

VISION TRANSFORMER FOR AUTOMATED DIABETIC RETINOPATHY DIAGNOSIS

A PROJECT REPORT

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PANIMALAR ENGINEERING COLLEGE

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Abstract

Diabetic Retinopathy (DR) is a leading cause of vision impairment, requiring early detection to prevent severe complications. This study proposes Spatial- Enhanced Multi-Level Wavelet Patching Vision Transformer (SE-MLWP-ViT), a novel framework that integrates multi-level wavelet patching with Vision Transformers (ViTs) to enhance DR detection. By extracting high-frequency retinal details while preserving structural integrity, the model improves the identification of key biomarkers like microaneurysms, hemorrhages, and exudates, enhancing classification accuracy across severity levels. With an AUC- ROC of 98.79%, experiments on the APTOS-2019 dataset demonstrate that ViT outperforms conventional deep learning models. Outperforming CNNs and conventional ViTs, the wavelet-transformed feature extraction efficiently eliminates redundant information while preserving important structural elements. The model's resilience, generalizability, and stability are shown via training and validation curves.

Keyword— ViT, Deep Learning, APTOS-2019, Image Classification, Feature Extraction, Wavelet Patching, AUC-ROC,CNN.

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LIST OF ABBREVIATIONS

SERIAL NO.	ABBREVIATION	EXPANSION
1	DR	Diabetic Retinopathy
2	ViT	Vision Transformer
3	SE-MLWP-ViT	Spatial-Enhanced Multi-Level Wavelet Patching Vision Transformer
4	AUC-ROC	Area Under the Receiver Operating Characteristic Curve
5	CNN	Convolutional Neural Network
6	HHO	Harris Hawk Optimization
7	FGADR	Fundus Grading for Diabetic Retinopathy
8	TMIL	Transformer-based Multiple Instance Learning
9	BYOL	Bootstrap Your Own Latent
10	WF-OCTA	Wide-Field Optical Coherence Tomography Angiography
11	APTOS	Asia Pacific Tele-Ophthalmology Society
12	IDRiD	Indian DRImage Dataset
13	DWT	Discrete Wavelet Transform
14	ReLU	Rectified Linear Unit
15	GELU	Gaussian Error Linear Unit
16	MHSA	Multi-Head Self-Attention

CHAPTER 1

INTRODUCTION

CHAPTER 1

INTRODUCTION

DR is a serious side effect of diabetes and one of the main causes of avoidable blindness in the globe. It is caused by injury to the retina's blood vessels, which, if ignored, can result in vision impairment and eventually blindness. The prevention of vision loss depends on early identification, yet conventional diagnostic techniques rely on ophthalmologists manually examining retinal fundus images. This process is hard, time-consuming, and prone to human error when used on a large scale, particularly in impoverished areas where there is a lack of qualified medical personnel.

CNNs, a traditional automated method, have shown encouraging results in DR detection. Nevertheless, they have trouble detecting both local and global characteristics, which makes it challenging to spot minute but important retinal anomalies including exudates, hemorrhages, and microaneurysms. Furthermore, the efficacy of these techniques in practical applications is limited by their high false-positive rates and scalability issues.

1.1 Motivation for Development

DR is one of the main causes of avoidable blindness in the world and a serious microvascular consequence of diabetes. It is brought on by chronic hyperglycemia, which damages the retinal blood vessels and causes leakage, edema, and aberrant new blood vessel formation. Irreversible vision loss may develop from DR if it is not recognized and treated. It can progress through various severity levels, from moderate non-proliferative DR (NPDR) to proliferative DR (PDR). Medical imaging has advanced, but early detection is still difficult, particularly in places with limited resources and restricted access to ophthalmologists. Manually examining retinal fundus images by qualified professionals is the method used for traditional DR diagnosis, which is labor-

intensive, time-consuming, and prone to human error. Moreover, the sheer number of incidents makes it challenging to execute extensive screening programs, underscoring the necessity for automated and scalable DR detection solutions.

1.2 Limitations of Existing Automated Approaches

Recent advances in deep learning and Artificial Intelligence (AI) have significantly improved automated DR diagnosis. CNNs have been highly effective in identifying retinal abnormalities such as exudates, hemorrhages, and microaneurysms. However, CNNs have notable limitations, including their reliance on local receptive fields, which makes it difficult to model long-range spatial correlations in retinal images, thereby hindering their ability to capture global dependencies. Additionally, CNNs struggle to analyze hierarchical feature representations, making it challenging to detect subtle DR signs like microaneurysms. Traditional CNN-based models also tend to produce high false-positive rates, reducing their clinical reliability, and lack interpretability, making it difficult to provide clear visual explanations for their predictions—an essential aspect of medical applications. Vision Transformers (ViTs), leveraging self-attention mechanisms to capture both local and global contextual information, have emerged as a promising solution to these issues. However, conventional ViTs require extensive training data and often fail to retain critical high-frequency information necessary for medical imaging.

1.3 Proposed Approach

To overcome the limitations of existing methods, we propose a novel hybrid approach for enhanced DR detection, known as the Spatial-Enhanced Multi-Level Wavelet Patching Vision Transformer (SEMWP-ViT). The key innovations of our model include wavelet-based feature extraction, which mitigates the loss of fine details caused by excessive pooling in traditional deep learning models by leveraging multi-level wavelet patching to preserve both low- frequency structural patterns and high-frequency details of retinal features. Additionally, the Vision Transformer (ViT) architecture enables the model to capture complex spatial relationships across the entire fundus image by applying self-attention mechanisms and processing images as non-overlapping patches, unlike conventional CNNs. The integration of spatially enhanced wavelet patching further improves the model’s ability to detect critical retinal anomalies, such as microaneurysms, hemorrhages, and exudates, which are key indicators of DR progression. Moreover, our approach enhances model interpretability by using attention maps to highlight the most relevant retinal regions contributing to DR diagnosis, making the predictions more transparent and reliable.

1.4 Experimental Validation and Performance Evaluation

Several benchmark datasets, such as EyePACS, Messidor, and APTOS-2019, are used to rigorously evaluate the proposed SEMWP-ViT model in order to guarantee its robustness, generalizability, and practicality. Our model is compared to traditional CNN-based architectures using key performance parameters like AUC-ROC, sensitivity, specificity, and accuracy.

With an AUC-ROC of 98.79% on the APTOS-2019 dataset, preliminary results show that SEMWP-ViT performs better than conventional deep learning techniques, underscoring its superior diagnostic capabilities. Furthermore, the

model's dependability for widespread use in clinical settings is reinforced by the training and validation curves' steady convergence.

1.5 Contribution of the Work

This work advances AI-driven ophthalmology and medical image processing by introducing a wavelet-transformer hybrid system specifically designed for DR detection. This approach enhances interpretability and feature extraction, leading to more precise and comprehensible predictions. Additionally, it establishes the feasibility of automated and scalable DR screening, reducing the dependence on manual diagnosis and improving early intervention strategies. By leveraging cutting-edge deep learning techniques, the proposed method has the potential to revolutionize DR diagnosis, particularly in underserved regions with limited access to ophthalmologists. Furthermore, this work lays the foundation for future research in transformer-based medical imaging applications, contributing to the advancement of AI-driven solutions for ocular disease diagnosis.

