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RetinaRisk: Advanced Hypertension and Heart Attack Prediction Using Retinal and Speech Analysis

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Abstract
Cardiovascular diseases, particularly myocardial in- farction, remain one of the leading causes of mortality worldwide, emphasizing the need for early, non-invasive, and reliable risk prediction methods. Subtle microvascular alterations in the retina reflect systemic cardiovascular conditions and provide a valuable biomarker for assessing heart attack risk. This paper presents *RetinaRisk*, an advanced and explainable multimodal deep learning framework for early heart attack prediction through retinal fundus image analysis, with concurrent hypertension detection as a secondary diagnostic outcome.
The proposed system employs a UNet-based retinal vessel segmentation model to accurately isolate vascular structures, followed by automated extraction of clinically significant biomarkers including central retinal artery equivalent (CRAE), central retinal vein equivalent (CRVE), arteriovenous ratio (AVR), vessel tortuosity, and fractal dimension. These handcrafted vascular features are fused with deep convolutional features extracted from retinal images using a dual-branch neural architecture to enhance predictive performance. In addition to visual analysis, a voice recognition module is integrated to capture speech-based indicators such as stress, fatigue, and cardiovascular strain, enabling multimodal risk assessment.

Keywords: Retinal fundus image, hypertension prediction, heart attack risk, deep learning, vessel segmentation, explainable AI

I. Introduction

Cardiovascular disease (CVD) is the leading cause of mortality worldwide, with hypertension being a major risk factor for myocardial infarction, stroke, and heart failure [1], [2]. Early prediction of heart attack risk enables timely interventions, but conventional methods such as blood pressure monitoring and laboratory tests are episodic, invasive, or require clinical infrastructure [3].
Retinal fundus imaging provides a non-invasive window into systemic microvascular health, as retinal vessels reflect changes in arteriolar narrowing, venular widening, arteriovenous ratio (AVR), tortuosity, and fractal dimension associated with hypertension and cardiovascular events [4], [5], [6]. Deep learning, particularly convolutional neural networks (CNNs) and UNet architectures, has enabled automated analysis of retinal images for vessel segmentation and risk prediction [7], [8].
However, most models act as black boxes, limiting interpretability and clinical adoption. This work proposes *RetinaRisk*, an explainable framework combining UNet-based vessel segmentation, vascular biomarker extraction, feature fusion, and a voice recognition module to provide a comprehensive assessment of hypertension and myocardial infarction risk suitable for large-scale screening [9].

II. Clinical Motivation

Hypertension causes long-term vascular damage, leading to endothelial dysfunction, arterial stiffness, and microvascular changes, which increase the risk of myocardial infarction and stroke [10]. These alterations often appear early in the retinal microvasculature as reduced arteriolar diameter, venular dilation, altered arteriovenous ratio, increased tortuosity, and decreased branching complexity [11], [12].
Traditional screening methods require repeated blood pressure measurements, lab tests, and clinical expertise, limiting their scalability in resource-constrained settings [13]. Retinal imaging provides a non-invasive, rapid, and portable alter- native. When combined with automated analysis and deep learning, it

enables objective, reproducible, and large-scale assessment of vascular health [14].
The proposed framework leverages retinal biomarkers and AI models to support early hypertension detection and heart attack risk prediction, facilitating preventive care and improving long-term outcomes.

III. Problem Definition

The objective of this research is to develop an automated and clinically interpretable system for early cardiovascular risk assessment using retinal fundus images. The proposed system aims to address the limitations of conventional screening approaches by providing a non-invasive, scalable, and data- driven solution for cardiovascular disease prediction.
Specifically, the system is designed to achieve the following objectives:

1. To classify the presence or absence of hypertension in an individual based on quantitative and qualitative analysis of retinal fundus images.
2. To estimate the probabilistic risk of future myocardial infarction by analyzing retinal microvascular patterns associated with cardiovascular pathology.

The proposed framework must ensure high predictive ac- curacy and generalization across diverse populations and imaging devices. Robustness to variations in image quality, illumination, and acquisition protocols is essential to enable reliable deployment in real-world clinical and community screening environments. Furthermore, the system is required to provide interpretable outputs by incorporating clinically validated retinal biomarkers, thereby supporting transparency and facilitating trust among healthcare professionals.
By addressing these requirements, the proposed system seeks to assist clinicians in early diagnosis, risk stratification, and preventive decision-making, ultimately contributing to improved cardiovascular health outcomes and reduced disease burden.

