Cardiovascular Risk Prediction Using Retinal Images

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Abstract

Cardiovascular disease (CVD) is one of the primary causes of death globally, with a need for early detection and risk stratification to improve patient outcomes. Recent advances in medical imaging and machine learning have made new, non-invasive diagnosis possible. The objective of this research is to use the unique information that retinal vascular structures provide to develop a mechanism for estimating the risk of cardiovascular disease based on retinal imaging. Retinal images are captured, preprocessed for quality enhancement, and subsequently machine learning models are used to identify relevant information. Precise predictions of the risk level are made based on these features, which are indicative of cardiovascular status. The aim of the proposed system is to provide an inexpensive, readily accessible, and efficient early diagnosis tool that will enable timely treatments and reduce the burden of cardiovascular diseases worldwide.

Keywords—Retinal imaging; Convolutional neural networks (CNNs); Deep learning; Feature extraction.

INTRODUCTION

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, accounting for approximately 17.9 million deaths annually according to the World Health Organization (WHO). Early detection and effective risk assessment are crucial for reducing the global burden of these diseases, as timely interventions can prevent complications and improve patient outcomes. Traditional diagnostic methods, such as blood tests, electrocardiograms, and imaging studies, although effective, are often invasive, time-consuming, and resource-intensive. These limitations have driven the need for innovative, non-invasive, and cost-effective approaches to predicting and monitoring cardiovascular risk.

Advances in technology in medical imaging and machine learning have recently made the possibility of solving these problems. One of the most promising approaches to estimating the cardiovascular disease risk of a patient is retinal imaging. The retina, an extension of the central nervous system, provides a unique window to an individual's vascular condition.Systemic illnesses like diabetes, hypertension, and cardiovascular diseases have been associated with alterations in retinal vascular structure like such as patterns of branching, tortuosity, and caliber. Thus, without the necessity for invasive therapies, retinal imaging analysis can provide significant information regarding an individual's cardiovascular status.

Deep learning, specifically convolutional neural networks (CNNs), has shown remarkable performance in image-based applications, such as medical image processing. CNNs are ideal for detecting subtle patterns and abnormalities in retinal images since they can learn hierarchical features automatically from images. CNNs can be employed in building prediction models that can determine the risk of cardiovascular disease effectively by studying retinal photographs. By eliminating the need for human feature engineering, the models facilitate faster and more scalable solutions.

This paper proposes an approach to the prediction of cardiovascular disease risk by combining CNN-based deep learning with retinal photography. Some of the stages in the process include retinal image acquisition, preprocessing, extraction of CNN features, and classification model risk estimation.. Fundus cameras, a very common non-invasive imaging gadget, are utilized to capture retinal images. The retinal images then go through the preprocessing steps so that quality improves and consistency is ensured. Vascular and other features of interest related to cardiovascular health are then extracted from the images within a CNN-based system.A machine classifier that foretells a person's risk

towards cardiovascular disease on the basis of these factors is subsequently trained on these factors, labeling them low-, medium-, or high-risk.

In addition to providing further research for the developing pool of knowledge surrounding artificial intelligence within healthcare, this study shows the manner in which retinal photography can change the assessment of cardiovascular risk.

PROBLEM STATEMENT

With millions of deaths annually, cardiovascular disease (CVD) remains one of the globe's leading causes of death. Successful prevention and timely intervention are contingent upon the early detection of high-risk individuals. Traditional methods for assessing the risk for CVD, such as utilizing clinical information such as blood pressure, cholesterol, and lifestyle factors, at times entail invasive testing or laboratory analysis. They delay the diagnosis of cardiovascular diseases and are not constantly available, especially in low-resource settings. Many of these traditional methods also depend on a set of risk factors, which might miss small but important changes within an individual's cardiovascular status. Retinal images, however, present a unique, non-invasive view into the circulatory system, allowing one to view microvascular changes that can be an indication of general cardiovascular healthAs retinal veins are in direct communication with the vascular system of the body, they can potentially serve as indicators of disease such as diabetic retinopathy, atherosclerosis, and hypertension by acting as markers of underlying disease in the cardiovascular system. To try to bridge this gap, in this research deep learning techniques—specifically, the DenseNet-121 convolutional neural network (CNN)—are utilized to examine retinal images for the estimation of cardiovascular risk. Cutting-edge DenseNet121 model has been known for its efficiency to process and extract intricate visual features from medical images. Applying deep learning automatically, this method examines retinal photographs and identifies pertinent features which are predictive of cardiovascular risk. By doing so, it is seeking to offer a very specific, non-invasive, and inexpensive way of assessing the risk of CVD which can be readily applied in regular clinical practice.