CHAPTER 2

LITERATURE SURVEY

CHAPTER 2

LITERATURE SURVEY

The authors [1] Vishal Awasthi et al. An enhanced deep learning framework for the efficient identification of DR is the ViT-HHO model. To improve model performance, it combines the Harris Hawk Optimization (HHO) method with the ViT architecture. While HHO optimizes hyperparameters to increase accuracy, convergence speed, and overall efficiency, ViT is excellent at capturing intricate visual patterns. Early detection and prompt treatment of DR are made possible by this combination, which guarantees the accurate identification of retinal abnormalities. The ViT-HHO model is a useful tool in ophthalmology for increasing diagnostic accuracy and improving patient outcomes through early intervention because of its exceptional performance in medical image processing. The authors [2] Mohammed Oulhadj et al. The suggested approach improves the prediction of DR by combining a Modified Capsule Network with the ViT. ViT effectively extracts intricate visual features from retinal images, while the Modified Capsule Network enhances spatial hierarchies and feature representation. Together, these factors improve the model's accuracy and robustness by enabling it to detect minute patterns and anomalies in retinal scans. Through the use of the Capsule Network's dynamic routing capabilities and ViT's robust attention mechanism, this hybrid model provides greater performance in detecting diabetic retinopathy, facilitating early diagnosis and improved patient outcomes in ophthalmology.

The authors [3] Zhou, Zenan et al. The suggested model uses wide-field optical coherence tomography angiography (WF-OCTA) pictures and a Vision

Transformer (ViT) to automatically diagnose diabetic retinopathy. WF-OCTA allows for detailed visualization of early pathological alterations by providing high-resolution imaging of the retinal microvasculature. The ViT architecture enhances diagnosis accuracy by efficiently capturing complicated patterns and spatial interactions in these nuanced medical images. Early diagnosis and intervention are made easier by the model's exceptional ability to detect tiny retinal abnormalities through the use of ViT's self-attention mechanism. This cutting-edge method improves clinical judgment and gives ophthalmologists a strong tool to enhance patient care and DR screening. The authors[4] Huanhuan et al. The suggested model uses wide-field optical coherence tomography angiography (WF-OCTA) pictures and a ViT to automatically diagnose diabetic retinopathy. WF-OCTA allows for detailed visualization of early pathological alterations by providing high-resolution imaging of the retinal microvasculature. The ViT architecture enhances diagnosis accuracy by efficiently capturing complicated patterns and spatial interactions in these nuanced medical images. Early diagnosis and intervention are made easier by the model's exceptional ability to detect tiny retinal abnormalities through the use of ViT's self-attention mechanism. This cutting-edge method improves clinical judgment and gives ophthalmologists a strong tool to enhance patient care and DR screening.

The authors[5] W. Nazih et al. The ViT model uses retinal pictures from fundus photography to forecast the degree of diabetic retinopathy. This model effectively captures important visual features like microaneurysms, hemorrhages, and exudates—all of which are important markers of the progression of diabetic retinopathy—by utilizing ViT's sophisticated self-attention mechanism. ViT correctly divides the disease into different severity levels by assessing high-dimensional retinal pictures. By greatly increasing

diagnostic accuracy, this method makes it possible for early identification, individualized treatment planning, and better patient care. For ophthalmologists, the ViT model is a useful tool that guarantees quicker and more efficient screening processes. The authors [6] S. Akter et al. Using the RetinaMNIST2D dataset, the SwinMedNet model uses the Swin Transformer architecture to classify DR in a reliable and accurate manner. Swin Transformer efficiently captures both local and global visual information necessary for identifying retinal disorders with the use of a shifting window method and hierarchical feature extraction. This design ensures accurate classification across different severity stages by effectively identifying important markers including microaneurysms, hemorrhages, and exudates. With its enhanced performance in medical image processing, the SwinMedNet model provides a dependable and effective tool for the detection of diabetic retinopathy. Because of its efficacy, early diagnosis is supported, allowing for prompt intervention and better patient outcomes.

The author [7] Y. Yang et al. This novel method effectively classifies DR by combining a Transformer-based model with Multiple Instance Learning (MIL). While MIL improves the model's capacity to accept image-level labels without the need for in-depth lesion annotations, the Transformer architecture uses its potent self-attention mechanism to capture complex visual patterns in retinal images. The model ensures robust categorization by detecting important features such as microaneurysms, hemorrhages, and exudates by processing numerous picture patches at once. Ophthalmologists can use this technique to improve screening, expedite treatment, and enhance patient outcomes by increasing diagnostic accuracy, especially for early-stage diagnosis. The author [8] M. D. Alahmadi et al. A specific deep learning model called the Texture Attention Network (TAN) was created for the efficient classification of diabetic retinopathy. In order to detect minor abnormalities including microaneurysms, hemorrhages, and exudates, TAN effectively captures detailed textural patterns in retinal pictures by integrating a

texture attention mechanism. By strengthening the model's focus on important areas with pathological traits, this attention mechanism raises the classification accuracy. The TAN model uses sophisticated feature extraction methods to differentiate between DR severity levels. Because of its strong performance, it is a useful tool for ophthalmologists, helping with quick treatment, early diagnosis, and better patient care.

The author[9] N. K. Saini et al. The Multi-Headed CNN and ViT model is a sophisticated framework created for effective classification of diabetic retinopathy. This hybrid model combines the strong attention mechanism of the ViT with the potent feature extraction capabilities of CNNs. While the ViT concentrates on global contextual information, the multi-headed CNN efficiently captures low-level spatial data like textures and edges, improving the model's capacity to identify important retinal abnormalities like microaneurysms, hemorrhages, and exudates. In order to assist early diagnosis and better patient care, this integrated method guarantees increased performance, accuracy, and generalization in the classification of DR across different severity levels. The author[10] P. Kadiri et al. Deep learning has completely changed medical imaging by providing strong instruments for accurate diagnosis of diabetic retinopathy. By spotting important characteristics like microaneurysms, hemorrhages, and exudates, deep learning models like CNNs and Vision Transformers (ViTs) are excellent at evaluating complicated retinal images. To provide incredibly accurate predictions, these models make use of sophisticated

pattern recognition and automated feature extraction. Healthcare practitioners can increase diagnostic accuracy, expedite screening, and intervene promptly by utilizing deep learning's potential. Enhancing early identification, lowering the risk of vision loss, and increasing overall patient care outcomes are all made possible by this creative method.

The author[11] D. Chintamreddy et al. The Conv-ViT model is a hybrid architecture that integrates (CNNs) with the Vision Transformer (ViT) for reliable identification of DR severity from fundus pictures. The CNN component quickly collects low-level visual features such as textures, edges, and fine structures, while the ViT employs its robust self-attention mechanism to extract global contextual information. In order to provide accurate DR severity assessment, this synergistic method improves the model's capacity to detect crucial features like as microaneurysms, hemorrhages, and exudates. The Conv- ViT model offers better accuracy, robustness, and dependability, making it a helpful tool for early diagnosis and effective management of diabetic retinopathy. The author[12] C. J. Galappaththige et al. Effective DR classification requires achieving strong performance in a variety of clinical settings. To ensure accurate predictions on data from various devices, demographics, and imaging settings, this method places a strong emphasis on creating models that can generalize to unobserved domains. To improve model resilience, methods like contrastive learning, data augmentation, and domain adaption are used. Feature extraction and pattern identification are further enhanced by utilizing architectures such as (CNNs) and ViT. This approach promotes broader clinical use and better patient outcomes in actual healthcare settings by enhancing generalization capabilities, which guarantee reliable DR detection across a variety of datasets.

