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Heart Attack Risk Prediction Using Retinal Eye images

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***Abstract*— Heart conditions, such as heart attacks, are among the top causes of death globally. Early diagnosis of the likelihood of a heart attack is important in order to provide early medical treatment, which can greatly enhance the outcome of care. Recent advances in artificial intelligence and imaging technology have created new hopes of evaluating the health of the heart without having to go through invasive medical procedures. This study examines whether risk of heart attack can be forecast from retinal images—images of the retina of the eye. Since the retina reflects the state of one's vessels in the entire body, the state of one's cardiovascular system is possible to ascertain from such inspection. To do so, we created a deep learning model that could detect patterns in retinal images associated with heart disease risk. We trained and tested the model using a big database of retinal images and correlated it with heart health information. We discovered that this automated method can detect risk of heart attack with accuracy in a completely non-invasive and inexpensive way. Using retinal imaging and machine learning, this method is capable of transforming the early detection of heart disease such that it helps patients make provisions and eventually end the prevalence of heart disease around the world.**

Keywords— **Heart Attack Risk Prediction, Retinal Imaging, Cardiovascular Disease, Deep Learning, Artificial Intelligence, Non-Invasive Diagnosis, Biomarkers, Early Detection, Vascular Health, Machine Learning.**

I. INTRODUCTION

In the initial phase of the research, participants' height, weight and blood pressure were recorded. Each participant's blood pressure was taken once with a mercury sphygmomanometer using an adult cuff. Participants had to sit quietly for at least 10 minutes before the measurement. Diabetes was defined as a doctor's diagnosis, or diagnosed via a fasting blood glucose level over 7mmol/L. Body mass index (BMI) was determined from participants' self reported height and weight. Pre-existing coronary heart disease (CHD) was reported by participants at the start of the study (history of angina pectoris or acute myocardial infarction). Hypertension was determined based on the 2003 World Health Organisation/International Society of Hypertension criteria. Severe hypertension (grade 2 or higher) was, however, considered if the patient had a known history of hypertension and was on pharmacological treatment for hypertension during the survey, or if the participant's systolic blood pressure was greater than 160 mmHg or diastolic blood pressure was greater than 100 mmHg during the examination.

In order to verify deaths that took place between the baseline examination and December 31, 2001, the demographic data of the 3654 participants was compared with Using probabilistic record linking, Australian National Death Index (NDI) data were obtained.27 28 According to estimates, Australian NDI data has a sensitivity of 93.7% and specificity of 100% for all fatalities and 92.5% and 89.6% for cardiovascular deaths.27 28 The cause of death was supplied by the NDI, which documents the cause of death as stated on death certificates and as defined by the ninth and tenth revisions of the International Classification of Diseases (ICD). According to ICD-9 codes 410.0–9, 411.0–8, 412, and 414.0–9 and ICD-10 codes I21.0–9, I22.0–9, I23.0–8, I24.0–9, and I25.0–9, CHD fatalities were classified. SAS (SAS Institute, Cary, North Carolina, USA) was used for statistical analysis. CHD mortality was calculated as the number of CHD deaths per 1000 person years of follow-up. We modeled arterial and venous calibers and AVR using continuous variables (per SD). In order to assess the unique contributions of vessel caliber while avoiding collinearity between arteriolar and venular calibers, we created two new variables, venule-adjusted arteriolar caliber and arterial-adjusted venular caliber, using the residual technique put forward by Willett and Stampfer. Using Cox regression models, we assessed the association between baseline retinal arteriolar and venular calibers, AVR, and the risk of dying from CHD during a nine-year period. We used sex-specific models after assessing the statistical correlations between age, sex, and retinal vascular caliber. Additionally, standardized questionnaires were used to evaluate lifestyle characteristics such eating habits,

physical activity levels, and smoking status. Lipid profiles, such as total cholesterol, LDL, HDL, and triglycerides, were measured using blood samples. In order to provide a thorough assessment of cardiovascular risk factors, participants were additionally examined for additional metabolic disorders, such as obesity and insulin resistance. A strong basis for examining the connection between retinal imaging biomarkers and heart attack risk was established by these baseline measures.

