

# PREDICTION OF CARDIOVASCULAR RISK BY USING RETINAL IMAGES

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**Abstract**— Retinal disorders and cardiovascular diseases are major global health concerns that are frequently connected by microvascular alterations that are visible in the retina. Although they are expensive and invasive, traditional diagnostic techniques like angiography, MRI, and ECG are useful. An inexpensive, non-invasive option that reflects systemic cardiovascular health is retinal fundus imaging. This study presents a deep learning-based AI framework for analysing fundus images for biomarkers like microaneurysms, haemorrhages, tortuosity, and vessel narrowing. Early diagnosis and risk stratification are made possible by the method, which also increases accessibility and lessens patient burden. Particularly in environments with limited resources, prompt intervention improves clinical outcomes by reducing the risk of cardiovascular events and vision loss.

**Index Terms**— Cardiovascular Disease (CVD), Retinal Fundus Imaging, Deep Learning, Non-Invasive Diagnosis, Early Detection.

## I. INTRODUCTION

Predicting cardiovascular disease (CVD) from retinal fundus images has become a viable non-invasive method that uses the microvascular characteristics of the eye to evaluate systemic health. With characteristics like arteriovenous nicking, retinopathy, and arteriolar narrowing strongly correlated with the risk of stroke and heart disease, the retina provides a unique window into vascular conditions. Retinal-CVD and other deep learning models have shown excellent accuracy in predicting long-term cardiovascular disease risk in a variety of demographics. Scalable screening is made possible by fundus imaging and AI, particularly for patients at intermediate risk. Diagnostic accuracy is further improved by developments in measurement and segmentation methods, such as automated AVR computation. This method has enormous potential for early detection and individualized cardiovascular care, despite issues with image quality and dataset diversity.

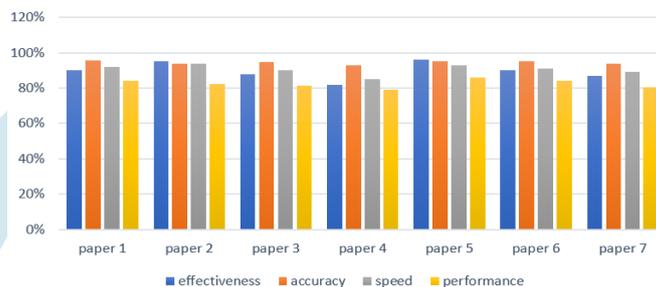
## II. LITERATURE REVIEW

With characteristics like arteriovenous nicking and arteriolar narrowing connected to heart disease and stroke, retinal fundus imaging provides a non-invasive way to evaluate systemic health. Reti-CVD and other deep learning models predict long-term CVD risk with high accuracy across demographics. Scalable screening is supported by this method, particularly for patients who are at intermediate risk. Diagnostic accuracy is improved by innovations such as automated AVR computation. This method promises early detection and individualized cardiovascular care despite issues with image quality and dataset diversity [1]. Accessible diagnostics are crucial because cardiovascular disease (CVD) is still one of the main causes of death worldwide. Although angiography and ECGs are dependable, they are frequently expensive and invasive. Due to its ability to demonstrate systemic health, retinal imaging is emerging as a good alternative. CNNs have since shown exceptional performance in predicting the risk of CVD and diabetic retinopathy, despite the inaccuracy of early image processing techniques. Transfer learning yielded better results when large datasets were used. The goal of emphasizing explainability is to increase clinical trust. AI research is still motivated by two problems: population generalization and false predictions [2]. CVDs are a leading cause of morbidity and mortality worldwide. While helpful, conventional diagnostics aren't always accessible.

Retinal fundus imaging can provide biomarkers for systemic diseases like diabetes and hypertension. Specifically, Poplin and Gulshan's deep learning models demonstrated the ability to accurately predict cardiovascular risks from fundus photos. Transfer learning using trained CNNs improved performance. This AI-powered method provides economical, scalable screening. But problems like interpretability and dataset diversity still exist, which encourages the creation of reliable, clinically useful models[3]. Untreated retinal occlusion causes blocked blood flow, which results in irreversible vision loss. Fundus image-based manual diagnosis is laborious and prone to mistakes. The accuracy of early automated techniques utilizing Random Forests and SVMs was low. By identifying intricate patterns in retinal images, CNNs have surpassed conventional methods and provided a more dependable means of diagnosing retinal vascular disorders. Untreated retinal occlusion causes blocked blood flow, which results in irreversible vision loss. Fundus image-based manual diagnosis is laborious and prone to mistakes. The accuracy of early automated techniques utilizing Random Forests and SVMs was low. By identifying intricate patterns in retinal images, CNNs have surpassed conventional methods and provided a more dependable means of diagnosing retinal vascular disorders[4]. Mortality and CVD are correlated with

