



Cardiovascular Risk Prediction From Retinal Images Using Vision Transformer

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Abstract: Cardiovascular diseases are among the leading causes of death worldwide, making early diagnosis essential for effective treatment and prevention. This paper presents a deep learning-based approach for predicting heart disease risk using retinal fundus images and a Vision Transformer (ViT) model. The proposed system utilizes the RFMiD2 retinal image dataset, where images are pre-processed through resizing, normalization, and binary classification. Unlike traditional Convolutional Neural Networks (CNNs), the Vision Transformer divides images into patches and employs a self-attention mechanism to capture both local and global retinal features. Transfer learning with a pre-trained ViT model improves feature extraction and enhances performance on a limited medical image dataset. The model is trained using the Adam optimizer and Cross-Entropy Loss for binary classification. A Streamlit-based web application is developed to provide an interactive interface for uploading retinal images and generating predictions with confidence scores. The proposed model achieved an accuracy of 98.62%, demonstrating its effectiveness in identifying retinal patterns associated with cardiovascular risk. This framework offers a non-invasive, cost-effective, and AI-assisted screening solution that can support healthcare professionals in the early detection of heart disease and highlights the potential of Vision Transformers in medical image analysis.

Keywords: Heart Disease Prediction, Retinal Fundus Images, Vision Transformer (ViT), Deep Learning, Transfer Learning, Medical Image Classification, Artificial Intelligence, Early Disease Detection, Loss ,Accuracy.

I. INTRODUCTION

Cardiovascular diseases (CVDs) are among the leading causes of death worldwide and pose a major public health challenge. According to the World Health Organization (WHO), millions of people lose their lives each year due to heart-related diseases, highlighting the importance of early diagnosis and timely treatment. Traditional methods for detecting heart disease often involve invasive procedures, expensive diagnostic equipment, and specialized medical expertise, making early screening difficult in many healthcare settings. Therefore, developing a non-invasive, accurate, and cost-effective diagnostic approach has become an important area of research. Recent advances in medical imaging and artificial intelligence have shown that retinal fundus images can reveal valuable information about cardiovascular health. The retina contains a network of blood vessels that reflects changes associated with systemic diseases, including hypertension, diabetes, and heart disease. These retinal biomarkers can be analysed using deep learning techniques to assist in the early prediction of cardiovascular risk. Convolutional Neural Networks (CNNs) have been widely used for medical image classification due to their ability to automatically extract visual features. However, CNNs mainly focus on local image patterns and may not effectively capture long-range relationships within retinal images. Vision Transformers (ViTs), based on the self-attention mechanism, overcome this limitation by dividing an image into patches and learning both local and global feature dependencies, resulting in improved feature representation and classification performance. This paper presents a Vision Transformer-based framework for predicting heart disease using retinal fundus images from the RFMiD2 dataset. The proposed system performs image preprocessing, transfer learning, model training, and binary classification to identify the presence or absence of heart disease. A user-friendly Streamlit web application is also developed to provide real-time prediction and confidence scores from uploaded retinal images. Experimental results demonstrate that the proposed approach achieves high classification accuracy, making it a promising AI-assisted, non-invasive solution for early heart disease screening and supporting healthcare professionals in clinical decisionmaking.

The key contributions of this work are:

- Vision Transformer Model: A transfer learning based ViT framework for accurate heart disease prediction using retinal fundus images.
- Automated Data Processing: A preprocessing pipeline that organizes and prepares the RFMiD2 dataset for binary classification.



- Interactive Prediction System: A Streamlit-based web application that enables real-time retinal image upload and heart disease prediction.

Performance Evaluation: Experimental analysis demonstrating high classification accuracy (98.62%) and the effectiveness of Vision Transformers over conventional CNN-based approaches for retinal image analysis.

