OcuCardio:Retinal Based Cardiovascular Risk Prediction System

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***Abstract*— Cardio Vascular Disease (CVD) is the leading cause of mortality among individuals with Type 2 Diabetes Mellitus (T2DM). Recent clinical evidence suggests that retinal microvascular changes observed in diabetic patients reflect systemic vascular health, providing a non-invasive window into cardiovascular risk. This project proposes a deep learning–based framework for predicting CVD risk specifically using retinal fundus images collected from T2DM patients. Retinal datasets from IDRiD, Messidor-2, and APTOS 2019 were unified and reformulated into a binary cardiovascular risk screening task (Low Risk vs. High Risk). We conducted a comprehensive performance evaluation using multiple advanced architectures, including EfficientNet variants, ConvNeXt, RegNet, ResNext-50 and Transformer-based models (Swin, CoAtNet). Our results demonstrate that these models can effectively capture retinal biomarkers, with top-performing architectures achieving an accuracy of 93% and an AUC-ROC of 0.98. To ensure clinical interpretability, Grad-CAM visualization was implemented to highlight the specific retinal regions driving CVD risk prediction. This approach highlights the potential of retinal imaging as a scalable, cost-effective tool for early cardiovascular risk assessment in diabetic populations, facilitating timely intervention. Furthermore, the predictive performance can be further enhanced by integrating additional clinical data, such as patient history, laboratory parameters, and demographic information.**

***Keywords:*Type 2 Diabetes Mellitus (T2DM), Cardio Vascular Disease (CVD), Retinal Fundus Imaging, Microvascular Biomarkers, Deep Learning, Vision Transformers, Explainable AI (XAI), Risk Stratification, Diagnostic Screening.**

I.Introduction

Cardiovascular Disease (CVD) is a group of conditions that affect the heart and blood vessels and is one of the leading causes of death worldwide. One of the main reasons for CVD is atherosclerosis, where fatty deposits build up inside the arteries. As these deposits increase, the arteries become narrow and blood flow is reduced, which can eventually lead to heart attacks or strokes.

Type 2 Diabetes Mellitus also increases the risk of cardiovascular disease. High blood sugar levels can damage blood vessels over time and weaken the circulatory system. The retina provides a useful way to observe blood vessels because retinal vessels have similar characteristics to the body’s vascular system. Therefore, retinal fundus images can help in identifying early signs of cardiovascular risk in a non-invasive way.

Deep learning models are widely used for analyzing medical images, but many of them work as black-box systems, meaning it is difficult to understand how the model makes its predictions. To improve transparency, Explainable Artificial Intelligence techniques such as Grad-CAM are used. These methods highlight the important regions in an image that influence the model’s decision, helping doctors better understand the results.

To measure the performance of the model, several evaluation metrics are used, including accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC).

TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative predictions.

II.Literacy Survey

1. Syed MG (2023) investigated the use of retinal images as biomarkers for systemic diseases using artificial intelligence. The study used the GoDARTS (Genetics of Diabetes Audit and Research in Tayside Scotland) dataset and applied deep learning models such as VGG16, ResNet50, InceptionV3, DenseNet201, and EfficientNet-B2 to predict health indicators including age, sex, blood pressure, cholesterol, BMI, HbA1c, and diseases like cardiovascular disease, chronic kidney disease, and diabetic complications. The model predicted age with a mean error of 3.95 years and sex with about 81% accuracy (AUC ≈ 0.899). The study also introduced Predicted Age Difference (PAD), where a higher PAD was linked to increased cardiovascular risk and mortality. A multimodal approach combining retinal images with clinical data improved prediction performance. The results suggest that the retina can act as a non-invasive biomarker for detecting

systemic health conditions, though further clinical validation and explainable AI methods are needed.

2. American Diabetes Association Professional Practice Committee (2022) in *"Cardiovascular Disease and Risk Management: Standards of Medical Care in Diabetes"* provides clinical guidelines for preventing and managing cardiovascular disease (CVD) in people with diabetes. The report highlights that individuals with diabetes have a significantly higher risk of heart disease, stroke, and hypertension. It recommends regular screening and management of blood pressure, cholesterol, and blood glucose levels to reduce cardiovascular complications. The guidelines emphasize lifestyle modifications such as healthy diet, physical activity, weight management, and smoking cessation, along with the use of medications like statins, antihypertensive drugs, and antiplatelet therapy when necessary. Overall, the report stresses early risk assessment and comprehensive management strategies to reduce cardiovascular morbidity and mortality in diabetic patients.