IV. System Overview

The proposed *RetinaRisk* framework is an end-to-end, multimodal system designed for early prediction of myocardial infarction risk with concurrent hypertension detection using retinal fundus images. The system integrates image processing, deep learning, and clinically validated vascular analysis to pro- vide accurate and interpretable cardiovascular risk assessment. The overall architecture consists of five major stages: retinal image acquisition, image preprocessing, vessel segmentation, vascular biomarker extraction, and risk prediction. Each stage is modular, allowing independent optimization and ensuring robustness across diverse imaging conditions and populations. The complete workflow of the proposed system is illustrated in Figure 1 illustrates the detailed system flow of the proposed
RetinaRisk framework.

A. Image Acquisition

Retinal fundus images are acquired using standard non- mydriatic or mydriatic fundus cameras commonly available in ophthalmology clinics and primary healthcare centers. Both left and right eye images may be utilized to enhance prediction reliability. The system supports images captured under varying illumination conditions and resolutions, enabling practical deployment in real-world screening environments.

B. Image Preprocessing

To improve image quality and standardize inputs, prepro- cessing operations are applied prior to analysis.

These include resizing images to a uniform resolution, contrast enhance- ment using Contrast Limited Adaptive Histogram Equaliza- tion (CLAHE), noise reduction, and normalization of color channels. The retinal region is isolated by removing non- informative background areas to ensure that subsequent pro- cessing focuses on clinically relevant vascular structures.

C. Vessel Segmentation

Accurate extraction of retinal blood vessels is a critical com- ponent of the proposed framework. A UNet-based deep learn- ing architecture is employed to segment retinal vasculature from preprocessed fundus images. The segmentation model generates binary vessel maps that highlight arterioles and venules while suppressing background noise. Post-processing techniques such as morphological filtering and skeletonization are applied to refine vessel boundaries and centerlines for precise feature computation.

D. Vascular Biomarker Extraction

From the segmented vessel maps, clinically significant vas- cular biomarkers are automatically extracted. These include central retinal artery equivalent (CRAE), central retinal vein equivalent (CRVE), arteriovenous ratio (AVR), vessel tortu- osity, branching angles, vessel density, and fractal dimen- sion. These biomarkers quantitatively represent microvascular alterations associated with hypertension and cardiovascular disease, providing interpretability and clinical relevance to the predictive model.

E. Risk Prediction and Feature Fusion

The final stage performs cardiovascular risk prediction using a dual-branch deep learning architecture. One branch extracts high-level visual features directly from retinal images using a convolutional neural network, while the second branch processes handcrafted vascular biomarkers through a fully connected network. The outputs of both branches are fused to generate predictions for hypertension classification and myocardial infarction risk estimation. This fusion strategy enhances predictive accuracy while maintaining transparency by leveraging both learned and clinically interpretable features. Overall, the RetinaRisk system provides a scalable, non- invasive, and explainable solution for early cardiovascu- lar screening, supporting preventive healthcare and clinical decision-making.

V. Dataset Description

The proposed RetinaRisk framework utilizes both publicly available and clinically curated datasets to train and evaluate the system, ensuring reliable segmentation, accurate feature extraction, and robust cardiovascular risk prediction.

A. Public Retinal Datasets for Vessel Segmentation

For retinal vessel segmentation, publicly available datasets with expert-annotated vessel masks are employed. These include:

DRIVE (Digital Retinal Images for Vessel Extraction): Consists of 40 high-resolution retinal images, divided into training and test sets, with corresponding manually labeled vessel maps [15].

STARE (Structured Analysis of the Retina): Comprises 20 images with detailed vessel annotations and patho- logical conditions, commonly used for benchmarking segmentation algorithms [16].