II. RELATED WORK

A. Retinal Image Analysis for Cardiovascular Disease Prediction

Wong et al. [1] first demonstrated that retinal vascular abnormalities are closely associated with cardiovascular diseases such as hypertension, coronary artery disease, and stroke, establishing retinal imaging as a non-invasive diagnostic tool. Cheung et al. [2] further confirmed that retinal microvascular characteristics can effectively reflect systemic cardiovascular conditions. Poplin et al. [3] introduced a deep learning approach to predict cardiovascular risk factors directly from retinal fundus images, achieving promising prediction performance. Zhang et al. [4] extended this work by predicting hypertension and other cardiovascular risk factors using retinal photographs collected from a large population, demonstrating the clinical significance of retinal biomarkers for early cardiovascular disease screening.

B. Deep Learning-Based Disease Prediction Recent advances in deep learning have significantly improved automated cardiovascular disease prediction. Rekha et al. [5] proposed a retinal vascular feature extraction framework combined with Random Forest classification for cardiovascular risk assessment. Al-Absi et al. [6] introduced a multimodal deep learning model integrating retinal fundus and DXA images to improve disease prediction accuracy. Bisna et al. [7] developed an EfficientNet-based framework with attention mechanisms for retinal image analysis, while Mehmood et al. [8] introduced a deep convolutional neural network for cardiovascular disease prediction using medical image analysis, demonstrating that CNN-based approaches significantly outperform conventional machine learning algorithms.

Rustam et al. [9] demonstrated that convolutional neural networks outperform traditional machine learning methods in cardiovascular disease classification. The study “Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques” presents a novel approach to increase the precision of machine learning-based heart disease prediction. Using Support Vector Machines (SVM), Neural Networks (NN), and Decision Trees (DT), the authors examine current methods. Their suggested Hybrid Random Forest with Linear Model (HRFLM) approach claims higher accuracy than current approaches when used to the UCI Machine Learning Repository heart disease dataset since it uses all dataset attributes without feature selection.

C. Image Processing and Feature Extraction Image preprocessing plays an important role in improving retinal image quality and classification accuracy. Agurto et al. [10] proposed automated retinal vessel enhancement and feature extraction techniques for retinal disease detection. Srilakshmi et al. [11] combined image segmentation with deep learning to improve cardiovascular disease prediction from retinal images. Huang et al. [12] introduced graph-based retinal vascular analysis for coronary artery disease prediction. Recent studies have also adopted transfer learning using pretrained CNN models such as VGG16, ResNet50, and Efficient Net to improve feature extraction and reduce training complexity. Gulshan et al. [13] demonstrated the effectiveness of transfer learning using pretrained convolutional neural networks for medical image classification.

D. Gap Analysis Although previous studies have demonstrated the effectiveness of retinal image analysis for cardiovascular disease prediction, several challenges still exist.

- Most existing methods rely on CNN-based architectures, which mainly capture local image features.
- Several approaches require additional clinical information such as blood pressure, cholesterol levels, or patient history, making automated screening difficult.
- Many studies use small or limited datasets, which can reduce the model's ability to generalize to new data. □

Existing models often show reduced performance in capturing complex retinal vascular patterns, affecting prediction accuracy. To address these limitations, The proposed system performs image preprocessing, data augmentation, and deep learningbased feature learning to improve prediction accuracy while enabling a simple, noninvasive, and efficient screening approach. Furthermore, the proposed framework employs a Vision Transformer (ViT) to effectively capture both local and global retinal features through its self-attention mechanism, thereby overcoming the limitations of conventional CNNbased models and enhancing cardiovascular risk prediction performance.



III. PROPOSED SYSTEM ARCHITECTURE

A. System Overview

The proposed system introduces an intelligent framework for predicting cardiovascular risk from retinal fundus images using a Vision Transformer (ViT) model. Unlike conventional approaches that rely on manual feature extraction or convolution-based architectures, the proposed method leverages transformer-based learning to automatically identify complex retinal patterns associated with cardiovascular abnormalities. The system provides a non-invasive, efficient, and automated solution for early cardiovascular risk assessment through retinal image analysis.