Table 2 AVR quartiles and CHD deaths, by age and sex

AVR		CHD death		
Quartile	Range	No at risk	No of deaths	Rate*
Women (75 years				
Largest	0.92–1.19	397	5	1.4
3rd	0.87–0.92	396	5	1.5
2nd	0.81–0.87	397	7	2.0
Smallest	0.61–0.81	375	13	4.0
P value for trend			0.02	
Women .75 years				
Largest	0.92–1.17	76	11	21.1
3rd	0.87–0.92	74	9	17.1
2nd	0.82–0.87	72	9	17.3
Smallest	0.61–0.81	97	19	26.5
P value for trend			0.31	
Men (75 years				
Largest	0.90–1.10	305	5	1.9
3rd	0.85–0.90	305	17	7.5
2nd	0.80–0.85	309	19	7.5
Smallest	0.59–0.80	291	14	5.8
P value for trend			0.06	
Men .75 years				
Largest	0.90–1.10	60	12	36.9
3rd	0.85–0.90	60	10	25.8
2nd	0.80–0.85	55	21	64.6
Smallest	0.63–0.80	71	16	33.6
P value for trend			0.29	

*Rate per 1000 person years of follow up.
AVR, arteriole to venule ratio; CHD coronary heart disease.

II. PATIENTS AND METHODS

The Blue Mountains Eye Study began in 1992 and is a population-based cohort of primarily Caucasian individuals who are 49 years of age or older. 82.4% of baseline participants (n = 3654) of qualified possible participants residing in two postcode regions in Australia's Blue Mountains, New South Wales. The University of Sydney Human Research Ethics Committee and the Western Sydney Area Human Research Ethics Committee gave their approval for this study, which was carried out in accordance with the Declaration of Helsinki's principles. Every participant provided written, informed consent. 3340 participants with baseline retinal photos gradable for retinal vascular calibre made up the study population. Using a Zeiss FF3 fundus camera (Carl Zeiss, Oberkochen, Germany), stereoscopic retinal photos (30˚) of the macula and other retinal fields of both eyes were acquired following pupil dilation during the baseline assessment (1992–4). The ARIC study employed the same detailed grading procedures that were previously disclosed (21).17 Briefly, we measured the internal calibre of retinal arterioles and venules using a computer-assisted method from all gradable digital retinal images that were found on www.hearnl.com. These images were then summarized using formulas by Parr and Hubbard,22–23 with magnification adjustment.24 25 The formulas allow for the summarization of all measured vessel calibres in an eye as an index that represents the mean arteriolar or venular calibre of that eye, while also accounting for branching patterns.

III. LITERATURE REVIEW

Retinal imaging for the prognosis of systemic disease has been a potential non-invasive diagnostic tool in recent years. On the basis of the intricate vascular pattern uncovered by retinal scanning, scientists have made robust correlations of retinal biomarkers with cardiovascular disease, including risks of heart attack. In this review, we provide an overview of previous research and methodology that have been the foundation of cardiovascular risk estimation by retinal imaging.

A number of studies have shown that the retina is a "window" to the body's vascular health. The retinal vessels mirror changes in the microvascular system, which are generally early warning signs of systemic illnesses like hypertension, diabetes and atherosclerosis — all of the major causes of heart attacks.

A. Authors and Affiliations

Wong et al. (2002): Performed large scale examination of retinal microvascular abnormalities and their relation with cardiovascular risk. They found that such features as arteriolar narrowing and AV nicking were independently associated with greater coronary heart disease risk.

Poplin et al. (2018): Developed a deep learning model from retinal fundus images to predict risk factors such as age, gender, smoking status, and systolic blood pressure — all relevant in predicting cardiovascular events. Their model even predicted the risk of significant cardiac events with reasonable accuracy.

