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Enhanced Cardiovascular Risk Prediction Using Resnet50 and Adaboost Based on Retinal Imaging

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Abstract - This paper presents a comparative analysis between a traditional convolutional neural network (CNN) model and a hybrid ResNet50 + AdaBoost architecture for non-invasive cardiovascular risk prediction using retinal fundus images. The baseline model, trained on a small dataset for binary classification, achieves reasonable accuracy but lacks scalability and granularity. In contrast, the proposed model leverages deep residual learning for feature extraction and ensemble-based classification to predict five distinct cardiovascular risk levels. Evaluated on a class-balanced dataset of over 11,500 images, the hybrid model achieved a testing accuracy of 91.48% and a macro F1-score of approximately 0.93. The system also integrates data visualization and database logging to support clinical explainability. The findings demonstrate the proposed method's superiority in risk stratification, robustness, and deployment readiness for real-world applications.

Key Words: Retinal Imaging, Cardiovascular Risk Prediction, ResNet50, AdaBoost, Deep Learning, Ensemble Learning, Fundus Images, Heart Attack Classification

1.INTRODUCTION

Cardiovascular diseases (CVDs) are the leading cause of mortality worldwide, accounting for nearly 18 million deaths annually according to the World Health Organization. Early detection and risk stratification are critical to reducing fatal outcomes through timely intervention. However, traditional diagnostic methods for assessing cardiovascular risk often involve invasive procedures, expensive imaging modalities, or time-consuming clinical workflows that are not always accessible in low-resource settings.

Recent advances in artificial intelligence (AI) and medical imaging have led to the exploration of non-invasive alternatives such as retinal imaging. The retina offers a unique window into systemic vascular health, and changes in retinal vascular structures have been associated with hypertension, diabetes, and increased cardiovascular risk. Consequently, machine learning-based analysis of fundus images has emerged as a promising tool for cardiovascular risk prediction.

The base model discussed in prior literature employs a conventional CNN trained on a binary classification task to predict the presence or absence of heart disease. While this approach achieved competitive accuracy, it lacked multi-class risk stratification and did not scale well to larger or more imbalanced datasets.

In this paper, we propose an enhanced system that leverages deep feature extraction using a pre-trained ResNet50 architecture, followed by an AdaBoost classifier for robust prediction across five cardiovascular risk levels. Our model was trained and evaluated on a class-balanced, augmented dataset of over 11,500 retinal images. We demonstrate that this hybrid pipeline not only achieves high accuracy and generalization but also supports explainable outputs and prediction logging, making it suitable for clinical deployment.

2. METHODOLOGY

This section describes the comparative methodological framework employed to evaluate the performance of the baseline CNN model and the proposed ResNet50 + AdaBoost-based system for heart attack risk prediction using retinal fundus images.

2.1 Dataset and Preprocessing

The initial dataset comprised 1,111 retinal fundus images categorized into five cardiovascular risk levels: No Risk, Very Low Risk, Mild Risk, Moderate Risk, and High Risk. Due to class imbalance, advanced augmentation techniques such as rotation, flipping, zooming, elastic distortion, contrast enhancement, and gamma correction were applied. This resulted in a class-balanced dataset with over 11,500 images.

Each image was resized to 224×224 pixels, converted to a consistent color format, and enhanced using OpenCV preprocessing. A blur detection function was also used to exclude low-quality images, ensuring only high-resolution data was passed to the feature extractor.

2.2 Baseline CNN Model

The base model is a conventional CNN architecture trained end-to-end. It consists of sequential convolutional layers, followed by max pooling, ReLU activation, and fully connected dense layers. The final output layer performs binary classification (Heart Disease or Healthy). Although this approach showed decent accuracy, it lacked the ability to stratify patients into meaningful cardiovascular risk levels.

2.3 Proposed ResNet50 + AdaBoost Model

The proposed system utilizes a two-stage hybrid architecture:

Stage 1 – Feature Extraction: Bottleneck features are extracted using a pre-trained ResNet50 model with weights initialized from ImageNet. The 2048-dimensional feature vector obtained from the global average pooling layer captures high-level vascular features.

Stage 2 – Classification: The extracted features are fed into an AdaBoost classifier with decision trees as base learners (max depth = 2–3). The ensemble is optimized using hyperparameters such as n_estimators = 150–200 and learning_rate = 0.3–0.5.