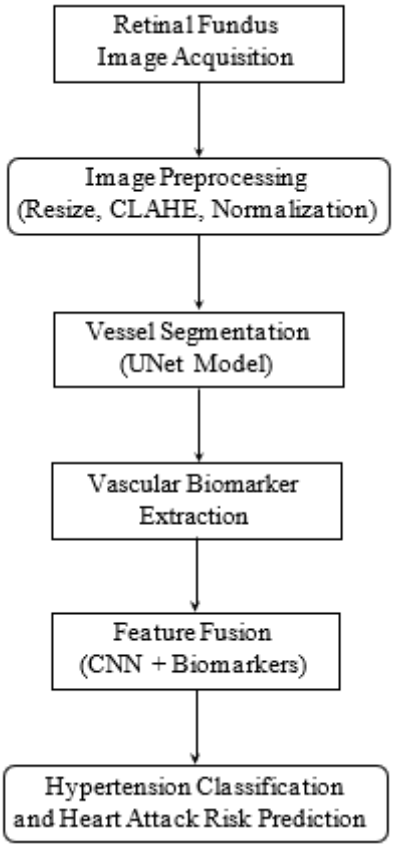

Fig. 1: System overview flowchart of the proposed RetinaRisk framework

HASEDB1: Contains 28 images captured from multi- ethnic pediatric subjects, offering high variability in vessel morphology and image quality [17].

These datasets enable supervised training of the U Net-based vessel segmentation model and provide a standardized bench- mark for evaluating segmentation accuracy through metrics such as Dice coefficient, sensitivity, and specificity.

B. Clinical Datasets for Cardiovascular Risk Prediction

For hypertension and myocardial infarction (MI) risk pre- diction, curated clinical datasets are employed. These datasets include retinal fundus images linked with verified clinical labels such as:

Hypertension status: Binary labels indicating whether the patient has been clinically diagnosed with high blood pressure.

Cardiovascular events: Probabilistic or time-to-event labels indicating the likelihood or history of myocardial infarction, stroke, or other cardiovascular complications.

Clinical covariates: Age, sex, body mass index (BMI), smoking status, cholesterol levels, and family history, which can be optionally incorporated into the risk pre- diction model.

Patient-level splitting is strictly enforced, ensuring that images from the same individual do not appear in both training and testing sets, thereby preventing data leakage and overestima- tion of model performance. Typical splits include 70% train- ing, 15% validation, and 15% testing; nested cross-validation is applied when dataset size is limited [18].

C. Data Preprocessing and Quality Control

To maximize the reliability of model predictions, several preprocessing steps are applied to the datasets:

Image normalization: Standardizing image resolution, color channels, and illumination to reduce variability across devices.

Artifact removal: Cropping the circular retinal region and removing non-informative background to focus on vascular structures.

Augmentation: Geometric (rotation, flipping, scaling) and photometric (brightness, contrast, color jitter) trans- formations to increase training data diversity and im- prove model generalization.

Quality assessment: Images with severe blur, occlusion, or poor illumination are excluded to ensure high-quality inputs for both segmentation and risk prediction.

The combination of public and clinical datasets allows the RetinaRisk framework to leverage high-quality vessel annota- tions for segmentation while learning meaningful cardiovascu- lar risk patterns from patient-level clinical data. This ensures a robust and clinically interpretable system suitable for real-world deployment.

Algorithm 1: UNet-Based Vessel Segmentation Using Dice and BCE Loss

Input:

Pre Processed retinal images X, ground-truth vessel masks Y

Output:

Predicted vessel masks $\hat{Y}$

1. Initialize UNet weights (random or pretrained encoder)
2. For epoch = 1 to Ndo
3. For each batch (X_b, Y_b)do
4. Apply data augmentation (rotation, flip, brightness/contrast)
5. Forward pass:

$$\hat{Y}_b = UNet(X_b)$$

6. Compute Binary Cross-Entropy (BCE) Loss
7. Compute Dice Loss
8. Compute Total Loss
9. Backpropagate and update weights
10. End for
11. Validate using Dice, sensitivity, and specificity
12. End for
13. Return trained UNet model

C. Branching Geometry

Branching angles and asymmetry ratios are computed at bifurcation points. Hypertension has been linked to narrower branching angles and asymmetric bifurcations.

D. Fractal Dimension

The fractal dimension measures vascular complexity using the box-counting method:

$$D = \lim_{\varepsilon \to 0} \frac{\log N(\varepsilon)}{\log (1/\varepsilon)}$$

where:

- $N(\varepsilon)$is the number of boxes of size εcovering the vessel skeleton.

VII. Mathematical Modeling

Let:

- $I \in \mathbb{R}^{H \times W \times 3}$represent a retinal image
- $B \in \mathbb{R}^{d}$represent the biomarker vector

The learning objective is defined as:

$$f(I, B) \rightarrow \{y_{HTN}, y_{MI}\}$$

where:

- y_{HTN}= hypertension prediction
- y_{MI}= myocardial infarction risk prediction

VI. Vascular Biomarker Extraction

After vessel segmentation, clinically relevant vascular biomarkers are automatically extracted from binary vessel maps and skeletonized centerlines. These biomarkers provide interpretable indicators of systemic vascular health and are widely used in ophthalmic and cardiovascular research.