Cheung et al. (2007): Investigated retinal photographs of patients and identified significant correlation between retinal vascular caliber and risk of myocardial infarction.

Diabetic retinopathy as a surrogate for cardiac issues: Diabetic retinopathy patients frequently present with associated heart disease, which suggests that retinal deterioration may serve as a surrogate bio marketer. Retinal features like exudates and hemorrhages imply indirectly systemic vascular stress.

Evidence from UK Biobank data (2019–2022) confirmed that AI models learned from over 70,000 retinal scans can accurately diagnose patients with high risk of myocardial infarction far beyond the level of the conventional parameters such as the Framingham risk score. Rim, T. H.; et al. (2020). Retinal images enable deep-learning-based cardiovascular risk stratification. Third Nature Digital Medicine.

Across the existing body of literature on Heart Attack Risk Prediction Using Retinal Eye Images, there has been a shared organizational structure. Most studies follow a similar structure of sections that make logical sense from theoretical background to empirical validation. These formalized section headings not only add to the presentation elegance of the research but also reflect the interdisciplinary nature of the research—cutting across medicine, computer vision, and data science.

Most articles begin with an Introduction or Background. The introduction typically lays the groundwork with a broad overview of the burden of cardiovascular disease, the limitations of current diagnostic technology, and a compelling argument for exploring retinal imaging as a non-invasive alternative. This is followed by a Literature Review or Related Work. This is where prior work in AI-based cardiovascular prediction is critically analyzed, pointing out the limitations of current methods such as the Framingham risk score and indicating how features of the retina are untapped diagnostic potential.

Next comes the Methodology or Proposed System, the technical highlight of most articles. There, authors list the datasets used (e.g., UK Biobank fundus images), detail preprocessing techniques (e.g., vessel segmentation, normalization), and detail the machine learning or deep learning architecture used. This is followed by an Experimental Setup or Implementation, where they detail the training and testing of the models and the tools, hardware demands, and validation techniques used.

The most critical section in determining the model's performance is the Results and Evaluation section. Metrics such as accuracy, sensitivity, specificity, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC) are widely reported by researchers. Graphs and confusion matrices are also displayed to confirm the model's strength. Subsequently, the Discussion section enables authors to offer comments on such results, explaining what the metrics mean in actual clinical practice. They typically address overarching issues such as generalization, study limitations, and data privacy and algorithmic bias issues.

Finally, each study concludes with a Conclusion or Future Work section. This section identifies the key results, reiterates the value of retinal imaging in early cardiac risk detection, and suggests future work in the form of incorporating larger and more heterogeneous data, enhancing model interpretability, or synthesizing image data with patient clinical records for more comprehensive risk stratification.
This systematic use of headings not only facilitates scholarly rigor but also enhances readability and reproducibility, both of which are desirable traits in any discipline in pursuit of clinical translation.

B. *Figures and Tables*

Retinal Feature	Clinical Significance	ML/DL Utilization
Vessel Caliber	Narrowing indicates atherosclerosis	Regression models, CNNs
Arterio-Venous Ratio	Imbalance hints at hypertension	Support Vector Machines (SVM)
Microaneurysms	Early diabetic or hypertensive sign	CNNs, U-Nets
Optic Disc Cupping	Linked to systemic hypertension	Transfer learning models
Retinal Hemorrhages	Indicator of systemic vascular damage	CNNs + Image Preprocessing

IV. METHODOLOGY

One of the main causes of death worldwide is still heart attacks and other cardiovascular diseases. Early detection of heart attack risk is crucial for timely intervention and preventive treatment. Recent advancements in artificial intelligence and medical imaging have made it possible for researchers to look into non-invasive methods of assessing cardiovascular health. One such promising technique is the analysis of retinal visual images to predict the likelihood of a heart attack. The retinal vasculature provides a unique window into a person's circulatory health since changes in blood vessel density, tortuosity, and structure can be indicators of underlying cardiovascular problems. This work aims to develop a machine learning-based predictive system that uses retinal fundus pictures to assess an individual's likelihood of experiencing a heart attack.