LITERATURE SURVEY

With the advent of deep learning algorithms that can automate analysis as well as provide more accurate analysis, the use of retinal images to predict the risk of cardiovascular disease (CVD) has become extremely popular in recent years. One of the non-invasive, easily accessible ways of measuring a person's vascular health, which is directly related to cardiovascular diseases, is retinal imaging. Numerous studies have investigated the use of deep learning and sophisticated neural networks and machine learning methods to analyze retinal images and predict cardiovascular risk.

One such method is discussed by Zhang et al. (2023), in which a deep learning model is employed to improve stability in CVD risk prediction using retinal images. Their study focuses on the capability of employing deep learning methods to improve the predictability of CVD, noting the improvement in stability and accuracy compared to conventional methods【1】. Likewise, Kujalambal et al. (2023) applied a neural network algorithm to predict heart disease from retinal images and proved that deep learning models are capable of identifying subtle retinal structures associated with cardiovascular risk factors like hypertension and atherosclerosis【2】.

The focus of research is on detecting abnormalities in retinal images that might reflect cardiovascular risk as well as prediction algorithms. As an example, Prakash et al. (2024) utilized deep learning algorithms to classify retinal features linked with cardiovascular disorders to identify retinal abnormalities for predicting CVD【5】. Their study employed a combination of VGG-16 and ResNet-50 models to enhance prediction accuracy. The ensemble approach of these models demonstrated improved generalization and classification performance. The performance comparison of the individual models and the ensemble model is shown in Table 1.

Author	Method	Accuracy (%)	Precision (%)	Sensitivity (%)	F1 Score
Latha and Jeeva (2019)	Majority vote with NB, BN, RF, and MLP	85.48	-	-	-
Ali et al. (2019)	L1 Linear SVM + L2 Linear & RBF SVM	92.22	-	82.92	-
Mohan et	HRFLM	88.4	90.1	92.8	90

al. (2019)					
Repaka et al. (2020)	NB and AES	89.77	-	-	-
Samuel et al. (2020)	ANN and Fuzzy_AHP	91	-	-	-
Proposed Method	Randomized decision tree ensemble	93	96	91	93

Table 1:Comparative Study of Different Methods for Heart Disease Prediction from [5] (Prakash et al.,2024)

In studies such as Mellor et al. (2023), deep learning from retinal images is combined with established risk factors to enhance the prediction of CVD in patients with diabetes. The combination of deep learning and existing risk factors has also been explored. From their prospective cohort study, the predictive accuracy of traditional risk models for diabetes could be enhanced through the use of retinal image analysis【3】. Hu et al. (2023) performed a more extensive study that systematically examined the application of deep learning methods in cardiovascular risk prediction. By integrating the findings of multiple studies, they established that retinal imaging is a promising method for evaluating the risk of CVD. A meta-analysis of the effectiveness of these models in various populations was also part of this review【4】.

Several studies, such as those conducted by Shaikh et al. (2023), have also pointed out the broader application of retinal imaging in heart disease prediction, indicating that due to its cost-effectiveness and ease of use, this method could possibly find itself as a standard screening procedure in the future【6】.

Recent advances have also compared recent clinical risk scores with retinal markers derived from deep learning. A study by Yi et al. (2023) assessed the performance of a deep learning-derived retinal biomarker (Reti-CVD) against established CVD risk scores such as the Framingham Risk Scores and the Pooled Cohort Equations (PCE). According to their study, retinal biomarkers, particularly in multicultural populations, can play a substantial role in the identification of high-risk patients【7】.

Table 2 compares the performance of the Reti-CVD model with three standard cardiovascular disease (CVD) risk assessment tools: the Pooled Cohort Equation (PCE), QRISK3, and the Framingham Risk Score (FRS). Reti-CVD demonstrated strong sensitivity and specificity across different population cohorts, highlighting its potential as a non-invasive screening tool for early CVD detection. The high negative predictive value (NPV) for QRISK3 suggests that Reti-CVD is particularly effective at identifying low-risk patients, thereby reducing false positives and improving patient triage[7].