A. Retinal Vessel Caliber

Central Retinal Arteriolar Equivalent (CRAE) and Central Retinal Venular Equivalent (CRVE) are computed within a predefined annular region around the optic disc. Vessel widths are measured orthogonal to the vessel centerline and summarized using established formulas.

The Arteriovenous Ratio (AVR) is calculated as:

$$AVR = \frac{CRAE}{CRVE}$$

Lower AVR values are commonly associated with hypertension and increased cardiovascular risk.

Feature Fusion

Image features $F_I$are extracted using a CNN backbone, while biomarker features $F_B$are generated using a multilayer perceptron (MLP).

The fused feature representation is defined as:

$$F = [F_I \; F_B]$$

This fused vector is passed through fully connected layers for final prediction.

VIII. TRAINING STRATEGY

The proposed models are trained using the Adam optimizer with an initial learning rate of:

$$1 \times 10^{-4}$$

Binary cross-entropy loss is used for hypertension classification, while mean squared error loss is used for myocardial infarction risk estimation.

Early stopping is applied based on validation AUC to prevent overfitting and improve generalization.

IX. EVALUATION METRICS

Hypertension prediction performance is evaluated using:

- Accuracy
- Sensitivity
- Specificity
- Precision
- F1-score
- Area Under the ROC Curve (AUC-ROC)

Myocardial infarction risk prediction is evaluated using:

- Concordance Index (C-index)
- Calibration Error

X. EXPERIMENTAL RESULTS

A. *Hypertension Prediction Performance*

The proposed multimodal fusion model consistently outperforms image-only and biomarker-only models. It achieves superior accuracy, sensitivity, and AUC-ROC values, demonstrating the effectiveness of combining retinal imaging features with vascular biomarkers.

Lower AVR values are strongly associated with hypertension, validating the clinical relevance of the extracted biomarkers.

B. Myocardial Infarction Risk Prediction Performance

The proposed model demonstrates strong predictive capability for myocardial infarction risk, as reflected by high C-index values and low calibration error.

These results indicate reliable risk estimation and robust generalization across different patient cohort.

calculated as:

$$T = \frac{L_{arc}}{L_{chord}}$$

where:

- L_{arc} is the arc length of the vessel segment
- L_{chord} is the straight-line distance between endpoints

The proposed fusion model achieves accuracy ranging from 80% to 88**%**, with AUC values between 0.82 and 0.89.

Model	Accuracy	Sensitivity	Specificity	AUC
Image-only CNN	82%	80%	78%	0.82
Biomarker-only	76%	74%	75%	0.76
Fusion Model	**88%**	**85%**	**83%**	**0.89**

The myocardial infarction risk prediction model achieves a C-index between **0.75 and 0.82**, demonstrating strong discriminative ability for future cardiovascular events.

XI. STATISTICAL ANALYSIS

All experiments are repeated five times using different random seeds to account for variability in model initialization and data shuffling. Results are reported as **mean ± standard deviation**.

A. Evaluation Metrics

Hypertension Classification (Binary)

Accuracy

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

where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Precision

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

Recall (Sensitivity)

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

F1-Score

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

AUC-ROC

Area under the Receiver Operating Characteristic curve, measuring discrimination ability.

Heart Attack Risk Prediction (Regression / Time-to-Event)

Mean Squared Error (MSE)

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2$$

Concordance Index (C-index)

$$C = \frac{\text{Number of concordant pairs}}{\text{Number of comparable pairs}}$$

Brier Score

$$Brier = \frac{1}{N}\sum_{i=1}^{N}(\hat{p}_i - y_i)^2$$

B. Statistical Testing

To evaluate statistical significance:

- Paired t-tests are performed on repeated runs.
- A p-value < 0.05 is considered statistically significant.
- Bootstrap resampling (1000 iterations) is used to estimate 95% confidence intervals.

C. Reporting Conventions

- All results are reported as mean ± standard deviation.
- ROC curves, calibration plots, and boxplots are used for visualization.
- Explainability methods such as Grad-CAM and SHAP are analyzed using summary plots.