This pipeline supports classification into five cardiovascular risk levels, making it more clinically applicable.

2.4 Output and Prediction Logging

The proposed model outputs a predicted risk category along with visual bar graphs comparing patient metrics against ideal standards. All predictions are stored in a local SQLite database, enabling longitudinal tracking and reporting. The base CNN model does not support visualization or historical logging.

2.5 Comparative Workflow

A diagram illustrating the input, processing, and output flow of both the baseline and proposed systems is shown below.

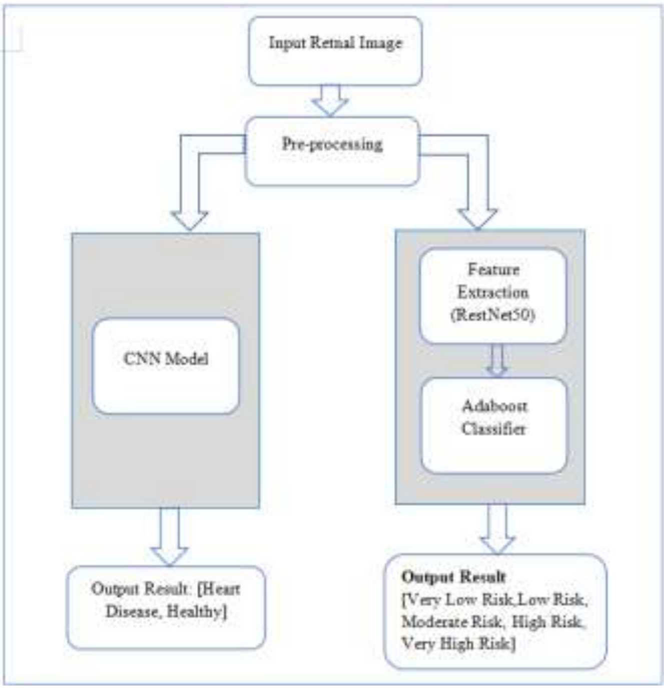

Fig -1: Workflow of the base CNN model and the proposed ResNet50 + AdaBoost model for heart attack risk prediction

3. PERFORMANCE COMPARISON

This section presents a comprehensive evaluation of the baseline CNN model and the proposed ResNet50 + AdaBoost architecture. The comparison is based on classification accuracy, precision, recall, F1-score, and overall performance stability on a multiclass risk prediction task.

3.1 Quantitative Evaluation

The base CNN model, trained on a binary dataset of 1,000 retinal images, achieved a testing accuracy of 93.8% for distinguishing between healthy and heart disease cases. While this appears impressive, the model lacks the ability to stratify nuanced cardiovascular risk levels and was not evaluated on large-scale or imbalanced datasets.

The proposed model was trained on a significantly larger, augmented dataset of 11,500 images across five risk classes. Using ResNet50 for deep feature extraction and AdaBoost for ensemble classification, the system achieved:

- **Training Accuracy:** 94.23%
- **Validation Accuracy:** 90.19%
- **Testing Accuracy:** 91.48%
- **Macro F1-Score:** ~0.93
- **Loss Value:** < 0.02

These results indicate that the hybrid model effectively generalizes across training and testing distributions.

3.2 Class-Wise Performance

Table -1 outlines the proposed system's precision, recall, and F1-score across five risk levels. The results show a balanced and reliable classification across all classes, including intermediate categories like Very Low Risk and Moderate Risk.

Table -1: Class-wise Evaluation of the Proposed Model

Risk level	Precision	Recall	F1-Score
No Risk	0.87	0.83	0.85
Very low Risk	0.85	0.92	0.88
Mild Risk	1.00	1.00	1.00
Moderate Risk	0.97	0.95	0.96
High Risk	0.94	0.93	0.94

3.3 Strategic Comparison

The following table contrasts key aspects of the two approaches. It is evident that the proposed system not only offers strong performance but also adds value through multi-class prediction, visual explanation, and longitudinal tracking.