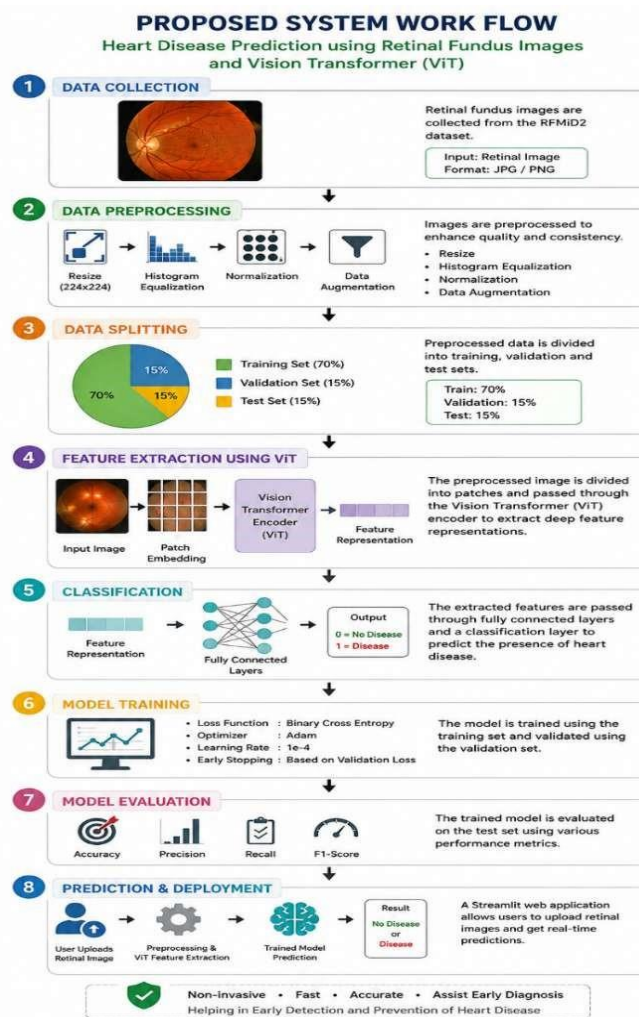


Fig.1. Proposed system of heart disease prediction using Vit

B. Proposed Architecture

The proposed framework consists of four major components: retinal image acquisition, dataset preparation, Vision Transformer-based feature learning, and cardiovascular risk classification. Initially, retinal fundus images are collected and organized into predefined classes. The images are then processed and supplied to the Vision Transformer model, which learns discriminative retinal representations through self-- mechanisms. Finally, the trained model predicts the cardiovascular risk category and generates the corresponding confidence score through a user-friendly web application.

C. Key Features of the Proposed System

The proposed system offers several advantages over traditional image classification approaches. The Vision Transformer effectively captures both local retinal features and long-range spatial relationships, enabling improved feature representation. The proposed framework performs end-to-end learning without requiring manual feature engineering,



making the prediction process more efficient and reliable. Furthermore, the integration of the trained model into a webbased application enables rapid and accessible cardiovascular risk prediction, supporting early screening and clinical decision-making.

IV. METHODOLOGY

The proposed methodology employs a Vision Transformer (ViT)-based deep learning framework to predict cardiovascular risk from retinal fundus images. The complete methodology consists of six sequential stages: dataset preparation, image preprocessing, Vision Transformer-based feature extraction, model training, prediction, and result visualization. After preprocessing, the images are supplied to the Vision Transformer model for feature extraction and classification.

A. Dataset

The proposed work is based on the Retinal Fundus MultiDisease Image Dataset (RFMiD), a publicly available benchmark dataset developed for retinal disease analysis. Each image is annotated by expert ophthalmologists and includes labels for 46 retinal disease categories, allowing the dataset to support multi-label disease classification. The images capture important retinal structures such as the optic disc, macula, blood vessels, and fovea, which provide valuable diagnostic information for automated disease detection. RFMiD images have varying spatial resolutions depending on the acquisition device. During preprocessing, all images are resized to 224×224 pixels, which is the required input size for the Vision Transformer model used in this work. The dataset was carefully preprocessed to guarantee consistency and dependability. To standardize input size and increase computational performance, the retinal images were reduced to a uniform dimension of 224×224 pixels because they were taken at varying resolutions.