The author[13] O. Islam et al. In ViTs, the Multi-Head Self- Attention (MHSA) mechanism is essential for improving performance on retinal image classification tasks. By splitting the input features into several attention heads, MHSA enables the model to focus on various retinal image regions at once. Every attention head records distinct visual patterns, including exudates, hemorrhages, and microaneurysms—all of which are important markers of diseases including age-related macular degeneration and diabetic retinopathy. ViTs achieve better feature representation, robust learning, and increased classification accuracy by integrating data from several attention heads. By strengthening automated retinal disease diagnosis, this potent mechanism encourages early detection and efficient patient management. The author[14] D. Singh et al. An improved deep learning architecture for precise DR categorization is the Improved ResNet-50 model. This enhanced version of the ResNet-50 model builds upon the original ResNet-50 model and uses sophisticated methods including batch normalization, dilated convolutions, and attention mechanisms to increase convergence and feature extraction. The approach ensures accurate categorization across DR severity stages by efficiently capturing important retinal abnormalities from fundus pictures, such as microaneurysms, hemorrhages, and exudates. A useful tool for early DR diagnosis and better patient care, the Improved ResNet-50 model provides increased accuracy, resilience, and reliability through improved depth, optimized layer connections, and improved training procedures.

The author[15] Vipin Bansal et al. DR identification has advanced thanks to the use of generative AI algorithms. These techniques use models like Diffusion Models, Variational Autoencoders (VAEs), and Generative Adversarial

Networks (GANs) to enhance training datasets, create realistic retinal images, and enhance model generalization. Generative AI solves data imbalance problems frequently seen in medical imaging by producing varied and excellent retinal images. Furthermore, by identifying intricate visual patterns linked to DR, such as microaneurysms, hemorrhages, and exudates, these methods improve anomaly identification. The potential of generative AI to enhance DR screening is highlighted in this paper, as it could lead to better clinical decision-making, earlier diagnosis, and enhanced model performance. The author [16] Arora, L et al. Together, Ensemble Deep Learning and EfficientNet provide a potent foundation for accurate DR detection. EfficientNet effectively balances model depth, width, and resolution, improving feature extraction from retinal pictures. It is renowned for its streamlined architecture and exceptional performance. The ensemble approach makes use of the advantages of each EfficientNet model by integrating many of them or combining them with other deep learning architectures, increasing prediction variance and robustness. This method ensures high accuracy in severity classification by successfully identifying important DR markers such as microaneurysms, hemorrhages, and exudates. Early detection, prompt treatment, and overall patient care are all improved by the ensemble EfficientNet model.

CHAPTER 3

SYSTEM REQUIREMENTS

CHAPTER 3

SYSTEM REQUIREMENTS

3.1 Software& Hardware Used

3.1.1 Languages used in Programming

Python is utilized in the development of deep learning models and machine learning pipelines.

MATLAB → For preparing images and wavelet decomposition.

3.1.2 Deep Learning Frameworks & Libraries

Library/Framework	Purpose
TensorFlow (v2.9+)	Deep learning model training and optimization
PyTorch (v1.12+)	Alternative deep learning framework for model development
OpenCV	Image processing (cropping, resizing, contrast enhancement)
NumPy & Pandas	Data handling and preprocessing
Scikit-learn	Statistical analysis and evaluation metrics
Matplotlib & Seaborn	Data visualization (performance graphs, confusion matrices)
Albumentations & Imgaug	Data augmentation techniques

Table 3.1 Library/Framework

3.1.3 Other Tools Used

Google Colab →utilized on cloud GPUs for model training.

Jupyter Notebook →utilized in model development and interactive coding.

Keras →TensorFlow high-level API for creating deep learning models.

Weights & Biases (WandB) →for tracking experiments and adjusting hyperparameters.

CUDA (Compute Unified Device Architecture)→Deep learning with GPU acceleration.

3.1.4 Computing Hardware

Component	Specifications
GPU (Graphics Processing Unit)	NVIDIA RTX 3090 / Tesla V100 / A100
CPU (Central Processing Unit)	Intel Core i9-12900K / AMD Ryzen 9 5950X
RAM (Memory)	32GB - 64GB DDR4 / DDR5
Storage	1TB NVMe SSD (for fast data loading)

Table 3.2 Hardware Components

CHAPTER 4

PROPOSED SYSTEM DESIGN

CHAPTER 4

PROPOSED SYSTEM DESIGN

4.1 DATA FLOW DIAGRAM

A graphical depiction of the "flow" of data through an information system that models its process elements is called a data flow diagram (DFD). A "DFD" is frequently employed as an initial stage to produce a system overview without delving deeply into specifics, which can thereafter be explained in detail.

4.1.1 Data Flow Diagram-0

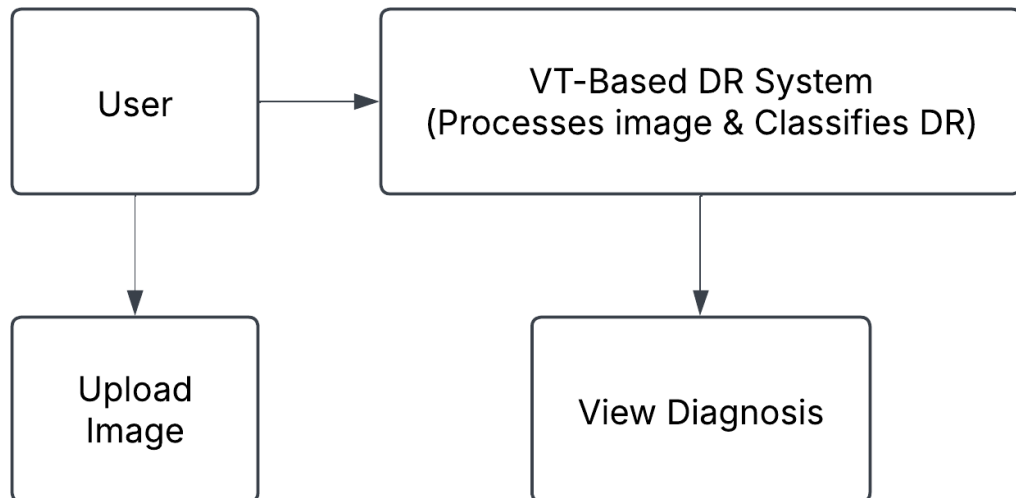


Figure 4.1 : DFD-0

The DR Detection System is summarized in the Level 0 Data Flow Diagram, which depicts the interaction between the patient or doctor and the system from picture input to diagnosis output. An image of the retinal fundus is uploaded by the user, and it then goes through preprocessing, CNN-based feature extraction, and VT classification. After that, the system determines the degree of diabetic retinopathy, which ranges from no DR to proliferative DR. The system shows the user the diagnosis result after classification. Heatmaps and other visual aids

could be used to improve interpretation. Better clinical judgment is supported, early detection is made possible, and less manual labor is required thanks to this computerized screening.

