Sensitivity Analysis will be determined using partial derivatives and permutation importance (equations 11–12).

$$S_i = \left| \frac{\partial f(x)}{\partial x_i} \right| \quad (11)$$

Where the sensitivity of the output S_i , is equal to partial derivatives of $f(x)$ and the function x_i is i^{th} input

$$PI_i = Acc_{\text{base}} - Acc_{\text{perm}(i)} \quad (12)$$

Where PI_i is the permutation importance of i , Acc_{base} is the baseline accuracy, and $Acc_{\text{perm}(i)}$ is the accuracy after permuting i .

Computational Environment The Study will use Python with TensorFlow, Keras, and PyTorch.

4. SYSTEM ARCHITECTURE OF THE PROPOSED MODEL

The architecture of the proposed ensemble deep learning framework consists of three major components:

Preprocessing Phase, Classification Phase and Evaluation Phase, as illustrated in Figure 1

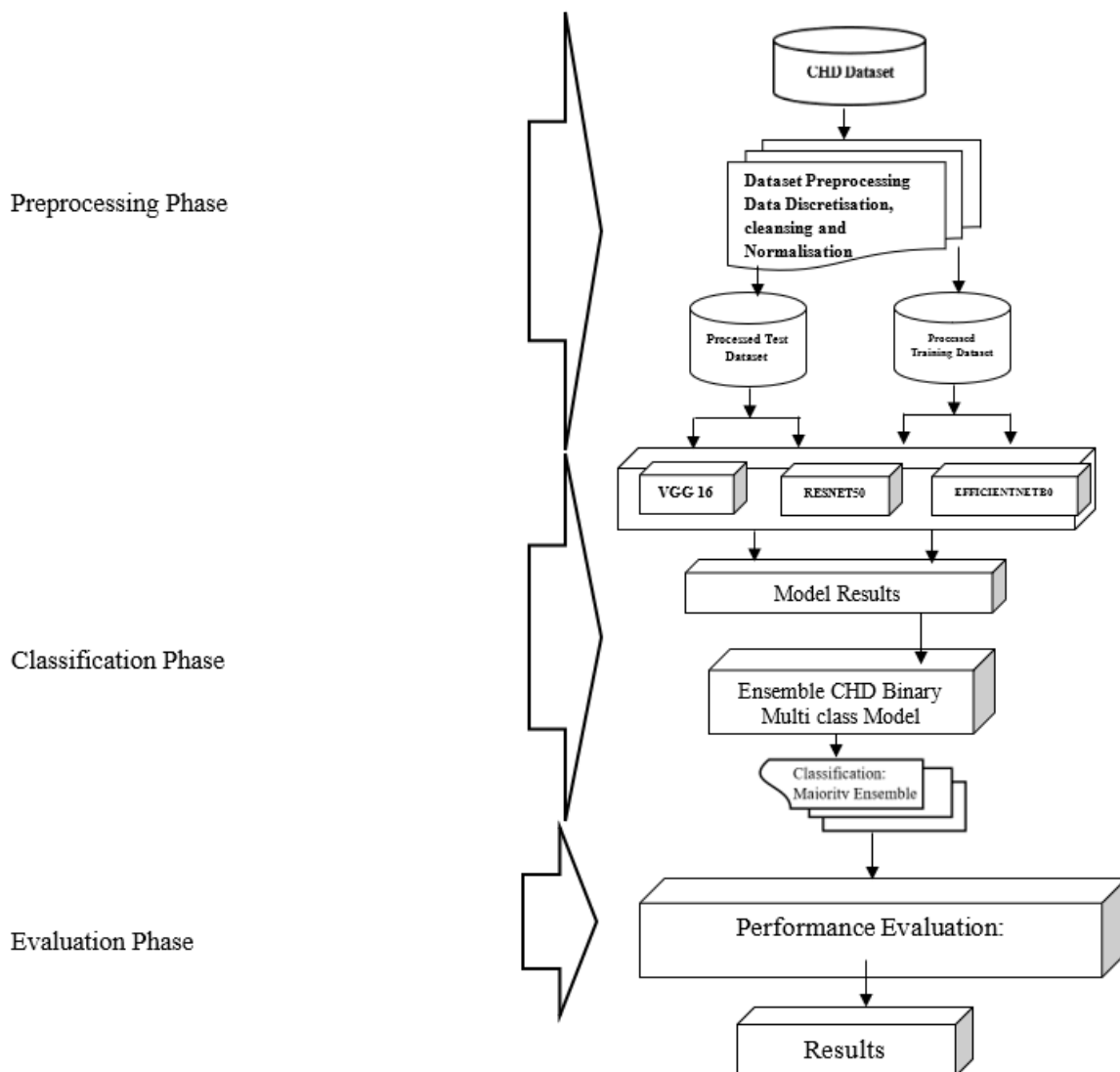


Figure 1: The System Architecture of the proposed model

5. COMPARISON WITH EXISTING CHD DETECTION MODELS

Table:1

Study	Method	Accuracy
Kavitha et al. (2021)	Random Forest	89%
Korial et al. (2024)	Ensemble ML	92.5%
Gupta et al. (2025)	CNN	93%
Yasmeen et al. (2025)	Hybrid ensemble	96%
Proposed model	CNN ensemble	Expected >97%

As table 1 indicates, the accuracies of existing studies depend on the experimental setups, datasets, and evaluation measures used, which can be of various sizes, quality and preprocessing methods. Thus, direct comparison is meant to be read between the lines. It is expected that the proposed model will

achieve a high level of performance (>97%), as achieved through the combination of state-of-the-art convolutional neural network architectures and ensemble learning techniques, to enhance generalisation, decrease overfitting and increase predictive robustness in the detection of coronary heart disease (CHD).

6. CONCLUSION

The sphere of medical diagnosis has changed with the use of artificial intelligence. Deep learning algorithms are well-suited to the analysis of more complicated medical imaging data. Nonetheless, single CNN models might not record the best performance in heterogeneous datasets. Ensemble learning is a valuable approach to enhancing the performance of a model through the integration of predictions made by several models.

The suggested ensemble model is a combination of the ResNet50, VGG16, and EfficientNetB0 models that enhance the accuracy of coronary heart disease detection. The model will be able to offer better classification performance and assist as a sound clinical decision support system.

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