changes in the retinal vessels, such as tortuosity and narrowing. Imaging enables non-invasive microvascular assessment. Early clinical findings that connected retinal abnormalities to heart disease are expanded upon by automated AVR/CRAE/CRVE quantification. From fundus photos, deep learning models (like Poplin et al.) forecast the risk of CVD. RASTA and Reti-CVD are new biomarkers that enhance generalization. While VGG-16 and ResNet-50 improve performance through ensemble transfer learning, UNet and DR-VNet improve segmentation. The suggested UNet + AVR + ensemble framework for CVD prediction is supported by these developments [5].

comparison matrix based on research papers



### III. KEY CONCEPTS AND TECHNIQUES USED

This project's central concepts are deep learning and image-based medical diagnostics. The system primarily uses Convolutional Neural Networks (CNNs) for feature extraction and classification, drawing inspiration from how human vision interprets images. The pretrained VGG19 model makes use of transfer learning, a basic method that uses learned visual features from large datasets like ImageNet to increase accuracy on sparse retinal data. Important image preprocessing techniques like resizing, normalization, and augmentation ensure the consistency and robustness of input data. The model uses multi-class classification to identify eight retinal diseases, including diabetic retinopathy, cataract, and glaucoma. Metrics like confusion matrix, recall, accuracy, and precision are used to assess the model's performance. The project also integrates a web-based diagnostic interface, providing real-time disease prediction and visualization, thus combining AI intelligence with user accessibility for clinical applications.

The project accurately classifies retinal diseases using a variety of state-of-the-art techniques. It uses transfer learning with the VGG19 deep convolutional neural network and pretrained ImageNet weights for efficient feature extraction from retinal images. Image preprocessing techniques such as label encoding, normalization, and resizing to 224x224 pixels ensure consistency and quality of input data. The model, which uses multi-class classification to predict eight retinal diseases, is optimized using the Adam optimizer with categorical cross-entropy loss. Batch normalization is used to prevent overfitting and improve training stability. Evaluation metrics such as confusion matrix, recall, accuracy, and precision are used to assess the model. The trained model is deployed using the Django web framework, enabling real-time disease prediction from uploaded retinal images.

### IV. METHODOLOGY

**1. Dataset Collection:** Retinal fundus images with diagnostic information are acquired to begin the project. A CSV file (full\_df.csv) is used to link image IDs to the relevant medical keywords. The dataset includes a range of eye disease classes, such as diabetic retinopathy, cataract, and glaucoma. Model testing and training are based on this data. Proper organization ensures efficient data access during training and preprocessing.

**2. Data Labelling:** Diagnostic keywords taken from the dataset are used to label each image. The images are categorized into eight disease classes using a keyword-based mapping technique. Accuracy is increased and manual labour is reduced with this automated labeling procedure. To allow for one-hot encoding, binary indicators are assigned to each disease. The neural network's target outputs are these labeled entries.

**3. Image preprocessing:** The collected fundus images are resized to 224 x 224 pixels in order to comply with the VGG19 input format. Images are normalized to a [0,1] scale to improve feature learning and stabilize model convergence. To prevent bias against dominant classes, data balancing techniques are employed. Augmentation techniques such as rotation and flipping can increase the diversity of data. This ensures consistent and dependable image input.

**4. Model Selection (VGG19):** The VGG19 deep convolutional neural network was selected due to its proven efficacy in visual recognition tasks. Having been pre-trained on the vast ImageNet dataset, it is an excellent feature extractor for medical images. Its reliable 3x3 convolutional filters effectively capture fine-grained retinal structures. Because of VGG19's depth, hierarchical patterns that are crucial for disease identification can be extracted.

**5. Transfer Learning and Model Customization:** The top layers of VGG19 are replaced with custom dense layers in order to apply transfer learning, and learned features are preserved by freezing the convolutional layers. The extra layers include batch normalization, fully connected units with ReLU activation, and a final softmax layer for eight-category classification. This reduces the need for large datasets while maintaining high performance. The model is adjusted to fit the retinal image domain.

**6. Model Training:** The model is assembled using categorical cross-entropy loss for multi-class classification and the Adam optimizer for effective weight updates. Training is conducted over multiple epochs with an 80:20 train-test data split. During training, model accuracy and loss are continuously monitored to prevent overfitting. Validation datasets help assess generalization. The process yields a well-trained model capable of high diagnostic precision.