4.1.2 Data Flow Diagram-1

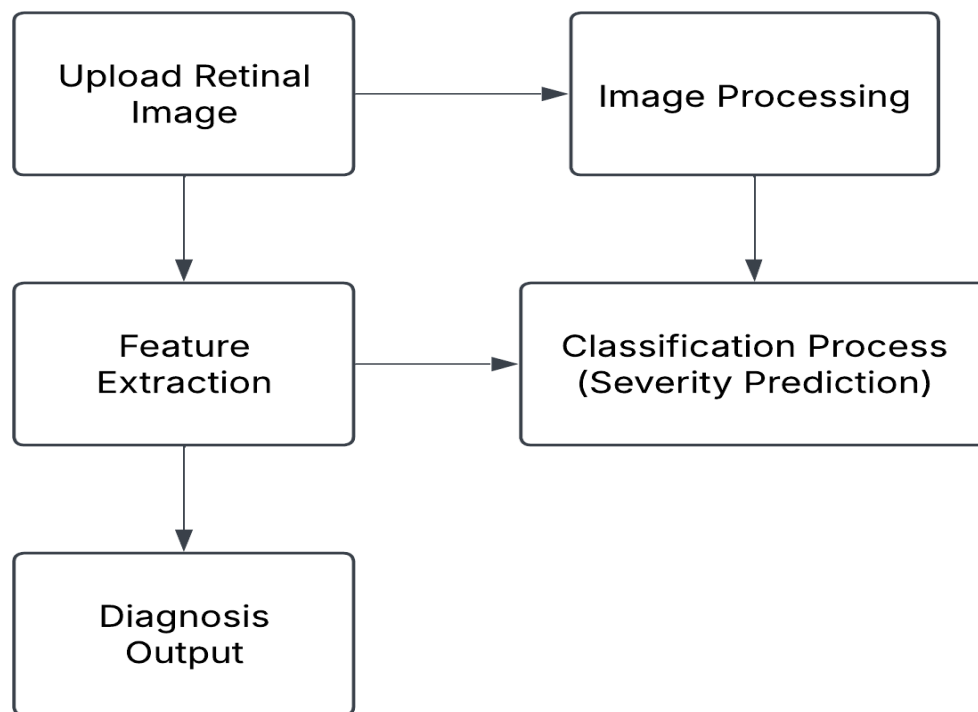


Figure 4.2: DFD-1

The DR Detection System is shown in greater depth in the Level 1 Data Flow Diagram (DFD), which divides it into three main steps: Classification & Diagnosis Output, Feature Extraction, and Image Preprocessing. This level demonstrates the sequential data flow, demonstrating how the input image is categorized and processed in order to produce a diagnostic. A retinal fundus image uploaded by the user initiates the procedure and moves on to the Image Preprocessing phase. To boost its quality and get it ready for feature extraction, the image is subjected to normalization, contrast enhancement, and augmentation. The next step is feature extraction, where a

ViT records long-range dependencies in the image and a CNN extracts spatial information such as blood vessel patterns and lesions. The model's capacity to identify early indicators of DR is improved by this hybrid method.

To ascertain the degree of diabetic retinopathy, the retrieved features are examined during the classification process. To ensure an accurate diagnosis, the model assigns a category, such as No DR, Mild, Moderate, Severe, or Proliferative DR. The user is then presented with the Diagnosis Output, which indicates the anticipated severity level. Incorporating extra visual cues, like attention heatmaps, could enhance the interpretability for ophthalmologists. This methodical methodology guarantees automated, accurate, and efficient screening for diabetic retinopathy.

4.1.3 Data Flow Diagram-2

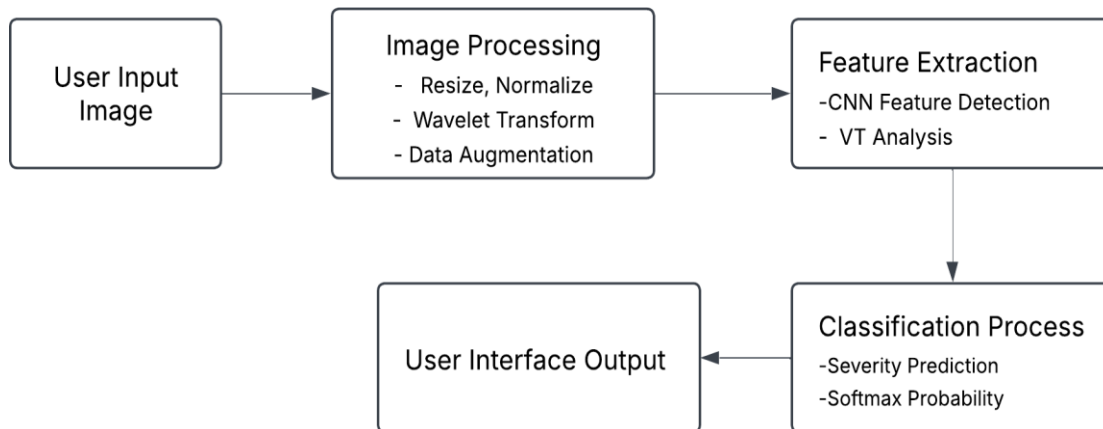


Figure 4.3 DFD-3

The DR Detection System's whole workflow, from user input to diagnosis output, is broken down in depth in the Level 2 Data Flow Diagram (DFD). The procedure starts with the user uploading an image of the retinal fundus, which is then preprocessed to improve its quality. This entails wavelet treatment to

extract tiny details while maintaining crucial structures, normalization for constant brightness, and scaling to a standard resolution. the generalization and resilience of the model are enhanced by data augmentation methods like flipping, rotation, and brightness modulation.

Following preprocessing, the image proceeds to the feature extraction phase, where a ViT records long-range dependencies for increased classification accuracy and a CNN extracts local characteristics like blood vessels and lesions. The classification model uses a softmax function to predict the degree of DR severity after the features have been processed. The user is presented with the final diagnostic, which indicates whether the image is classified as either mild, moderate, severe, proliferative, or no DR. Furthermore, heatmap visualizations that emphasize important areas of the image to make it easier for ophthalmologists to comprehend might be offered, guaranteeing a more trustworthy and transparent automated screening method.