Risk Tool	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)
PCE	82.7	87.6	86.5	84.0
QRISK3	82.6	85.5	49.9	96.6
Framingham	82.1	80.6	76.4	85.5

Table 2: Comparison of Reti-CVD with Traditional Risk Scores from [7] (Yi et al., 2023)

A study by Abdiakhmetova et al. (2024) introduced a deep learning-based system for identifying cardiovascular diseases from retinal images obtained through Optical Coherence Tomography (OCT). Their model was trained on data from fundus images and used the InceptionV3 convolutional neural network combined with fuzzy k-means clustering for pattern recognition. The system demonstrated a high predictive accuracy of 92%, with specific accuracy rates of 96% for hypertensive retinopathy and retinal artery occlusion. This approach highlighted the advantages of deep learning in detecting early vascular changes associated with CVD, reinforcing the potential of retinal imaging in preventive cardiology【8】.

Moreover, a systematic review of literature applying deep learning to predict cardiovascular predictors from fundus retinal images was conducted by Li et al. (2024), which provided enlightening insight into how such technologies are created and with the capability of complementing routine CVD risk estimations【9】.

Rajan et al. (2020) proposed a deep learning-based system for predicting cardiovascular diseases (CVD) using retinal images by analyzing the cup-to-disc ratio (CDR). The proposed model employed support vector machines (SVM) and artificial neural networks (ANN) for classification, where the CDR was calculated through segmentation of the optic disc and cup. The system involved preprocessing steps such as gray-scale conversion, median filtering, and

multi-level 2D wavelet decomposition to enhance vessel visibility and reduce noise. The extracted blood vessel features were classified into arteries and veins using SVM, and the CDR was computed to assess the presence of CVD. The model demonstrated high accuracy in detecting early signs of hypertensive retinopathy, glaucoma, and other vascular abnormalities. The authors highlighted that the automated nature of this system allows for faster diagnosis and improved accuracy compared to manual methods, reinforcing the potential of retinal imaging for early CVD risk assessment[10].

In addition, in defining the current standards and limitations in the treatment of ASCVD, Alagona Jr. and Ahmad (2015) provided an essential perspective on the assessment and prevention of cardiovascular disease risk. Based on their research, ASCVD imposes significant concern upon public health, as it accounts for over one-third of all United States deaths and remains a leading cause of disability【11】.

From around 150 research papers, Muhammad Mateen et al. (2023) presented a systematic review of the detection of diabetic retinopathy (DR). The collection of retinal datasets, different approaches used for the detection of DR, and the performance metrics used to depict results are all presented in their study. The paper further gives a complete overview of the importance of deep learning-based techniques and outlines the function of assessment metrics in computeraided diagnostic (CAD) systems. To solve the problems in DR detection, authors also suggest directions for future work [12].

As per K. Shankar et al. (2023), the HPTI-v4 model makes use of segmentation alongside feature extraction techniques based on histograms and Inception v4.Inception v4 applies an MLP to the task of classification upon hyperparameter fine-tuning under Bayesian optimization.Most of the test results reflect that the HPTI-v4 model acts remarkably efficiently with 99.49% accuracy, 98.83% sensitivity, and 99.68% specificity. DR image classification model is being advertised as a self-driving diagnosis model. The study also highlights the general health risks of diabetes, such as neuropathy, infection of the retina, renal failure, and hypersensitivity to heart attack and stroke due to diabetic neuropathy and retinopathy [13].

The European Society of Cardiology and the European Atherosclerosis Society created SCORE2 risk prediction equations based on individual-participant data from 45 cohorts in 13 countries. The algorithms apply population-level CVD incidence and distributions of risk factors to recalibrate to model four European risk regions, considering features such as age, sex, smoking status, systolic blood pressure, and lipid profiles. The models performed well in external validation, with Cindices across cohorts ranging from 0.67 to 0.81. The importance of local alterations in cardiovascular risk prediction models is illustrated by the striking regional differences in the predicted 10-year CVD risk [14].