B. Image Processing
Image preprocessing is an essential stage in the proposed system, as it prepares the retinal fundus images for efficient feature extraction and accurate classification. Since retinal images are captured using different imaging devices and may vary in size, resolution, and illumination, preprocessing is performed to ensure that all input images have a consistent format before they are provided to the Vision Transformer model. Initially, each retinal image is resized to 224×224 pixels, which is the standard input size required by the Vision Transformer (ViT-Base Patch16-224) architecture. Resizing ensures that all images have identical dimensions, allowing the model to process them efficiently while reducing computational complexity.

After resizing, the images are converted into tensor format. Tensor conversion transforms the pixel values of the retinal image into a numerical representation that can be processed. The next step is image normalization, where the pixel intensity values are standardized using the ImageNet mean values (0.485, 0.456, 0.406) and standard deviation values (0.229, 0.224, 0.225). Normalization reduces variations in image brightness and contrast while maintaining important retinal structures such as blood vessels, the optic disc, and the macula. It also improves the stability of the learning process, accelerates model convergence, and enhances the overall prediction performance. After completing these preprocessing operations, the retinal images become standardized and compatible with the Vision Transformer model.

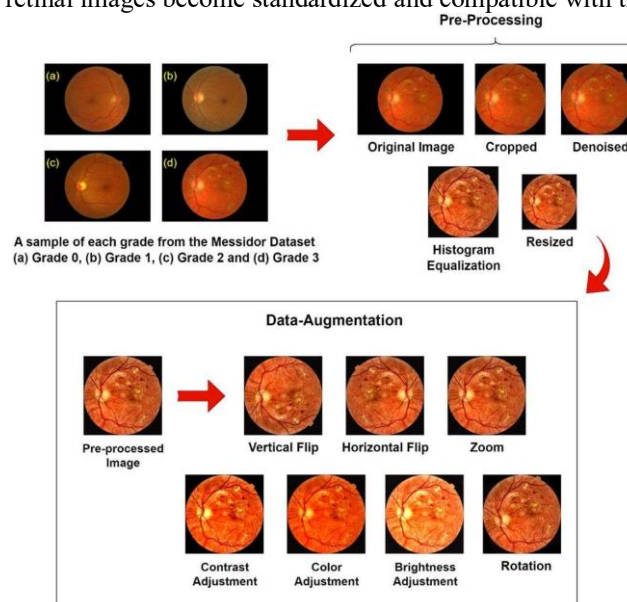


Fig.2 Retinal Image Preprocessing and Data Augmentation



C. Vision Transformer Architecture

The proposed system employs the Vision Transformer (ViT) as the core deep learning model for cardiovascular risk prediction using retinal fundus images. Unlike traditional Convolutional Neural Networks (CNNs), which extract features using convolution operations, the Vision Transformer utilizes a transformer-based architecture with a selfattention mechanism to learn meaningful feature representations from retinal images .

1. Image Patch Generation.

Instead of processing the entire image at once, the Vision Transformer divides the retinal image into fixed-size patches of 16×16 pixels. Each patch represents a small region of the retina containing important visual information such as blood vessels, optic disc, and macular structures. For an input image of 224×224 pixels, the model generates 196 image patches. These patches serve as the basic input units for the transformer.

2. Patch Embedding and positional encoding.

Each image patch is flattened into a one-dimensional vector and transformed into a numerical feature representation known as a patch embedding. Positional embeddings are then added to preserve the spatial location of each patch within the retinal image. This enables the transformer to understand where each retinal feature is located.