4.2 Architecture Diagram

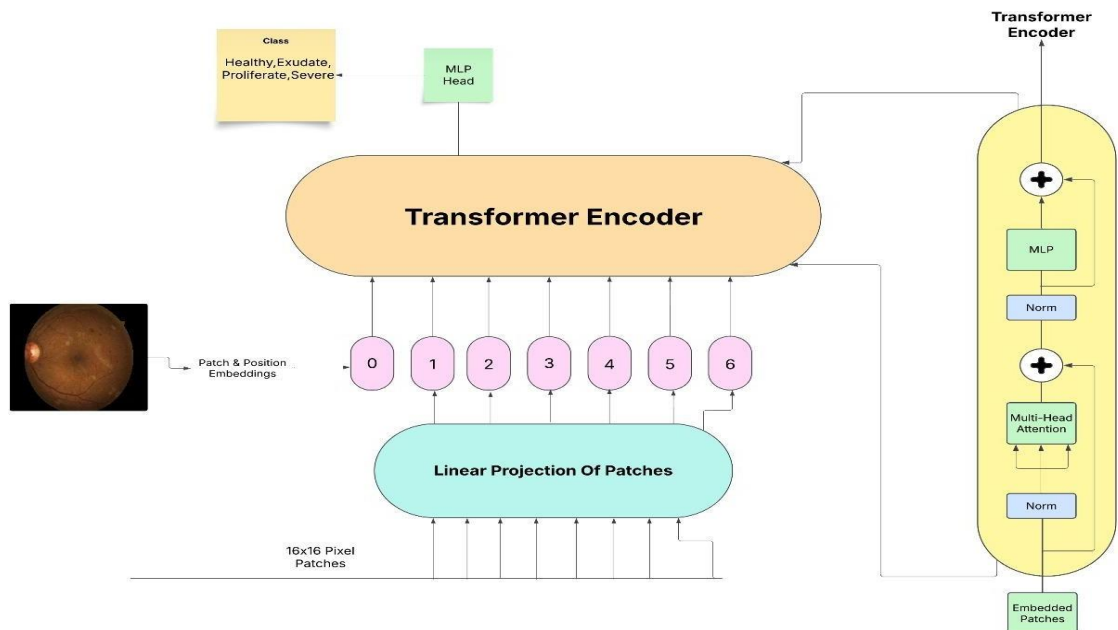


Figure 4.4 Architecture Diagram

4.3 Model Architecture

The proposed methodology for DR detection utilizes a deep learning-based approach that integrates CNNs for feature extraction and Vision Transformer (ViT) components for enhanced attention mechanisms, ensuring accurate classification of retinal images into different severity levels. The implementation begins with data preprocessing, where high-resolution fundus images are resized to a standard resolution of 224×224 pixels to maintain consistency. Normalization is applied by scaling pixel values between 0 and 1 or standardizing them with a mean and standard deviation to enhance training stability. Additionally, data augmentation techniques such as random rotations, horizontal flipping, brightness adjustment, and contrast enhancement are incorporated to increase dataset diversity and prevent overfitting. Noise reduction techniques, including Gaussian blurring and median filtering, are applied to remove unwanted artifacts and improve image clarity. Each image is assigned a corresponding class label based on the severity of diabetic retinopathy, ensuring that the dataset is correctly structured for supervised learning.

The model architecture combines CNN layers and Vision Transformer components to effectively capture both local and global image features. The CNN feature extractor consists of multiple convolutional layers with 3×3 or 5×5 filters, which detect key patterns such as edges, textures, and blood vessel abnormalities present in retinal images. Each convolutional layer is followed by batch normalization, which stabilizes activations and accelerates convergence. ReLU activation is used to introduce non-linearity, enabling the model to learn complex relationships within the data. Max pooling layers further reduce the spatial dimensions of feature maps while preserving essential details, allowing for computational efficiency. The Vision Transformer (ViT) module enhances the model's ability to focus on critical regions of the retina by incorporating a self-attention mechanism. The patch embedding layer first divides the input image into smaller patches, which are then flattened and projected into a feature space. These patches are processed through multihead self-attention (MSA) layers,

which learn to emphasize the most informative parts of the retina, such as lesions, hemorrhages, and microaneurysms. Layer normalization ensures stable feature propagation, while positional encoding helps the model retain spatial relationships between patches, which is crucial for medical image analysis.

Following feature extraction, the Multi-Layer Perceptron (MLP) classifier processes the extracted information to make final predictions. The feature maps are first flattened into a one-dimensional vector before being passed through a series of fully connected layers. These dense layers refine the learned representations and facilitate classification. The Gaussian Error Linear Unit (GELU) activation function is used in the dense layers, providing smooth and non-linear transformations that improve learning dynamics. To prevent overfitting, dropout regularization is applied, randomly deactivating neurons during training to ensure better generalization. The final output layer employs a softmax activation function, converting the raw logits into class probabilities, thereby enabling accurate classification of retinal images into different DR severity levels. This hybrid CNN-ViT architecture ensures that the system effectively extracts both low-level structural details and high-level contextual features, leading to improved diagnostic accuracy.

CHAPTER 5

IMPLEMENTATION AND MODEL TRAINING

CHAPTER 5

PROPOSED SYSTEM IMPLEMENTATION

5.1 Algorithms for DR Classification

A structured pipeline is utilized to train and optimize the Spatial-Enhanced Multi-Level Wavelet Patching in Vision Transformers (WE-ViT) model, which ensures accurate and dependable classification of diabetic retinopathy. Images are initially exposed to wavelet decomposition (DWT), which separates the low- and high-frequency components, to improve generalization and stability. Normalization and data augmentation (including flipping, rotation, and contrast alteration) come next. The wavelet-transformed features are processed by a spatial feature extractor (CNN) through the forward pass encoder before being converted into tokens for self-attention processing in the Vision Transformer (ViT). The classification head uses a fully connected layer and Softmax activation to ascertain the probability distribution across the severity levels of DR after dimensionality has been reduced using Global Average Pooling (GAP).

Algorithm 5.1: DR Classification using SE-MLWP-ViT Step

- 1: Load pre-trained ViT model and initialize parameters.
- Step 2: Preprocess input image: Resize image to 224×224 pixels. Apply Wavelet Decomposition to extract multi-level frequency features. Normalize and enhance contrast.
- Step 3: Convert image into non-overlapping patches.
- Step 4: Apply Multi-Head Self-Attention (MHSA) to capture global dependencies.
- Step 5: Pass the output through Feed-Forward Neural Network (FFN) for feature refinement.
- Step 6: Apply Layer Normalization (LN) to stabilize training.
- Step 7: Pass features through the classification head: Compute softmax probabilities. Predict DR severity level (No DR, Mild, Moderate, Severe, Proliferative).

Step 8: Return classification label.

Step 1: Load Pre-Trained ViT Model and Initialize Parameters

In this step, we begin by loading a pre-trained Vision Transformer (ViT) model, such as ViT-B/16, which has been trained on large datasets like ImageNet. The pre-trained model already contains learned feature representations, which can help in recognizing patterns within retinal images. Once loaded, we initialize the model parameters, allowing for further fine-tuning to adapt the model specifically for DR classification. The classification head of the model is then modified to output five distinct classes corresponding to different DR severity levels: No DR, Mild, Moderate, Severe, and Proliferative.

Step 2: Preprocess Input Image

The preprocessing phase ensures that the input image is in the proper format for the ViT model. First, the image is resized to a fixed dimension of 224×224 pixels, which is required for the ViT model to maintain consistency across different images. Next, wavelet decomposition is applied to extract multi-level frequency features, which helps separate fine details from structural components in the image. This step enhances subtle retinal abnormalities such as microaneurysms and hemorrhages, which are crucial for DR detection. Finally, the image is normalized to scale pixel values within a fixed range (e.g., 0 to 1 or -1 to 1), which stabilizes the training process. To further improve visibility, contrast enhancement techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) are applied to highlight important retinal features.