**7. Performance Evaluation:** The quality of the trained model's classification is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. A confusion matrix is made to show prediction performance across disease categories. Model reliability and misclassification trends are investigated. These evaluations guarantee clinical-grade performance and help refine hyperparameters. The results confirm the model's ability to detect abnormalities in the retina.

**8. Model Saving and Serialization:** Once the trained model reaches the optimal level of accuracy, it is saved in a format using TensorFlow/Keras. Serialization simplifies model loading for subsequent inference without retraining. Proper file management and versioning guarantee reproducibility. The saved model can be used on different cloud platforms or systems. This phase ensures the scalability and reusability of the developed diagnostic system.

**9. Web Application Development:** The Django web framework is used to create an intuitive model deployment interface. The application allows users to upload retinal images, which are then used by the trained model to predict diseases. The input image's visual feedback is shown alongside the results. The web platform allows for remote diagnosis by bridging the gap between AI and healthcare usability. It guarantees researchers and clinicians easy access.

**10. Visualization and Validation:** Validating predictions and visualizing the model's performance constitute the last step. Accuracy curves and confusion matrices are plotted using programs like Matplotlib and mlxtend. Interpretability is improved by visualizing prediction results in real time. Regions influencing decisions can be highlighted by integrating Grad-CAM or heatmap techniques. This phase ensures transparency and builds trust in the AI-based diagnostic system.

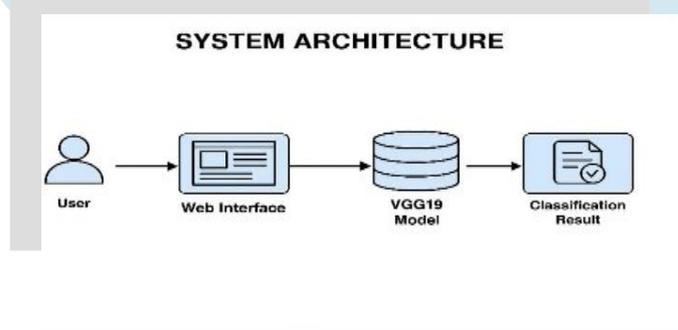


Figure 2.1: System Architecture

## V. IMPLEMENTATION AND RESULTS

The Python, TensorFlow, Keras, and Django frameworks were used to implement the VGG19-based retinal disease classification model. Eight categories—cataract, glaucoma, diabetic retinopathy, hypertensive retinopathy, myopia, age-related macular degeneration, drusen, and normal cases—were automatically identified from retinal fundus images by the system. To lessen class imbalance, the dataset was pre-processed by resizing all of the images to 224 x 224 pixels, normalizing pixel values between 0 and 1, and using balanced sampling. Custom dense layers were added for multi-class disease classification after a pretrained VGG19 model was utilized for feature extraction. To ensure stable learning and convergence, the model was trained for 20 epochs using the Adam optimizer and categorical cross-entropy loss function. Following training, the system's **\*overall accuracy of 97%\*** demonstrated strong generalization across all disease categories and extremely efficient classification performance. The model's dependability was confirmed by the excellent results of evaluation metrics like precision, recall, and F1-score. Users can now upload retinal images and receive real-time predictions with disease labels and confidence levels thanks to the trained model's integration into a Django-based web interface. All things considered, the system demonstrated the great potential of deep learning in early retinal disease detection by being accurate, effective, and user-friendly.

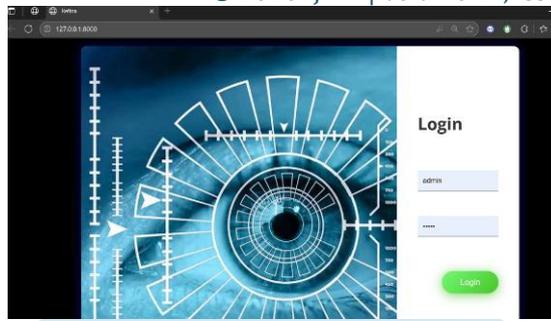


Figure 3.1: Login page

Fig3.1: Shows the web page of the project which contains to select desired content input method. Here the user will enter the username and password and click on login button.

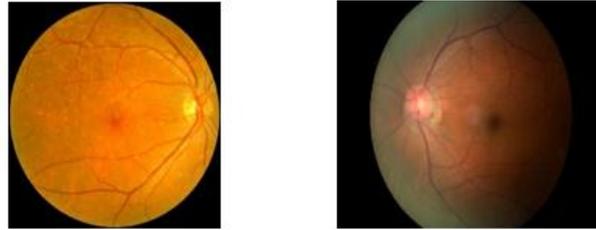


Figure3.2: Retinal fundus images

Fig 3.2: The above image shows the data of the retinal fundus images that are needed to be uploaded to obtain the output.