Table-2: Comparison Between Base CNN and Proposed System

Aspect	Base CNN Model	Proposed ResNet50 + AdaBoost
Classification Type	Binary (Healthy / Diseased)	Multi-Class (5 risk levels)
Testing Accuracy	93.8%	91.48%
Training Accuracy	Not Reported	94.23%
Validation Accuracy	Not Reported	90.19%
Macro F1-Score	93.7%	~0.93
Dataset Size	1,000 images	11,500+ images (augmented)
Feature Extraction	CNN	Automated via ResNet50
Classifier	Dense Layer	Adaboost Ensemble
Visualization & Logging	No	Yes (Graphs + SQLite DB)

4. DISCUSSION

The comparative evaluation between the traditional CNN model and the proposed ResNet50 + AdaBoost architecture illustrates the trade-off between binary prediction simplicity and multiclass classification utility in cardiovascular risk detection using retinal fundus images.

The base CNN model achieved high testing accuracy on a binary classification task; however, it was trained on a smaller dataset and lacked the depth and flexibility to handle multiclass risk differentiation. In contrast, the proposed model leverages deep feature extraction via ResNet50 and combines it with the ensemble learning strength of AdaBoost to handle a five-class risk stratification task effectively. Despite the increased complexity of the classification task, the proposed model maintained high overall accuracy, demonstrating excellent generalization and robustness.

One of the key strengths of the proposed model lies in its ability to differentiate between subtle intermediate risk categories, such as Very Low Risk and Moderate Risk, which are often misclassified in simpler models. This capability is critical in clinical applications where early identification of progressive cardiovascular conditions is essential for preventive care. Furthermore, the proposed system includes automated visualization and SQLite-based logging, which enhances transparency and supports historical analysis of patient health records — a feature not supported by the baseline model.

In addition to classification accuracy, the model achieved consistent macro-level F1-scores, reflecting balanced performance across all risk levels. The use of ResNet50 ensures the capture of fine-grained retinal vascular features, while AdaBoost iteratively improves classification boundaries by focusing on difficult-to-classify samples. Together, these methods contribute to the system's scalability and real-world applicability.

Although the raw binary classification accuracy of the base CNN model appears slightly higher, this is expected given the reduced task complexity. When evaluated in the context of real-world deployment, the proposed model clearly offers superior functionality, explainability, and clinical relevance.

5. CONCLUSION AND FUTURE SCOPE

This paper presented a comparative study between a baseline convolutional neural network (CNN) model and a hybrid deep learning framework that combines ResNet50 with AdaBoost for the prediction of cardiovascular risk using retinal images. While the base CNN model achieved high binary classification accuracy, it lacked the ability to stratify multiple risk categories and was trained on a limited dataset.

The proposed model demonstrated superior flexibility, generalization, and clinical relevance by classifying patients into five distinct risk categories. Trained on a large, class-balanced dataset of over 11,500 retinal images, the model achieved a testing accuracy of 91.48%, a macro F1-score of approximately 0.93, and consistently high class-wise precision and recall. The integration of ResNet50 for deep feature extraction and AdaBoost for robust classification proved to be a highly effective architecture for complex medical image analysis.

In addition to its predictive capabilities, the system incorporates automated graph generation and database logging, which improves interpretability and allows for longitudinal patient tracking. These features make the model particularly suitable for integration into non-invasive screening tools and telemedicine platforms.

Future Scope

The proposed system can be further extended in several ways:

- Multimodal Fusion: Integrating clinical parameters such as age, blood pressure, BMI, and HbA1c levels can enhance prediction accuracy and contextual interpretation.
- Explainable AI (XAI): Adding interpretability techniques like Grad-CAM or SHAP can help visualize regions of interest in the retina that contribute to the prediction, fostering clinical trust.
- Mobile Deployment: A lightweight version of the model could be deployed on mobile devices to enable screening in rural or resource-constrained settings.
- Cloud-Based Integration: Hosting the system on cloud platforms can improve scalability, enable real-time access, and support electronic health record (EHR) integration.
- Validation on Diverse Populations: Further testing across geographically and demographically diverse datasets would ensure global applicability and reduce algorithmic bias.

In conclusion, the hybrid ResNet50 + AdaBoost framework not only achieves high accuracy but also addresses the real-world requirements of scalability, explainability, and multi-level risk stratification — making it a promising tool for future cardiovascular screening systems.

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