3. Mordi et al. (2022) conducted a population cohort study to predict major adverse cardiovascular events (MACE) in individuals with type 2 diabetes using retinal images, clinical variables, and genomic data. The study applied machine learning methods and Cox proportional hazards models to analyze multimodal data. The results showed that the retinal-only model achieved a C-statistic of about 0.68, while adding clinical variables improved the prediction to around 0.72, and the combined retinal, clinical, and genomic model reached approximately 0.75. The findings indicate that integrating retinal biomarkers with clinical and genetic information improves cardiovascular risk prediction, suggesting retinal imaging can serve as a non-invasive biomarker for early cardiovascular risk assessment in patients with type 2 diabetes.

4. Syed et al. (2021) investigated whether cardiovascular risk information obtained from retinal images and genomic data are complementary in individuals with type 2 diabetes. The study used a deep learning CNN model (ResNet-50) to analyze retinal fundus images and compared its predictions with genomic risk scores (GRS) derived from genetic data. The retinal image model achieved an AUC of about 0.67, while the genomic risk score model showed an AUC of around 0.63. When both retinal features and genomic risk scores were combined, the prediction performance improved to an AUC of approximately 0.70. The results suggest that retinal biomarkers and genomic data provide complementary information, and integrating them using AI techniques can improve cardiovascular risk prediction in diabetic patients.

III.Limitations of Existing Systems

Several studies have explored the use of retinal imaging and artificial intelligence for predicting cardiovascular risk in diabetic patients. For example, Syed et al. (2023) demonstrated that deep learning models can identify systemic biomarkers from retinal images. Similarly, Mordi et al. (2022) showed that combining retinal features with clinical and genomic data can improve the prediction of major adverse cardiovascular events in individuals with type 2 diabetes. Another study by Syed et al. (2021) indicated that retinal image–based models and genomic risk scores provide complementary information for cardiovascular risk assessment.

Although these studies demonstrate promising results, several limitations remain. Many previous approaches rely on small or population-specific datasets, which may reduce the generalizability of the models. Some studies also depend on multimodal data such as clinical records and genomic information, which may not always be available in realworld clinical settings. In addition, many deep learning models used in medical image analysis operate as black-box systems, providing predictions without clear explanations, which can reduce clinical trust and interpretability.

IV.Proposed System

To address these limitations, this project proposes a deep learning–based cardiovascular risk prediction system using retinal fundus images from patients with Type 2 Diabetes Mellitus (T2DM). The proposed framework integrates retinal images from multiple publicly available datasets, including IDRiD, Messidor-2, and APTOS 2019, to create a larger and more diverse dataset that improves model robustness and generalization. The problem is formulated as a binary classification task (Low Risk vs High Risk) for cardiovascular risk screening.

The system evaluates several state-of-the-art deep learning architectures, including EfficientNet variants, RegNet, ConvNeXt, ResNext-50, DenseNet-121, and transformer-based models such as Swin Transformer and CoAtNet, to

identify the most effective model for cardiovascular risk prediction. Experimental results show that these architectures can successfully capture retinal biomarkers associated with systemic vascular damage, with the EfficientNet-B5 model achieving the best performance with an accuracy of 93.4% and an AUC-ROC of 0.982.

To improve transparency and clinical reliability, the system integrates Explainable Artificial Intelligence (XAI) using Grad-CAM, which generates visual heatmaps highlighting the retinal regions that influence the model's predictions. Additionally, a user-friendly interface is developed to allow healthcare providers to upload retinal images and obtain immediate cardiovascular risk predictions along with interpretable visual explanations. This approach provides a non-invasive, scalable, and interpretable solution for early cardiovascular risk assessment in diabetic populations.