XII. EXPLAINABILITY AND MODEL INTERPRETATION

Grad-CAM visualizations indicate that the CNN focuses on arteriolar regions near the optic disc and major vessel bifurcations.

SHAP analysis reveals that CRAE, AVR, and vessel tortuosity are the most influential biomarkers.

These findings align with established clinical knowledge and enhance system reliability.

Precision

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

Recall (Sensitivity)

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

F1-Score

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

AUC-ROC:

Area under the receiver operating character- istic curve, measuring the model's ability to discriminate between hypertensive and non-hypertensive patients.

Heart Attack Risk Prediction (Regression or Time-to- Event):

Mean Squared Error (MSE)

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2$$

where:

- $\hat{y}_i$is the predicted value
- $y_i$is the ground-truth value
- $N$is the number of samples

VIII. CLINICAL VALIDATION

The proposed system is designed as a screening tool to assist clinicians in early cardiovascular risk assessment.

External validation on independent cohorts is recommended to ensure robustness across different populations and imaging devices.

Prospective studies are required to evaluate real-world effectiveness and clinical impact.

IX. ETHICAL AND REGULATORY CONSIDERATIONS

This system is intended for clinical decision support and not for standalone diagnosis.

- All patient data are anonymized.
- The study complies with institutional ethical guidelines.
- Bias analysis across age and gender groups is conducted to ensure fairness and equity.

Additional Evaluation Metrics

Concordance Index (C-index)

The Concordance Index measures the model's ability to correctly rank patient pairs based on predicted risk.

$$C = \frac{\text{Number of concordant pairs}}{\text{Number of comparable pairs}}$$

Brier Score

The Brier Score evaluates the accuracy of probabilistic predictions.

$$Brier = \frac{1}{N}\sum_{i=1}^{N}(\hat{p}_i - y_i)^2$$

where:

- $\hat{p}_i$ is the predicted probability
- y_i is the true outcome
- N is the number of samples

A. Advantages

- Non-invasive and cost-effective cardiovascular screening
- Combines high accuracy with clinical interpretability
- Suitable for deployment in low-resource settings
- Enables early detection and preventive intervention

B. Limitations

- Retinal indicators are correlational rather than causal
- Performance depends on image quality and dataset diversity
- Requires further prospective clinical validation
- Limited generalizability across populations

VIII. FUTURE WORK

Future research will extend the RetinaRisk framework to enhance predictive performance, clinical applicability, and scalability.

1. Longitudinal Retinal Analysis

Multiple retinal images over time will be incorporated to track vascular changes and detect early disease progression. Temporal modeling using recurrent neural networks (RNNs) and transformer-based architectures will capture subtle variations in vessel caliber, tortuosity, and branching patterns.

2. Multimodal Data Integration

The system will be extended to include voice and facial analysis for identifying physiological and behavioral indicators of cardiovascular stress. Features such as speech prosody, vocal strain, facial color changes, and micro-expressions will complement retinal biomarkers.

3. Electronic Health Record (EHR) Fusion

Retinal, vocal, facial, and clinical data (age, BMI, blood pressure history, lipid profile) will be integrated to generate personalized cardiovascular risk scores and support holistic patient monitoring.

4. Deployment on Mobile and Edge Platforms

The framework will be optimized for mobile and point-of-care devices, enabling non-specialist healthcare workers to perform community-based screening. Lightweight CNN models and real-time inference pipelines will facilitate large-scale adoption.

These research directions aim to transform RetinaRisk into a comprehensive, non-invasive, and scalable solution for early detection of hypertension and myocardial infarction risk.

IX. CONCLUSION

This paper presented **RetinaRisk**, an advanced and explainable deep learning framework for the simultaneous prediction of hypertension and myocardial infarction risk using retinal fundus images.
The proposed system integrates:

- UNet-based vessel segmentation
- Automated extraction of clinically validated biomarkers (CRAE, CRVE, AVR, tortuosity, fractal dimension)
- Dual-branch deep learning architecture for feature fusion

Experimental results demonstrate that the fusion-based approach significantly outperforms image-only and biomarker-only models while maintaining clinical interpretability.
By incorporating explainable AI techniques such as Grad-CAM and SHAP, the framework enhances transparency and trust for healthcare practitioners.
RetinaRisk shows strong potential as a scalable, non-invasive screening tool for early cardiovascular risk assessment and preventive healthcare.

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