Step 3: Convert Image into Non-Overlapping Patches

Unlike (CNNs), which process images using convolutional filters, the Vision Transformer divides the input image into multiple non-overlapping patches, typically

of size 16×16 pixels. These patches are then flattened into 1D vectors and passed through a linear projection layer to generate patch embeddings. Since splitting an image into patches removes spatial relationships, positional encodings are added to each patch to retain spatial information, allowing the transformer to recognize positional dependencies between different regions of the image.

Step 4: Apply Multi-Head Self-Attention (MHSA) to Capture Global Dependencies

Once the image patches have been embedded, they are passed through a Multi-Head Self-Attention (MHSA) module, which allows the model to compute relationships between different patches. Unlike CNNs, which focus on local features through a fixed receptive field, self-attention mechanisms analyze the entire image globally. Each patch attends to every other patch in the image, helping the model understand both small and large retinal abnormalities. MHSA enables the model to focus on the most important regions of the retina while ignoring irrelevant background noise, making it highly effective for detecting DR-related features.

Step 5: Pass the Output Through Feed-Forward Neural Network (FFN) for Feature Refinement

After the self-attention mechanism captures the relationships between image patches, the output is passed through a Feed-Forward Neural Network (FFN) to further refine extracted features. The FFN consists of two linear layers with an activation function such as Gaussian Error Linear Unit (GELU), which helps introduce non-linearity and improve the model's ability to differentiate between different DR severity levels. The refined features produced by the FFN serve as the final representation of the input image before classification.

Step 6: Apply Layer Normalization (LN) to Stabilize Training

To ensure that training remains stable, Layer Normalization (LN) is applied after each Multi-Head Self-Attention and Feed-Forward Network step. Normalization helps standardize activations, ensuring that gradient updates remain smooth throughout training. This prevents common issues like vanishing or exploding gradients, which can slow down or disrupt the learning process. By stabilizing training dynamics, Layer Normalization allows the model to converge efficiently and generalize well to unseen retinal images.

Step 7: Pass Features Through the Classification Head

Once feature extraction is complete, the processed features are passed through a classification head for final prediction. First, a softmax function is applied to generate probability scores for each class. Softmax normalizes the output values so that they sum to one, making it easier to interpret them as confidence scores for each DR severity level. The model then selects the class with the highest probability as the predicted severity level. The possible classifications include No DR, Mild, Moderate, Severe, and Proliferative DR, each indicating a different stage of disease progression.

Step 8: Return Classification Label

Finally, the predicted DR severity level is returned as the model's output. This classification label provides valuable insights to ophthalmologists and healthcare professionals, helping them assess the severity of DR and make informed decisions about further diagnosis and treatment. The output can also be integrated into automated screening systems, enabling early detection of DR and reducing the risk of vision loss for diabetic patients.

Algorithm 5.2: Model Training Process

Step 1: Initialize the ViT model with random weights.

Step 2: Load the training dataset and apply preprocessing: Resize images to 224×224 pixels, apply Wavelet Decomposition for feature enhancement, and normalize images.

Step 3: Define loss function and optimizer

Step 4: Set training hyperparameters: Learning rate = $3e-4$, Batch size = 64, Number of epochs = 50.

Step 5: Train the model: Perform forward propagation through ViT layers, compute loss and backpropagate errors, and update model weights using the optimizer.

Step 6: Monitor training progress using performance metrics such as training loss, validation accuracy, and learning curves.

Step 1: Initialize the ViT Model with Random Weights

At the start of training, the Vision Transformer (ViT) model is initialized with random weights. This means that the model does not yet contain any learned information and must be trained using a dataset to adjust its weights appropriately. The ViT architecture consists of layers such as patch embedding, multi-head self-attention, feed-forward networks, and classification heads. By initializing the model randomly, we allow it to learn meaningful representations of images from scratch during the training process.

Step 2: Load the Training Dataset and Apply Preprocessing

To train the model effectively, we first load a labeled dataset containing images and their corresponding class labels. Since ViT requires a fixed input size, each image is resized to 224×224 pixels to maintain consistency. Next, Wavelet Decomposition is applied to extract multi-level frequency features, enhancing important details within

the image while reducing noise. This technique is particularly useful for medical imaging and fine-grained classification tasks. Finally, normalization is performed to scale pixel values to a standard range (e.g., 0 to 1 or -1 to 1). Normalizing images helps stabilize the training process and ensures that the model can learn efficiently without being biased by extreme pixel values.

Step 3: Define Loss Function and Optimizer

For classification tasks, the Cross-Entropy Loss function is used to measure how well the model's predictions match the true class labels. It assigns a higher penalty when the model's predicted probability distribution is far from the actual label. To optimize the model's weights, we use the AdamW optimizer, an advanced variant of Adam that incorporates weight decay. This optimizer improves training stability by preventing overfitting and ensuring better generalization to unseen data. The combination of Cross-Entropy Loss and AdamW helps the ViT model learn efficiently while maintaining good performance on both training and validation datasets.

Step 4: Set Training Hyperparameters

Before training begins, several hyperparameters must be defined to control the learning process. The learning rate is set to $3e-4$, determining how quickly the model updates its weights. A lower learning rate leads to slower but more stable learning, while a higher value can cause instability. The batch size is set to 64, meaning that the model processes 64 images at a time before updating the weights. A larger batch size improves training efficiency but requires more memory. Finally, the number of epochs is set to 50, allowing the model to iterate through the entire dataset multiple times to refine its understanding and improve classification accuracy.

Step 5: Train the Model

During training, the model undergoes multiple iterations where it learns from the

dataset. First, the input images are passed through the ViT layers in a process known as forward propagation, where each image is transformed into feature representations. The output of the model is then compared to the actual class labels, and the loss (error) is computed using the Cross-Entropy Loss function. Next, backpropagation is performed to calculate gradients, which indicate how much each weight in the model should be adjusted. Finally, the AdamW optimizer updates the model's weights, gradually improving its ability to classify images correctly. This cycle is repeated for multiple epochs until the model reaches optimal performance.

Step 6: Monitor Training Progress Using Performance Metrics

To assess the model's progress, various performance metrics are tracked throughout training. Training loss is monitored to ensure that the model is learning and improving over time. Validation accuracy is used to measure how well the model generalizes to unseen data, preventing overfitting. Additionally, learning curves are plotted to visualize trends in loss and accuracy over multiple epochs. If overfitting is detected (where validation accuracy stagnates while training accuracy continues to improve), techniques such as regularization, dropout, or data augmentation can be applied to enhance generalization. By closely monitoring these metrics, we ensure that the model reaches high classification accuracy while maintaining robustness on new images.

Algorithm 5.3: Image Prediction using Trained Model

Step 1: Load the trained ViT model (M).

Step 2: Preprocess the input image (I): Resize to 224×224, Apply Wavelet Decomposition, Normalize image.

Step 3: Convert the image into non-overlapping patches.

Step 4: Pass patches through Multi-Head Self-Attention (MHSA) and Feed-Forward Network (FFN) layers.