In a study of 50 patients with no cardiovascular disease, Huang et al. (2020) investigated the association between retinal vascular geometry and cardiac anatomy. Transthoracic echocardiography was employed to quantify cardiac structural indices such as the left atrial volume index, left ventricular mass index, left ventricular internal diameter end diastole index, and left ventricular internal diameter end systole index. Geometric vascular parameters such as branching angle, curvature tortuosity, and fractal dimension were investigated using retinal imaging. Multivariate linear regressions controlling for factors such as age, sex, BMI, and comorbidities identified significant associations. For example, increased retinal arteriolar branching angles were associated with each unit increase in heart structural indices. The results highlight the promise of retinal imaging in more comprehensive cardiovascular evaluation by demonstrating that retinal vascular geometry may yield information regarding heart structural alterations [15].

Taken as a whole, these studies demonstrate the ability of deep learning to transform the forecasting of cardiovascular risk. Deep learning models represent a scalable, non-surgical, and cost-effective alternative to traditional risk evaluation tools in that they eliminate the need for the interpretation of retinal images by automating this process. The collective body of evidence supports the reliabilities and accuracies of the techniques as well as their ability to allow for early diagnosis and facilitate early intervention and enhanced patient outcomes.

METHODOLOGY

Data Collection

The dataset used in this study is the Diabetic Retinopathy Detection dataset from Kaggle, which includes

high-resolution retinal fundus images. Although this dataset was originally designed for diabetic retinopathy classification, it is highly suitable for cardiovascular risk prediction due to the shared vascular pathology between diabetic retinopathy and cardiovascular disease. Both conditions are characterized by microvascular dysfunction, including endothelial damage, increased vascular resistance, and abnormal vessel remodeling, which are observable through changes in the retinal vasculature.

The dataset includes left and right eye scans from a demographically diverse patient population, encompassing various ethnicities, age groups, and genders. Each image is annotated with a severity label based on the extent of retinal vascular abnormalities. The original diabetic retinopathy severity labels were mapped onto five CVD risk levels: No Risk, Mild Risk, Moderate Risk, Severe Risk, and Proliferative Risk. The distribution of samples across these five categories is illustrated in Figure 1.

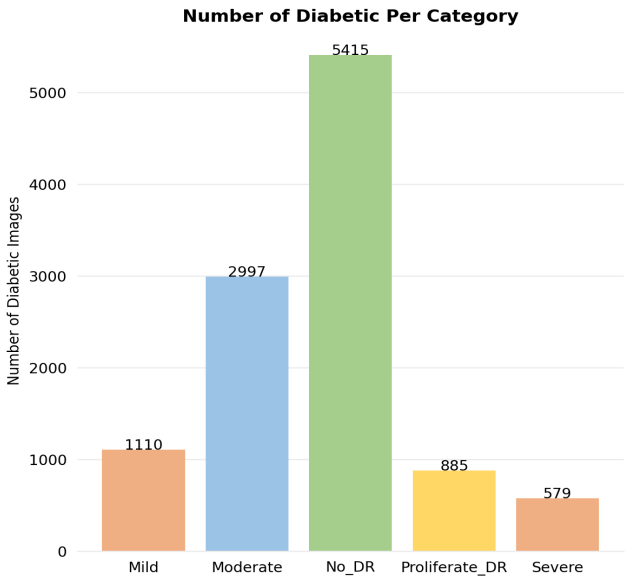

Figure 1: Class Distribution Across Cardiovascular Risk Levels

Data Preprocessing

To ensure consistency across the dataset and enhance the visibility of retinal vascular structures, a structured preprocessing pipeline was applied. All images were resized to **100 × 100 pixels** using bicubic interpolation to match the input dimensions required by the CNN model. Bicubic interpolation computes pixel values based on the weighted average of the 16 nearest neighboring pixels, which helps preserve edge details and vessel morphology more effectively than bilinear or nearest-neighbor interpolation.

Color consistency across the dataset was maintained by setting the color mode to **RGB**. This ensures that the model receives consistent three-channel input, which is critical for learning color-based variations in the vascular structure. Pixel intensities were normalized using z-score normalization to eliminate variations in brightness and contrast caused by different imaging conditions. This transformation ensures that the input data is centered around zero with unit variance, which facilitates more stable and efficient learning during training.

Data Augmentation

To improve the model's ability to generalize across variations in imaging conditions and patient demographics, data augmentation was applied using the imgaug library. Augmentation introduces diversity in the training set, which helps reduce overfitting and improves the model's ability to handle unseen variations.