3. Transformer Encoder:

After generating the patch embeddings, they are passed to the Transformer Encoder, which is the core component of the Vision Transformer architecture. The transformer encoder consists of multiple encoder blocks that process all image patches simultaneously. Each encoder block contains MultiHead Self-Attention (MHSA), Layer Normalization, Feed Forward Network (MLP), and Residual Connections. The self-attention mechanism enables every image patch to interact with every other patch in the image. This allows the model to capture both local retinal features and long-range spatial relationships. Important retinal structures such as blood vessels, optic disc, and macular regions are analyzed together instead of independently. The encoder gradually learns meaningful feature representations by processing these interactions through multiple layers. As a result, the extracted features become more informative and suitable for accurate cardiovascular risk prediction.

4. Feature Extraction:

The transformer encoder generates high-level feature representations from the retinal fundus images. These features describe important retinal characteristics that help distinguish normal retinal conditions from diseaserelated abnormalities. Unlike manual feature extraction methods, the Vision Transformer automatically learns the most relevant features during training. The model focuses on significant retinal regions without requiring handcrafted feature selection. Self-attention enables the network to assign greater importance to image patches containing useful diagnostic information. This improves the model's ability to identify subtle retinal changes associated with cardiovascular risk. The extracted feature vectors contain rich spatial and contextual information that improves classification performance. These learned features are then forwarded to the classification layer for final prediction.

5. Classification Layer:

The extracted feature vectors are passed to the Multi-Layer Perceptron (MLP) Classification Head for disease prediction. The classification layer analyzes the learned retinal features and determines the corresponding output class. Since the proposed system performs binary classification, the output consists of two categories: Heart Disease and No Heart Disease. The classifier calculates the probability for each class using the learned feature representation. The class with the highest probability is selected as the final prediction. During training, the prediction error is computed using the Cross Entropy Loss function. The model parameters are continuously updated to minimize the classification error and improve prediction accuracy. This process enables the classifier to achieve reliable cardiovascular risk prediction from retinal fundus images.

6. Model Prediction:

After completing the training process, the optimized Vision Transformer model is saved and used for prediction. During testing or deployment, a user uploads a retinal fundus image through the Streamlit application. The uploaded image undergoes the same preprocessing operations used during model training to maintain consistency. The preprocessed image is then passed through the trained Vision Transformer model. The model extracts retinal features and performs classification using the learned parameters. It predicts whether the retinal image belongs to the Heart Disease or No Heart Disease category. Along with the predicted class, the model also computes a confidence score representing the reliability of the prediction. This enables users to obtain fast and accurate cardiovascular risk assessment through an easy to-use application.