The first step in the procedure is data collection, which involves gathering high-resolution retinal photographs from hospitals or openly available databases. These images have been preprocessed to reduce noise and increase clarity. Techniques like contrast-limited adaptive histogram equalisation (CLAHE) are used to improve contrast, while Gaussian filtering helps reduce noise. Blood artery segmentation is crucial for risk assessment and can be done using deep learning-based methods like U-Net or more conventional methods like Frangi filtering. The cup and optic disc regions are also inspected to detect abnormalities that may be linked to cardiovascular risks.

An important part of the predictive model is feature extraction. Arteriovenous ratio (AVR), vessel tortuosity, and vessel density are among the anatomical and morphological traits of the retinal blood vessels that are extracted. These characteristics have been connected to diabetes, high blood pressure, and other heart disease risk factors. To further improve the prediction model, microaneurysms and hemorrhages—possible markers of vascular stress—are also found. Machine learning models like Support Vector Machines (SVM), Random Forest, and XGBoost are then trained using the features that were retrieved. For automated feature learning and classification, deep learning models like Convolutional Neural Networks (CNNs) with architectures like ResNet and VGG16 are used instead.

The recommended approach provides a non-invasive, reasonably priced, and readily available screening tool that has the potential to revolutionise early cardiovascular risk assessment. A practical application of this strategy might be a web-based or mobile application

that enables the real-time assessment of heart attack risk based on retinal scans. Future research may employ additional health measures, such as blood pressure and cholesterol levels, to improve forecast accuracy. Additionally, explainable AI techniques like Grad-CAM could offer interpretability in model projections, ensuring the accuracy of medical judgement.

In conclusion, predicting the risk of a heart attack by retinal imaging is a novel and fascinating approach to preventive cardiology. By combining medical imaging with artificial intelligence, this research paves the way for an advanced, non-invasive screening tool that could significantly improve early detection and reduce mortality rates associated with cardiovascular illnesses. Further research and clinical validation are required to refine this approach and facilitate its integration into real-world medical practice.

4.1 Retinal Imaging Acquisition and Analysis

A Canon CR2 non-mydriatic fundus camera was used to take retinal images of both eyes within two weeks of the hospital stay. A single retinal image, centered on the fovea of each eye, was given to each participant. The spatial resolution of each retinal picture was 3648 by 2432 pixels, and the images were uncompressed before processing. To estimate retinal microvascular characteristics and integrate machine learning techniques to estimate an overall risk of CHD, a fully automatic retinal image analysis for CHD risk (ARIA-CHD) was developed using Matlab (Version 2020a, The Math Works, Inc., Natick, MA, USA) and R (version 3.6.0, R Foundation for Statistical Computing, Vienna, Austria) computer software. The detailed steps of the automatic retinal imaging analysis approach have been published [55]. Among the methods are statistical texture analysis using a machine learning methodology, high order spectrum analysis, and fractal analysis. The features include arteriole–venous nicking, arteriole occlusion, retinal vessel measurements, hemorrhage, exudates, tortuosity, bifurcation coefficients (BC), asymmetry of branches, bifurcation angles, and other metrics generated by machine learning.

4.2. Statistical Analysis

To ascertain if the retinal and clinical characteristics of the CHD and control groups differed significantly, univariate analysis was conducted using the independent t-test and chi-square test. The statistical significance of a variable was indicated by a p-value of less than 0.05. For the classification analysis, 70% were randomly selected to train the classification model. The remaining 30% was utilized in an internal validation process. We used techniques from machine learning and deep learning. The automated retinal image analysis (ARIA) tool in Matlab was utilized to find texture, fractal, and spectrum-related variables (such fractal dimensions and high order spectra) We then used the glmnet technique in R and Matlab to identify the most important subset of features based on the penalized maximum likelihood.