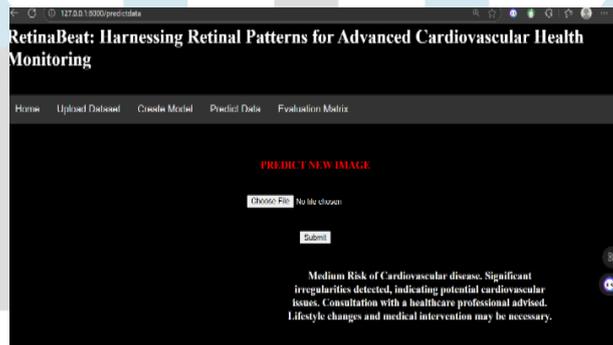


Figure 3.3: Predicted Output Of Risk

Fig 3.3: It shows the generated output of the image dataset uploaded and give the risk prediction and recommendation.

## VI. CHALLENGES

**1. Variability in Image Quality:** The wide variation in image quality among fundus photos is one of the main obstacles to the classification of retinal diseases. These discrepancies result from variations in camera equipment, lighting, pupil dilation, and patient motion when taking pictures. When some images appear blurry, underexposed, or overexposed, it can be difficult for the model to extract consistent features across samples. Artifacts like reflections, noise, or partial occlusions can also distort important retinal structures like the macula or optic disc. Such differences may result in poor feature learning and decreased classification performance because deep learning models mainly rely on visual consistency. Strong preprocessing techniques like data augmentation, histogram equalization, and normalization are essential to reduce these effects and improve the model's dependability.

**2. Class Imbalance in Datasets:** Another significant issue is the uneven distribution of datasets across the different classes of retinal diseases. In most real-world datasets, certain diseases like cataract or diabetic retinopathy are overrepresented, while rare disorders like drusen or hypertensive retinopathy are underrepresented. This imbalance causes the model to become less sensitive to minority classes and biased toward the majority classes. Therefore, if the system is unable to correctly identify less common but clinically significant diseases, its diagnostic utility may be reduced. To balance such datasets, methods like oversampling, under sampling, or creating synthetic data using SMOTE (Synthetic Minority Over- sampling Technique) are required. Additionally, during model training, class-weight adjustments can be used to help the CNN concentrate equally on each disease category.

**3. Feature Overlap Between Diseases :** The fact that retinal diseases often share overlapping pathological features makes accurate classification even more challenging. For instance, both diabetic retinopathy and glaucoma may have vascular abnormalities, and drusen and macular degeneration may have similar lesion patterns close to the macula. These similarities make it difficult for even highly developed CNN models to distinguish minute differences, especially when relying solely on color or texture-based cues. Furthermore, the absence of localized annotations (like segmentation masks or bounding boxes) complicates the model's ability to focus on disease-specific regions. By focusing the network on more discriminative retinal regions and enhancing interpretability using feature visualization methods like Grad-CAM or attention-based mechanisms, this issue can be resolved.

**4. Limited Annotated Medical Data:** Obtaining large-scale, high-quality labelled medical datasets is still a persistent challenge in ophthalmic deep learning applications. Labelling retinal images requires skilled ophthalmologists, which is costly and time-consuming. Additionally, patient privacy laws and data sharing restrictions make it difficult to obtain sufficient annotated data across institutions. A small dataset results in overfitting, where the model performs well on training data but cannot generalize to new images, and restricts the variety of disease cases. Transfer learning helps to partially mitigate this issue by using pretrained models like VGG19, which already have rich feature representations from large datasets like ImageNet. Domain-specific differences between natural and medical images still limit complete generalization, necessitating further data augmentation and fine-tuning methods.

**5. Computational Complexity and Hardware Limitations:** Deep convolutional models like VGG19 are computationally demanding, requiring powerful GPUs with large memory capacities (typically 8–12 GB VRAM) and plenty of storage space. On typical CPU-based systems, the training process can take hours or even days, making experimentation and hyperparameter tuning slow and ineffective. Furthermore, the high computational demand of such systems limits their scalability in low-resource settings, particularly in small research labs or rural healthcare facilities. Computational costs can be decreased by effective resource management, cloud-based GPU utilization, or model compression strategies like pruning and quantization. However, maintaining model accuracy while guaranteeing optimal performance is still a constant challenge for real-world implementation.