An augmentation pipeline was defined to apply the following transformations:

- Horizontal Flipping: Each image had a 50% probability of being flipped horizontally. This simulates variations in eye orientation and helps the model become invariant to left–right differences in retinal structures.
- Rotation: Random rotations within a range of −10° to +10° were applied using affine transformations. This improves the model's ability to detect vessels and patterns at different orientations, reflecting real-world variability in imaging conditions.

The augmentation factor was set to 3, meaning that each input image was augmented three times, thereby increasing the effective size of the training dataset by a factor of four (original + 3 augmented versions). Augmented images were saved in a separate output directory using the cv2 library, which ensures that the augmented dataset is readily accessible for training.

Data Splitting

The dataset was split into three subsets: 80% for training, 10% for validation, and 10% for testing. Stratified sampling was applied to ensure that the class distribution remained consistent across all subsets. Stratification prevents the model from becoming biased toward any particular class and ensures that underrepresented categories are adequately represented during training and evaluation. Maintaining the class balance across the splits is crucial for ensuring that the

model generalizes well to unseen data and performs consistently across all cardiovascular risk categories.

Model Configuration

The proposed model is based on the DenseNet121 architecture, a convolutional neural network (CNN) known for its efficient gradient flow and feature reuse. DenseNet121 was selected for its ability to capture complex spatial patterns and its reduced parameter count, making it well-suited for medical image classification tasks. A pretrained DenseNet121 model was initialized with weights from the ImageNet dataset, excluding the top classification layer to allow for task-specific customization. The input shape was defined as 100 × 100 × 3 to match the dimensions of the preprocessed retinal images. The convolutional layers of the base model were frozen to retain the pretrained feature extraction capabilities while reducing the risk of overfitting.

To adapt the model for CVD risk classification, a flatten layer converted the convolutional output into a single vector, followed by a dense layer with 1024 units and a ReLU activation, batch normalization, and a dropout layer with a rate of 0.4. A second dense layer with 512 units and a ReLU activation was followed by batch normalization and another dropout layer with a rate of 0.4. A third dense layer with 256 units and a ReLU activation was added before the final softmax layer, which consisted of five output nodes representing the five CVD risk categories. The softmax activation function generated a probability distribution over the five classes, with the predicted class corresponding to the highest probability value.The model was compiled using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss, which measures the divergence between the predicted class probabilities and the true labels.

Learning Rate Scheduling

A step-decay learning rate scheduler was implemented to dynamically adjust the learning rate during training. The learning rate was initially set to 0.001 and reduced by a factor of 10 after 20 epochs. Lowering the learning rate after the initial phase allowed the model to refine its learning and improve classification performance in the later stages of training. This strategy accelerated convergence in the early training phase while promoting more precise weight updates toward the end of the training process.

Class Weights for Imbalanced Data

To address the class imbalance in the dataset, class weights were computed based on the frequency of each class. The "No Risk" category was overrepresented, while the "Severe Risk" and "Proliferative Risk" categories were underrepresented, leading to potential bias during training. Class weights were calculated using the formula:

$$w_c = \frac{n_{samples}}{n_{classes} \cdot n_c}$$

where $n_{samples}$ is the total number of samples, $n_{classes}$ is the number of classes (5), and n_c is the number of samples in class c. The computed class weights were passed to the model during training to adjust the loss function, ensuring that misclassifications in underrepresented classes were penalized more heavily than those in overrepresented classes. This helped the model learn more balanced decision boundaries and improved sensitivity to minority classes.

Model Training

The model was trained for 30 epochs using a dataset generator with a batch size of 16. Early stopping was applied to prevent overfitting by terminating training if the validation loss failed to improve for five consecutive epochs. The Adam optimizer was used with an initial learning rate of 0.001. A step-decay learning rate scheduler reduced the learning rate by a factor of 10 after 20 epochs to refine weight adjustments in the later training phase.

Class weights were incorporated during training to address the class imbalance. Misclassifications in underrepresented classes were penalized more heavily than those in majority classes, ensuring balanced learning across all five CVD risk categories. The loss function was categorical cross-entropy, which measures the divergence between predicted and true class probabilities:

$$L = -\sum_{i=1}^{N}\sum_{j=1}^{5} y_{i,j} log(\widehat{y_{i,j}})$$

where $y_{i,j}$ is the true label and $\widehat{y_{i,j}}$ is the predicted probability for class j. A confusion matrix was generated to analyze classification performance across the five CVD risk categories.