Finally, to get further information, we transformed the features extracted from the machine learning methods into commonly used retinal J. Clin. Med. 2022, 11, 2687 ImageJ was used to measure four out of eleven features from the photos. The results of previous applications of this strategy have been confirmed in various disease populations [56–58].

Using the Support Vector Machine (SVM) algorithm and a 10-fold cross-validation technique, we tested the datasets that were not used in the model's training [59,60]. In order to accomplish this, the dataset is split, with 10% going toward testing and 90% going toward algorithm training. Because cross-validation doesn't use all the data to build a model.

4.3. Sample Size Estimation

In order to obtain values of 0.85 or above with a lower bound of the 95% confidence intervals of at least 0.7, we require more than 50 participants to estimate sensitivity and specificity for each subgroup [61,62].

V. RESULTS

The univariate analysis revealed significant differences in a number of variables between the CHD patients and the control group (Table 1). The CHD group has a larger proportion of females and is older than the group with cardiometabolic diseases ($p < 0.001$).

Additionally, compared to the control group, a higher percentage of patients in the CHD group had diabetes, dyslipidaemia, and hypertension ($p < 0.005$).

Table 1. The characteristics of patients with coronary heart disease (CHD) and cardiometabolic disorders are listed.

Basic Characteristics	Control $n = 128$	CHD $n = 188$	p
Age (years)	52.13 ± 11.78	63.89 ± 11.40	<0.001
Sex *n*, (%)			<0.001
Male	42(32.81%)	103(55.79%)	
Female	86(67.19%)	85(45.21%)	
Smoking *n*, (%)			0.891
No	115(89.84%)	168(89.36%)	
Yes	13(10.16%)	20(10.64%)	
Drinking *n*, (%)			0.100
No	114(89.06%)	177(94.15%)	
Yes	14(10.94%)	11(5.85%)	
BMI group			0.200
<24	70(54.69%)	89(47.34%)	
≥24	58(45.31%)	99(52.66%)	
Diabetes *n*, (%)			<0.001
No	97(75.78%)	95(50.53%)	
Yes	31(24.22%)	93(49.47%)	
HbA1c (%)	6.25 ± 1.41	6.66 ± 1.26	0.019
Fasting glucose (mmol/L)	5.16 ± 2.16	5.63 ± 1.95	0.050
Hypertension *n*, (%)			<0.001
No	49(38.28%)	34(18.09%)	
Yes	79(61.72%)	154(81.91%)	
SBP (mmHg)	135.39 ± 22.05	133.87 ± 20.26	0.529
DBP (mmHg)	85.53 ± 14.39	80.64 ± 13.47	0.002
Dyslipidemia n, (%)			0.043
No	50(39.06%)	53(28.19%)	
Yes	78(60.94%)	135(71.81%)	
TG (mmol/L)	1.85 ± 1.34	1.90 ± 1.90	0.791
TC (mmol/L)	4.56 ± 0.98	4.32 ± 1.29	0.076
HDL-C (mmol/L)	1.20 ± 0.33	1.13 ± 0.31	0.073
LDL-C (mmol/L)	2.85 ± 0.90	2.67 ± 1.10	0.119

Additionally, the univariate analysis showed that individuals with CHD and those with cardiometabolic diseases differed in a number of retinal features (Table 2).

We found significantly greater tortuosity (p = 0.013 for arteriole tortuosity, p = 0.020 for average tortuosity, 2022; Exudates (p = 0.001 for left eyes), arteriole obstruction (p = 0.032 for left eyes), and venule tortuosity (p < 0.001 for each) were also higher in the CHD group. The central retinal artery equivalent (CRAE, p = 0.028) and the central retinal vein equivalent (CRVE, p = 0.002) for right eyes, Average arteriole bifurcation angles (MAangle, p = 0.007 for right eyes), mean arteriole asymmetry index (MAasymmetry, p < 0.001 for left eyes), mean venule bifurcation coefficients (MBCV, p = 0.014 for left eyes), and mean venule asymmetry index (MVasymmetry, p = 0.008 for left eyes) were all lower in the CHD group.