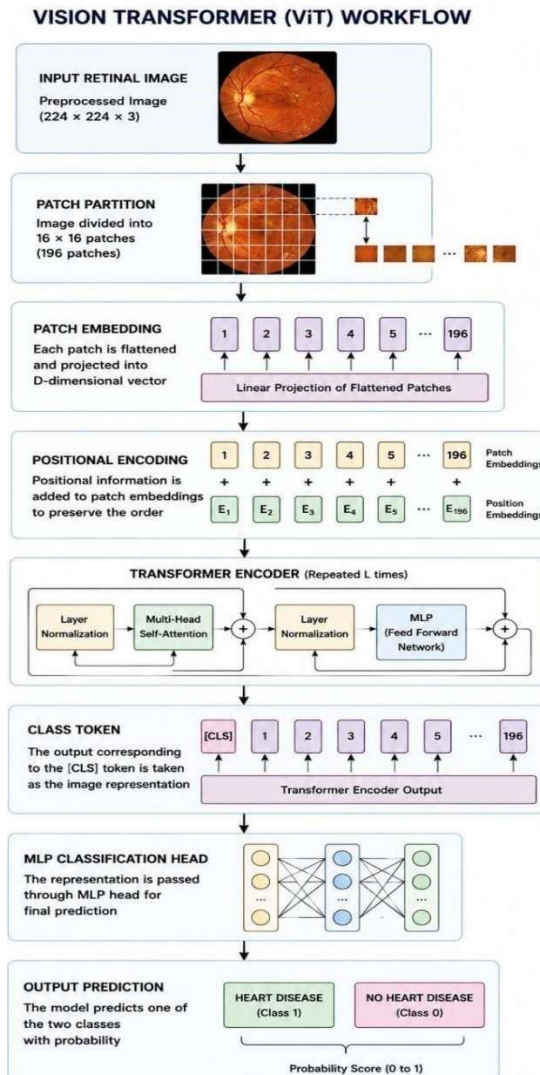


Fig.3. Proposed Methodology Work Flow

V. EXPERIMENTAL RESULTS

A. Experimental Configuration

The proposed system was implemented using Python and PyTorch, with the pretrained ViT-Base/16 (vit_base_patch16_224) architecture. The input retinal images were resized to 224×224 pixels, converted into tensors, and normalized using ImageNet mean and standard deviation values. The model was trained for 10 epochs using a batch size of 16 and a learning rate of 0.0001. Adam was used as the optimizer and Cross-Entropy Loss was used for binary classification.

B. Training Performance

The model showed rapid improvement during training. Accuracy increased from 86.98% in Epoch 1 to 97.83% in Epoch 2 and reached a maximum of 99.61% during Epochs 7–9. The lowest training loss was 0.0066 in Epoch 8. The final epoch produced 98.62% accuracy with a loss of 0.0497. The overall increase in accuracy and reduction in loss demonstrate that the pretrained Vision Transformer adapted effectively to the prepared retinal image classification task. The model maintained an accuracy above 97% from Epoch 2 onward, showing consistent learning throughout most of the training process. Although minor fluctuations were observed in some epochs, the overall training trend remained favourable, with the model converging toward a highperformance solution on the training dataset.

C. Training Loss and Accuracy Analysis

The training performance of the proposed Vision Transformer is illustrated in Fig. 2. The loss decreases considerably during training, from approximately 0.37 in the first epoch to 0.01 in the final epoch, indicating effective optimization of the model. At the same time, the training accuracy increases from approximately 87% to 98.6%, reaching a maximum of



99.61% during the training process. Minor fluctuations in both curves are observed in the intermediate epochs, but the overall trend indicates successful learning and convergence of the Vision Transformer .

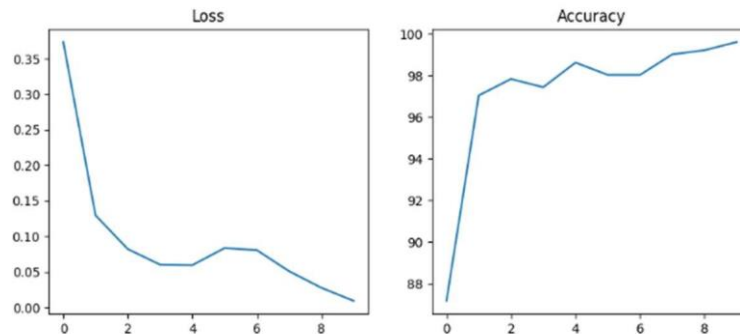


Fig. 5. Training Loss and Accuracy Curves of the Proposed Vision Transformer.

D. Model Saving and Application Deployment

After training, the learned model parameters were saved as vit_model.pth. The saved model is subsequently used by the Streamlit application for prediction .

```
PS C:\Users\sony sirisha\Downloads\heart-disease-prediction-with-retina-image-main> .\venv\Scripts\python.exe -m streamlit run app.py
2026-08-13 22:11:29.311 Unicorn server started on 0.0.0.0:8501

You can now view your Streamlit app in your browser.

Local URL: http://localhost:8501
Network URL: http://192.168.0.6:8501
```

Fig. 6. Deployment of the Proposed Streamlit Application.

The proposed cardiovascular risk prediction system was successfully deployed using a Streamlit-based web application. The application was launched through the Python virtual environment, and the Streamlit server was started successfully on the local system. The displayed local URL confirms that the application was ready to receive retinal fundus images for The developed interface allows the user to upload a retinal fundus image in JPG or PNG format. After selecting the image, the uploaded retinal photograph is displayed in the application for visual confirmation. This provides a simple and user-friendly interface for submitting retinal images to the trained Vision Transformer model.