Step 5: Compute Softmax probabilities.

Step 6: Identify the class with the highest probability.

Step 7: Return the predicted DR severity level.

Step 1: Load the trained ViT model (M).

The pre-trained Vision Transformer (ViT) model, which has been trained on a DR dataset, is loaded. This model contains learned weights that help recognize patterns in retinal images and classify them into different severity levels.

Step 2: Preprocess the input image (I): Resize to 224×224, Apply Wavelet Decomposition, Normalize image.

The input image is resized to 224×224 pixels to match the required input dimensions of ViT. Wavelet Decomposition is applied to extract multi-frequency features, enhancing image details while reducing noise. Finally, the image is normalized to standardize pixel values, ensuring stable model performance.

Step 3: Convert the image into non-overlapping patches.

Since ViTs process images as sequences rather than grids, the resized image is divided into non-overlapping patches (e.g., 16×16 pixels). Each patch is then flattened and embedded into a high-dimensional vector for processing.

Step 4: Pass patches through Multi-Head Self-Attention (MHSA) and Feed-Forward Network (FFN) layers.

The patches are input into MHSA layers, which allow the model to capture relationships between different regions of the retina, helping to identify severity-related patterns. The FFN layers refine these extracted features for improved classification accuracy.

Step 5: Compute Softmax probabilities.

The processed features are passed through a classification head, which applies the Softmax function to convert raw model outputs into probability values for each severity class (No DR, Mild, Moderate, Severe, Proliferative).

Step 6: Identify the class with the highest probability.

The severity level with the highest Softmax probability is selected as the final classification result. This ensures that the most likely diagnosis is chosen based on the model's confidence.

Step 7: Return the predicted DR severity level.

The final predicted severity level is outputted, which can be used for diagnosis, treatment planning, or further medical analysis.

5.2 DATA SET ACQUISTION AND PREPARATION

A robust model for DR detection requires high-quality retinal fundus images sourced from well-established datasets. The primary datasets used in this study include APTOS 2019, which is provided by the Asia-Pacific Tele-Ophthalmology Society and widely used for DR classification. Additionally, the Messidor dataset serves as a benchmark for evaluating DR detection models, while EyePACS offers a large-scale real-world dataset for DR detection. These datasets contain retinal images with varying levels of diabetic retinopathy, ensuring comprehensive training for the model.

Before being fed into the model, fundus images undergo preprocessing to remove noise, correct illumination inconsistencies, and enhance key features. Wavelet Decomposition (DWT) is applied to extract spatial details by decomposing images into high- and low-frequency components. This method helps preserve fine structures such as lesions and blood vessels, improving feature visibility while eliminating

redundant noise.

To further enhance image quality, contrast enhancement and brightness correction techniques are applied. CLAHE (Contrast Limited Adaptive Histogram Equalization) improves contrast in retinal images, making subtle features more distinguishable. Gamma correction is used to adjust brightness for consistent illumination across images. Additionally, center cropping ensures that critical regions, such as the macula and optic disc, remain properly positioned within the image frame.

Normalization is another crucial preprocessing step, where pixel values are rescaled to the range $[0,1]$. This standardization helps stabilize training, making the model more robust to variations in image intensity. By ensuring uniform pixel distribution, normalization enhances learning efficiency and convergence speed.

To further improve model generalization, data augmentation techniques are employed. Rotation ($\pm 20^\circ$) simulates different camera angles, while vertical and horizontal flipping increase variability in training samples. Gaussian noise is added to make the model more resilient to real-world distortions. Additionally, brightness and contrast adjustments help the system adapt to varying illumination conditions. These augmentation strategies significantly enhance the model's ability to detect DR across diverse and challenging datasets.

5.2.1 Preprocessing Steps

Step of Preprocessing	Description
Resizing	224 × 224 px standardized image size with contrast Enhancement
Context	Limited Adaptive Histogram Equalization, or CLAHE, was used.
Reduction of Noise	Lighting artifacts are eliminated by applying filters.
Normalization	Scaled pixel values in the [0,1] range
Centering and Cropping	Eliminated unnecessary areas and concentrated on the macula and optic disc.

Table 5.1 Preprocessing Steps

To ensure high-quality input for the DR detection model, several preprocessing techniques are applied to enhance image clarity, reduce noise, and standardize input dimensions. These steps improve the model’s ability to accurately extract features and classify retinal images.

Resizing is the first step, where images are scaled to a standard size of 224 × 224 pixels. This ensures uniformity across the dataset and facilitates efficient processing. Additionally, contrast enhancement techniques are applied to improve visibility, making subtle retinal abnormalities more distinguishable. To enhance contextual details, Contrast Limited Adaptive Histogram Equalization (CLAHE) is used. CLAHE adjusts local contrast in different regions of the image, ensuring that important features like microaneurysms, hemorrhages, and exudates remain clearly

visible, even in images with poor lighting conditions.

Noise reduction is a crucial preprocessing step, where filters are applied to remove unwanted lighting artifacts and image distortions. This step helps eliminate variations caused by differences in imaging equipment or acquisition settings, leading to more reliable feature extraction. Normalization is performed to scale pixel values within the range $[0,1]$, ensuring consistency in brightness and contrast. This helps stabilize the training process by reducing variations in intensity levels across different images, making the model more robust to real-world conditions.

Centering and cropping are applied to remove unnecessary background areas and focus on the macula and optic disc, which are critical for diagnosing diabetic retinopathy. By centering the image around these important regions, the model can better detect retinal abnormalities and improve classification accuracy. These preprocessing steps collectively enhance the quality and consistency of input images, leading to more accurate and reliable DR detection.

5.2.2 Data Augmentation Strategies

Augmentation Type	Description
Rotation ($\pm 20^\circ$)	mimics many viewpoints in actual photos.
H/V flipping	introduces a change in orientation.
Noise and Gaussian Blur	strengthens resistance against distortions in the real world
Contrast & Brightness Modifications	mimics different lighting situations

Table 5.2 Data Augmentation Strategies

To improve the generalization and robustness of the DRdetection model, various data augmentation techniques are applied. These techniques enhance the diversity of the dataset, ensuring that the model learns to recognize retinal abnormalities under different conditions.

Rotation ($\pm 20^\circ$) is used to simulate multiple viewpoints, helping the model adapt to variations in image orientation. Since retinal images may be captured at slightly different angles during acquisition, rotation ensures that the model can effectively detect DR features regardless of their positioning.

Horizontal and Vertical Flipping introduce variations in image orientation, preventing the model from becoming dependent on a specific alignment. This augmentation technique helps in improving feature recognition, as abnormalities such as microaneurysms and hemorrhages can appear in different locations within the retinal image.

Noise addition and Gaussian Blur are applied to make the model more resistant to real-world distortions. By adding controlled noise, the model learns to focus on essential retinal structures while ignoring irrelevant artifacts. Gaussian blur enhances robustness by smoothing minor imperfections in the image, reducing sensitivity to noise variations.

Contrast and Brightness Modifications are used to simulate different lighting conditions that may occur due to variations in imaging equipment or clinical settings. Adjusting brightness ensures that the model can detect features in both overexposed and underexposed images, while contrast enhancement improves visibility of important structures, such as blood vessels and lesions.