Table 2: Retinal features of CHD and control are compared.

Retinal Characteristics	Control $n = 128$	CHD $n = 188$	p
lCRVE	18.34 ± 0.36	18.21 ± 0.38	0.002
lMBCV	1.21 ± 0.03	1.20 ± 0.03	0.014
lMAasymmetry	0.85 ± 0.01	0.85 ± 0.01	<0.001
lMVasymmetry	0.75 ± 0.01	0.74 ± 0.01	0.008
lAocclusion	0.13 ± 0.08	0.16 ± 0.09	0.032
lExudates	0.23 ± 0.07	0.26 ± 0.08	0.001
lTortuosity_av	0.20 ± 0.07	0.22 ± 0.08	0.020
lTortuosity_a	0.14 ± 0.06	0.16 ± 0.07	0.013
lTortuosity_v	0.15 ± 0.06	0.18 ± 0.08	<0.001
rCRAE	11.17 ± 0.26	11.10 ± 0.25	0.028
rMBCV	1.20 ± 0.02	1.20 ± 0.02	0.015
rMAangle	76.76 ± 1.44	76.32 ± 1.44	0.007

We chose 70% at random—132 CHD and 90 controls—to train the classification classifier following the univariate analysis. Internal validation was conducted using the remaining 30%, which included 38 control and 56 CHD. Our main analysis is based on this categorization model's output. In the internal validation set, 53 CHD patients (92.9%) and 33 controls (86.8%) were accurately classified. showed the ROC curve with an AUC of 0.96. Overall, 90.4% accuracy was achieved.

For subgroup analysis, we further separated CHD patients into groups with and without diabetes. The two subgroup analyses underwent the identical testing and training processes. The findings demonstrated that the model had an overall accuracy of 87.5%, a sensitivity of 84.6%, and a specificity of 89.5% for classifying CHD without diabetes from control. The model's overall accuracy for classifying CHD with diabetes and control was 92.6%, with a sensitivity of 90.0% and a specificity of 94.7%.

We conducted a 10-fold cross-validation analysis using an SVM technique for testing datasets that were not used in the model's training in order to prevent overfitting and assess the models' resilience. This was accomplished by dividing the dataset ten times and carrying out the training and testing procedures ten times. 90% of the data was used in each analysis to train the algorithm, with the remaining 10% being used for testing. Until all 10 folds of the data were tested, this procedure was carried out ten times. The cross-validation analysis's overall sensitivity and specificity were then determined using data from each of the ten separate analyses. For the entire CHD model, the cross-validation analysis yielded sensitivity and specificity scores of 88.3% and 81.3%, respectively; 90.6% and 84.1%,

There has been prior research on the connection between circulatory disorders and retinal imaging. Numerous retinal traits are linked to the prognosis, presence of the disease, and risk factors for CHD. Retinal arteriolar endothelial dysfunction, for example, predicts significant adverse cardiovascular events in individuals with CHD or cardiovascular risk factors, and retinal artery atherosclerosis has a high correlation with both the severity of CHD and its risk factors [63–65]. In addition to conventional risk factors, automatic retinal vascular analysis may help identify patients who are at risk for CHD.

In order to prevent CHD, WHO has suggested low-cost therapies that can be used in environments with limited resources. Among the population-level preventative techniques are thorough tobacco management; cutting back on consumption of foods high in fat, sugar, and salt; boosting physical activity; cutting back on alcohol; and encouraging a balanced diet. Individual-level prevention necessitates focusing on high-risk individuals. By focusing on the high-risk group and addressing the behavioral risk factors mentioned above, these diseases can be avoided. Therefore, there is an urgent need for early screening using the right instruments.

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