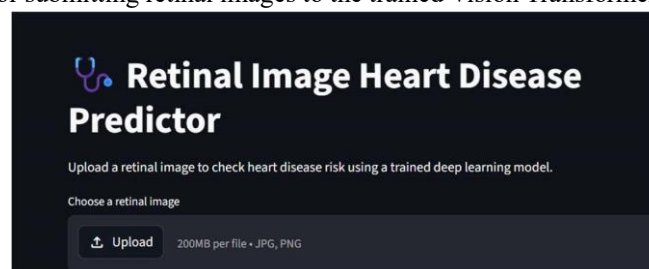


Fig. 7..Retinal Fundus Image Upload Interface

initiates the model inference process. The trained Vision Transformer processes the image and produces a binary prediction. For the sample image shown in the figure, the system predicted “No Heart Disease” with a displayed confidence of 100.00%. This demonstrates the end-to-end functionality of the proposed system, from image upload to automated prediction.

E. Cardiovascular Risk Prediction Output

The trained Vision Transformer was integrated into a Streamlit web application for practical demonstration. The application provides an interface for uploading retinal fundus images and displaying the uploaded image before prediction. After processing the input image, the trained model generates a binary cardiovascular-risk prediction .



Fig.8. Retinal Image Prediction Interface.

F. Comparison With Other Approaches

Approach	Image Feature Learning	Global Relationships	Suitable for Retinal Images
Random Forest	Limited	Low	Moderate
SVM	Limited	Low	Moderate
CNN	Strong	Moderate	High
Proposed Vision Transformer Based Model	Strong	Strong	High

Table :Comparison of Various approaches

CNNs primarily learn local spatial patterns through convolutional operations, whereas Vision Transformers use selfattention to model relationships between image patches. Traditional ML methods such as Random Forest and SVM generally require engineered or extracted features, while deep-learning models can learn image representations directly.

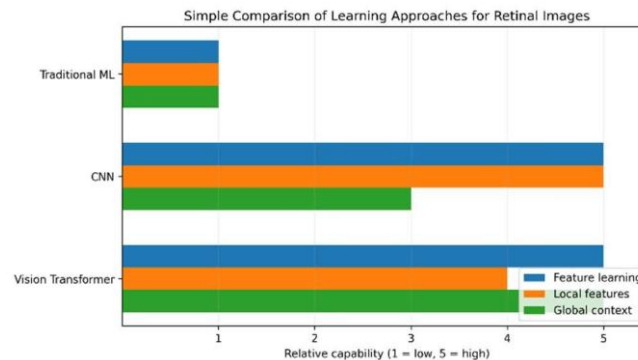


Fig.9. Qualitative comparison of traditional machine learning, CNN, and Vision Transformer

VI. DISCUSSION

The experimental results demonstrate that the proposed Vision Transformer effectively learns discriminative representations from retinal fundus images through its self-attention mechanism. The model achieved a highest training accuracy of 99.61%, indicating strong learning capability on the prepared dataset. The gradual reduction in training loss and improvement in accuracy confirm effective optimization and convergence throughout the training process. Furthermore, the integration of the trained model into a Streamlit application demonstrates its practical usability for automated retinal-image-based cardiovascular risk prediction. The self-attention mechanism enables the Vision Transformer to model relationships between different regions of the retinal image, which is useful for analyzing complex vascular patterns. Compared with conventional machine-learning approaches that generally rely on extracted features, the proposed approach learns image representations directly during training. The interactive application also provides a simple interface for uploading retinal images and obtaining an automated prediction with a confidence score. The obtained results indicate the potential of transformer-based architectures for retinal image classification and non-invasive cardiovascular risk screening.

VII. CONCLUSION

This study presented a Vision Transformer (ViT)-based framework for cardiovascular risk prediction using retinal fundus images. The proposed system included dataset preparation, image preprocessing, feature extraction, model training, and prediction through a Streamlit-based web application. The Vision Transformer effectively learned retinal image features and achieved a maximum training accuracy of 99.61%, demonstrating its capability for accurate binary classification. The developed system provides a non-invasive, efficient, and automated approach for early cardiovascular risk assessment. Overall, the proposed framework shows the potential of transformer-based deep learning techniques in supporting intelligent healthcare applications and assisting medical professionals in preliminary disease screening.