Model Evaluation

Model performance was evaluated using accuracy, precision, recall, F1-score, and AUC-ROC. Accuracy measured the proportion of correctly classified samples, while precision represented the proportion of true positive predictions among all positive predictions. Recall measured the proportion of actual positive cases correctly identified, and the F1-score provided a balance between precision and recall. AUC-ROC quantified the model's ability to distinguish between positive and negative cases, with higher values indicating better classification performance.

The confusion matrix showed that most samples were correctly classified, with higher accuracy in the "No Risk" and "Moderate Risk" categories due to larger sample sizes. Misclassification rates were higher for neighboring categories, such as "Severe Risk" and "Proliferative Risk," reflecting the clinical challenge of distinguishing similar retinal patterns. The final evaluation confirmed high classification accuracy and improved sensitivity to minority classes due to class weighting.

The performance metrics are defined as follows:

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

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

$$Recall = \frac{TP}{TP+FP}$$

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision+Recal}$$

RESULT

The proposed DenseNet121-based model achieved strong classification performance across all five cardiovascular disease (CVD) risk categories, with stable convergence during training and closely aligned training and validation accuracy curves, indicating effective generalization to unseen data. The highest accuracy and precision were recorded for the "No Risk" and "Moderate Risk" categories due to their larger representation, while the model's sensitivity to minority classes such as "Severe Risk" and "Proliferative Risk" improved significantly due to the use of class weights.

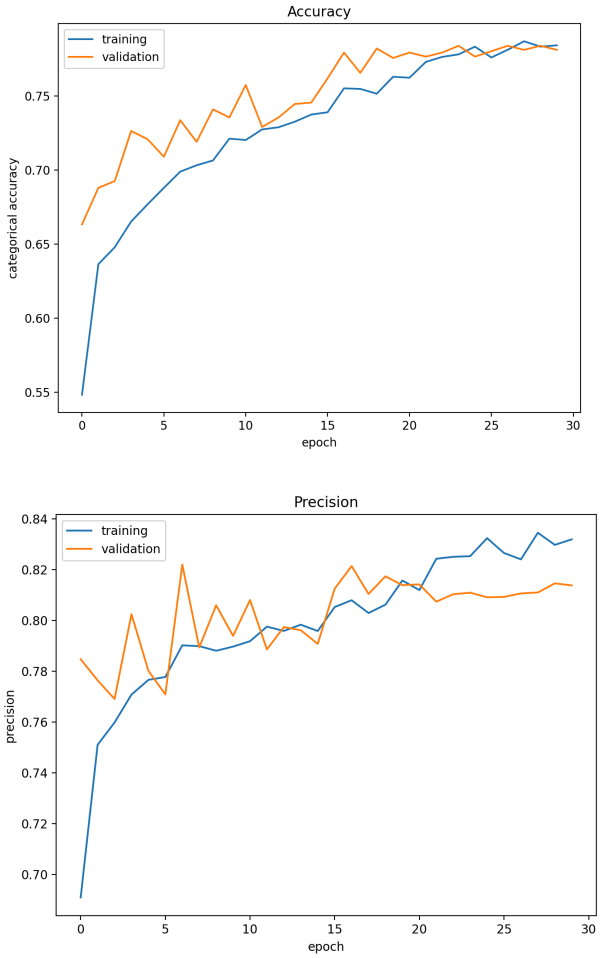

Figure 1: Accuracy and Precision Across CVD Risk Categories

As shown in Figure 1, the model maintained balanced learning across all categories, even with uneven class distribution. The area under the receiver operating characteristic curve (AUC-ROC) exceeded 0.90 for all classes, reflecting strong discriminatory power. Misclassifications primarily occurred between neighboring categories like "Mild Risk" and "Moderate Risk," highlighting the challenge of distinguishing similar retinal patterns. The model's consistent sensitivity and specificity confirmed its robustness in predicting varying levels of cardiovascular risk based on retinal imaging.

CONCLUSION

This work illustrates the viability of retinal imaging and deep learning models in predicting cardiovascular risk. Using DenseNet-121, we effectively learned useful features from retinal images to label individuals into varying risk groups. The new non-invasive technique presents a compelling alternative to the conventional CVD risk assessment protocols, which can potentially enhance accessibility and early diagnosis. Future research will need

to address model accuracy with larger datasets and the incorporation of multi-modal clinical data. Further model interpretability and robustness refinements will also increase its clinical usefulness and reliability.

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