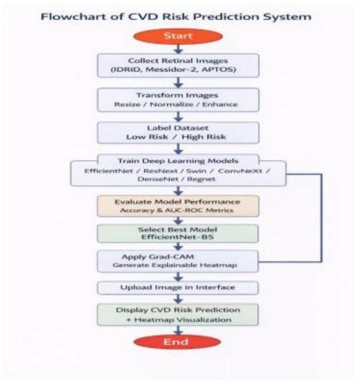


fig 1: Flowchart of the Proposed CVD Risk Prediction System

V.System Architecture

The system architecture presents the overall structure of the proposed cardiovascular disease (CVD) risk prediction framework. It illustrates the main components of the system and the flow of retinal image data through different stages to generate the final prediction. The architecture integrates dataset input, image transformation, deep learning models, explainable AI techniques, and a clinical interface to provide an interpretable CVD risk assessment system.

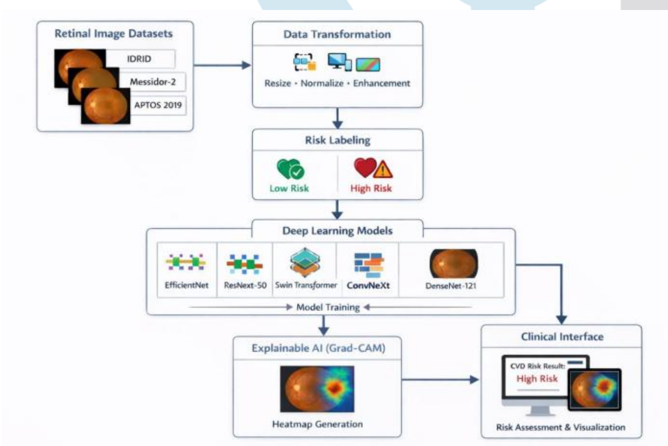


Fig 2: The Architecture of the Cardiovascular risk prediction.

VI.Diagrams

ExplainableAI

Deep learning models are often called "black boxes" because it is hard to see how they make decisions. To make our system more transparent, we used Explainable AI (XAI) through a technique called Grad-CAM.

This tool creates a heatmap over the retinal image, highlighting the exact areas the model focused on. By using XAI, we can confirm that the system is looking at the actual blood vessels to determine heart risk, which helps doctors trust the results.

EfficientNet B5

EfficientNet-B5 uses Compound Scaling. Unlike older models, it balances depth, width, and image resolution perfectly. This allows the model to capture the tiny, high-resolution details of retinal blood vessels. It also uses **Squeeze-and-Excitation** layers, which help the model focus specifically on vascular biomarkers rather than background noise.

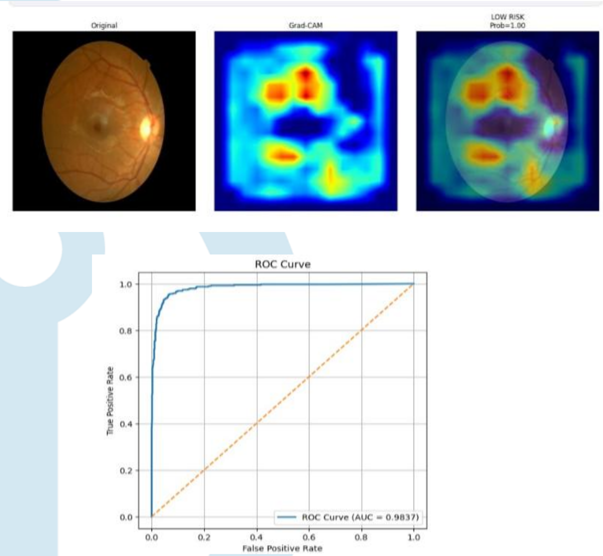


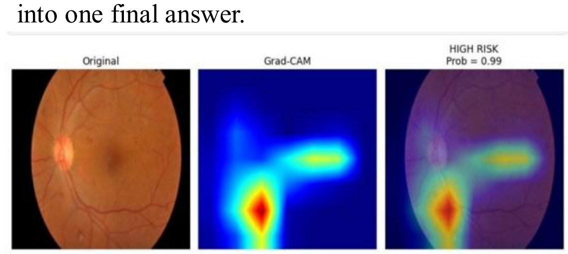
Fig 3: Grad-CAM visualization and ROC Curve of efficientNet-B5 highlighting important Retinal regions used for CVD risk

ResNext

This model uses a **'split-transform-merge'** strategy. It divides the learning process into multiple parallel branches (Cardinality). This allows the network to look at different vessel patterns at the same time, making it very accurate at spotting early signs of heart risk in diabetic patients.