REFERENCES

- [1]. T. Y. Wong and R. Klein, "Retinal microvascular abnormalities and their relationship with hypertension, cardiovascular disease, and mortality," *Survey of Ophthalmology*, vol. 46, no. 1, pp. 59–80, 2001.
- [2]. C. Y. Cheung, Y. Ikram, K. Chen, and T. Y. Wong, "Imaging retina to study dementia and stroke," *Progress in Retinal and Eye Research*, vol. 57, pp. 89–107, 2017.
- [3]. R. Poplin, A. V. Varadarajan, K. Blumer, et al., "Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning," *Nature Biomedical Engineering*, vol. 2, no. 3, pp. 158–164, 2018.
- [4]. K. Zhang, H. Liu, L. Wang, et al., "Deep-learning models for the prediction of cardiovascular risk factors using retinal fundus photographs," *npj Digital Medicine*, vol. 5, no. 1, pp. 1–10, 2022.
- [5]. G. Rekha and P. Arulselvi, "Cardiovascular disease prediction using retinal blood vessel features and Random Forest classifier," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 6, pp. 505–512, 2020.
- [6]. M. Al-Absi, M. G. Alhaj, and M. A. Al-Qaness, "Multimodal deep learning framework for cardiovascular disease prediction using retinal fundus and DXA images," *IEEE Access*, vol. 10, pp. 87345–87358, 2022.
- [7]. K. Bisna, S. Thomas, and A. George, "Attention-based EfficientNet model for retinal image classification," *Computers in Biology and Medicine*, vol. 147, 2022.



- [8]. Z. Mehmood, M. Saba, T. Mahmood, et al., “Deep convolutional neural network for automated cardiovascular disease prediction using retinal images,” *Biomedical Signal Processing and Control*, vol. 68, 2021.
- [9]. F. Rustam, A. A. Reshi, A. Mehmood, et al., “Effective heart disease prediction using hybrid machine learning techniques,” *Sensors*, vol. 23, no. 2, 2023.
- [10]. C. Agurto, V. Murray, H. Yu, et al., “A multiscale optimization approach to retinal blood vessel segmentation,” *IEEE Journal of Biomedical and Health Informatics*, vol. 18, no. 4, pp. 1320–1332, 2014.
- [11]. G. Srilakshmi and P. K. Rao, “Deep learning-based retinal image segmentation for cardiovascular disease prediction,” *Journal of King Saud University – Computer and Information Sciences*, vol. 35, no. 2, pp. 555–566, 2023.
- [12]. Y. Huang, X. Zhao, and H. Li, “Graph-based retinal vascular analysis for coronary artery disease prediction,” *Computer Methods and Programs in Biomedicine*, vol. 206, 2021.
- [13]. V. Gulshan, L. Peng, M. Coram, et al., “Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs,” *JAMA*, vol. 316, no. 22, pp. 2402–2410, 2016.
- [14]. A. Dosovitskiy, L. Beyer, A. Kolesnikov, et al., “An Image is Worth 16×16 Words: Transformers for Image Recognition at Scale,” *International Conference on Learning Representations (ICLR)*, 2021.
- [15]. A. Vaswani, N. Shazeer, N. Parmar, et al., “Attention Is All You Need,” *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 30, 2017.
- [16]. K. He, X. Zhang, S. Ren, and J. Sun, “Deep Residual Learning for Image Recognition,” *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 770–778, 2016.
- [17]. M. Tan and Q. Le, “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks,” *International Conference on Machine Learning (ICML)*, pp. 6105–6114, 2019.
- [18]. L. Breiman, “Random Forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
- [19]. J. Deng, W. Dong, R. Socher, et al., “ImageNet: A Large-Scale Hierarchical Image Database,” *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 248–255, 2009.
- [20]. A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 25, 2012.