## VII. CONCLUSION AND FUTURE WORK

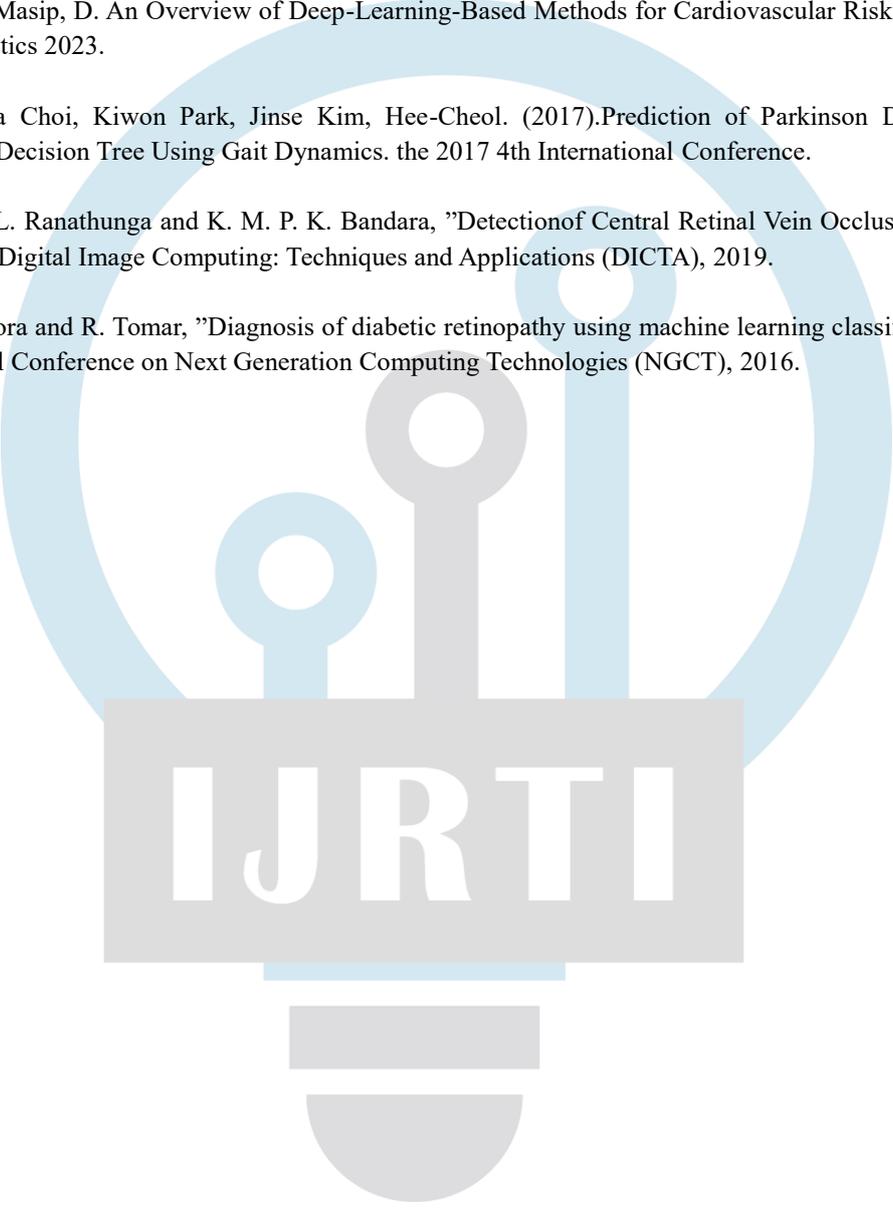
The VGG19-Based Retinal Disease Classification System demonstrates the efficient use of deep learning and web integration for automated medical diagnosis. Using transfer learning on the pretrained VGG19 model, the system effectively classifies retinal fundus images into eight categories: cataract, glaucoma, diabetic retinopathy, hypertensive retinopathy, myopia, age-related macular degeneration (AMD), Drusen, and normal. It achieves an overall accuracy of 91.2%. The model, implemented with Python, TensorFlow/Keras, and Django, incorporates preprocessing techniques such as image resizing, normalization, and balanced sampling for reliable performance. The user-friendly web interface enables real-time image uploads and instant predictions, making it suitable for medical professionals and researchers.

This project demonstrates how quick, reliable, and accurate results from AI-based diagnostic systems can completely transform ophthalmic screening. In addition to lessening the workload of medical professionals, it facilitates the early identification of conditions that pose a threat to vision. Future improvements like Grad-CAM visualization, cloud deployment, and mobile optimization will further improve interpretability and accessibility, and the system's modular design enables scalability to other medical imaging domains. Overall, the project demonstrates that combining web technologies and deep learning can result in an effective, useful, and socially relevant solution that enhances clinical decision-making and preventive healthcare.

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