Steps:

1. **Split:** The image of the eye is split into many small, identical paths.
2. **Transform:** Each path looks for something specific—like one path looks for thin vessels, another looks for twists, and another looks for leaks.
3. **Merge:** At the end, they combine all their findings into one final answer.



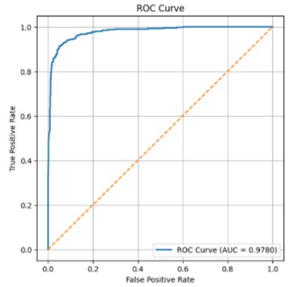


Fig 4: **Grad-CAM visualization of ResNext highlighting important Retinal regions used for CVD risk.**

VII.Results

Table 1: **Results reported in earlier studies for cardiovascular risk prediction using retinal and multimodal data.**

S.No	Study	Data Used	Model / Method	Reported Performance
1.	Syed et al. (2023)	Retinal Images	CNN Model	Age prediction error ≈ 3.95 years, Sex prediction AUC ≈ 0.899
2.	Mordi et al. (2022)	Retinal + Clinical + Genomic	Machine Learning + Cox Model	AUC ≈ 0.75
3.	Syed et al. (2021)	Retinal + Genomic	CNN (ResNet50) + Genomic Risk Score	AUC ≈ 0.70

Table 2: **Results of different deep learning models trained using retinal fundus images**.

S.No.	Model Name	AUC ROC (%)	Accuracy (%)
1.	EfficientNet B3	95.1	87.9
2.	EfficientNet B5	98.2	94.2
3.	EfficientNet V2	95.1	88
4.	RegNetY 32	95.2	88
5.	RegNetY 64	95.4	86
6.	CoAtNet-121	96.0	90
7.	Swin Transformer	96.6	89
8.	ConvNext	96.0	89
9.	ResNest-50	97.47	91.61
10.	DenseNet-121	95.7	86

VIII.Conclusion

In this project, we successfully developed a deep learning framework to screen for cardiovascular risk using retinal images from Type 2 Diabetic patients. By training and comparing multiple architectures, we found that deep learning models can identify complex vascular patterns that are often missed during manual observation. Our results showed that models such as EfficientNet and Vision Transformers are highly effective, achieving a top accuracy of 93% and an AUC of 0.98. To ensure the system is reliable, we used Grad-CAM heatmaps to confirm that the models focus on actual retinal blood vessels when making predictions. Ultimately, this research shows that deep learning is a powerful, non-invasive tool for early CVD risk assessment in diabetic clinics.

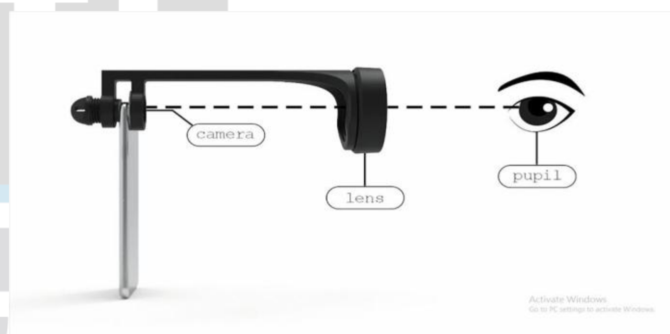
IX.Future Scope

Mobile Screening Tool: We can integrate our deep learning model into a mobile application. By using portable smartphone-based fundus lenses, healthcare workers in rural clinics can capture retinal images and get an instant risk assessment on their phones without needing expensive, bulky hospital equipment.

The Hardware: A clip-on medical lens(D-EYE) that allows the phone to capture high-resolution images of retinal veins.

The Safety: It uses low-intensity LED light to ensure patient comfort and eye safety.

The Goal: This setup replaces expensive hospital machines, allowing health workers in small clinics to screen for heart risk using just a smartphone.



X.References

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