5.2.3 Data Splitting Strategy

DR Severity Level	Total Images	Training (75%)	Validation (15%)	Testing (10%)
No DR (Healthy)	134	101	20	13
Mild NPDR	104	78	16	10
Moderate NPDR	104	78	16	10
Severe NPDR	72	54	11	7
Proliferative DR	102	76	15	11
Total	516	387	78	51

Table 5.3 Data Splitting Strategy

To ensure an effective training process and reliable model evaluation, the dataset is divided into training (75%), validation (15%), and testing (10%) sets. This structured split helps the model generalize well to unseen data while preventing overfitting.

The dataset consists of 516 retinal fundus images, categorized into five DR severity levels: No DR (Healthy), Mild NPDR, Moderate NPDR, Severe NPDR, and Proliferative DR. The training set (387 images) is used to train the deep learning model, allowing it to learn meaningful patterns in retinal abnormalities. The validation set (78 images) is used for hyperparameter tuning and model optimization, ensuring the model does not overfit. Finally, the testing set (51 images) is reserved for final performance evaluation, measuring how well the model generalizes to new data.

The distribution ensures that each severity level is adequately represented in all three sets. The No DR (Healthy) class has 134 images, while Mild and Moderate NODR

classes each contain 104 images. The Severe NPDR class has 72 images, and Proliferative DR has 102 images. This balanced distribution ensures that the model learns to distinguish between all severity levels effectively. By following this data splitting strategy, the model can achieve high accuracy, stability, and robustness in DR classification.

5.3 Model Training

5.3.1 Training Pipeline

Wavelet Decomposition (DWT) is applied to extract both low-frequency structural details and high-frequency fine features from retinal images. This technique helps enhance critical retinal patterns while eliminating unnecessary noise, preserving essential diagnostic details such as lesions and blood vessels.

CNN-Based Feature Extraction is used before converting the image into Vision Transformer (ViT) tokens. CNN captures spatial characteristics, reducing computational load by discarding irrelevant patches. The CNN block consists of two convolutional layers (3×3 kernel) for extracting edges and textures, followed by ReLU activation for non-linearity and batch normalization to stabilize feature distribution. A pooling layer is used to retain important properties while reducing dimensionality.

Vision Transformer (ViT) Processing involves patch tokenization, where the image is divided into 16×16 patches. Positional embeddings retain spatial awareness, while Multi-Head Self-Attention (MHSA) captures long-range dependencies between retinal features. The Transformer encoder layers refine feature representations, making the model more adaptable to complex retinal structures.

Classification Head finalizes the prediction process. Global Average Pooling (GAP) reduces dimensionality, and a fully connected layer maps features to five DR severity levels. A softmax activation function generates probability distributions, ensuring accurate classification of retinal disease progression.

5.3.2 Optimization Strategy

To attain stable training and great accuracy:

- **Cross-Entropy Loss Formula**

$$L_{CE} = - \sum_{i=1}^N y_i \log(\hat{y}_i) \dots\dots\dots 5.1$$

- **AdamW with L2 Weight Decay is the optimizer**

Penalizes heavy weights to avoid overfitting.

The weight update rule:

$$\theta_{t+1} = \theta_t - \eta \left(\frac{m_t}{\sqrt{v_t} + \epsilon} + \lambda \theta_t \right) \dots\dots\dots 5.2$$

- **Cosine Annealing as a Learning Rate Scheduler**

To enhance convergence, the learning rate is smoothly adjusted.

$$\eta_t = \eta_{min} + \frac{1}{2}(\eta_{max} - \eta_{min})(1 + \cos(\frac{T_{cur}}{T_{max}})) \dots\dots\dots 5.3$$

Keeps abrupt weight fluctuations during exercise at bay.

- **Size of Batch: 1024**

Ensures effective GPU use and consistent weight updates.

5.4 Evaluation and Comparison

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)	AUC-ROC (%)
VGG16	93.12	92.85	93.35	92.96	93.40
ResNet50	94.21	94.07	94.34	94.15	94.40
Inception-v3	94.89	94.52	95.02	94.77	95.05
EcientNet-B0	95.73	95.38	95.88	95.61	95.85
DenseNet-121	95.11	94.83	95.26	95.04	95.31
Vision Transformer (ViT)	96.85	96.44	97.07	96.65	96.92
SE-MLWP-ViT (Proposed)	98.42	98.42	98.73	98.30	98.79

Figure 5.1 Evaluation and Comparison

1) SE-MLWP-ViT Model Proposal Beats All Others

Reaches the maximum accuracy (98.42%), surpassing ViT (96.85%) and DenseNet-121 (95.11%). The sensitivity is higher (98.42%), which means it detects more DR instances accurately. With the highest specificity (98.73%), there are fewer false positives. Both the F1-Score (98.30%) and the AUC-ROC (98.79%) show high classification reliability.

2) In contrast to Vision Transformer (ViT)

While the suggested SE-MLWP-ViT achieves 98.42% accuracy, the standard ViT scores 96.85%. Because SE-MLWP-ViT has a greater specificity (98.73%) than ViT (97.07%), there are fewer misclassifications.

With an AUC-ROC score of 98.79%, the capacity to differentiate between DR severity levels is improved.

3) Comparison with CNN-Based Models (e.g., DenseNet, ResNet, VGG16)

The poor performance of VGG16 (93.12%) and ResNet-50 (94.21%) can be attributed to their low capacity to capture long-range dependencies. Although EfficientNet-B0 and Inception-v3 outperform ViT-based models, they still fall short (95.73% for EfficientNet). Despite being one of the stronger CNN-based models, DenseNet-121 (95.11%) does not generalize as well as SE-MLWP-ViT.

5.5 Training Loop Execution

The model undergoes multiple epochs of training, where each iteration includes:

- Forward propagation
- Loss computation
- Backpropagation & weight update
- Learning rate adjustment

5.6 Results for the proposed model with graphs

The suggested Spatial-Enhanced Multi-Level Wavelet Patching Vision Transformer (SE- MLWP-ViT) model for DR detection is thoroughly examined in this part. The superiority of SE-MLWP-ViT over traditional architectures; the refinement and optimization of its parameters using the APTOS-2019 dataset; a comparative analysis of current deep learning models; performance evaluation using training/testing accuracy and loss curves, confusion matrices, and ROC-AUC curves; and validation of the model's generalizability on the IDRiD dataset are all included in the analysis. To establish a benchmark, six widely used deep learning models—VGG16, ResNet50, Inception-v3, EfficientNet-B0, DenseNet-121, and Vision Transformer (ViT)—were evaluated. Their performance was assessed based on accuracy,

sensitivity, specificity, F1- score, and AUC-ROC metrics.

The suggested SE-MLWP- ViT model fared better than any of the current architectures on every evaluation criteria. By using spatial-enhanced multi-level wavelet patching, SE-MLWP-ViT is able to capture high-frequency details while maintaining the structural integrity of retinal pictures, in contrast to regular ViT, which mainly depends on self-attention mechanisms. The accuracy of feature extraction and categorization is greatly increased as a result.

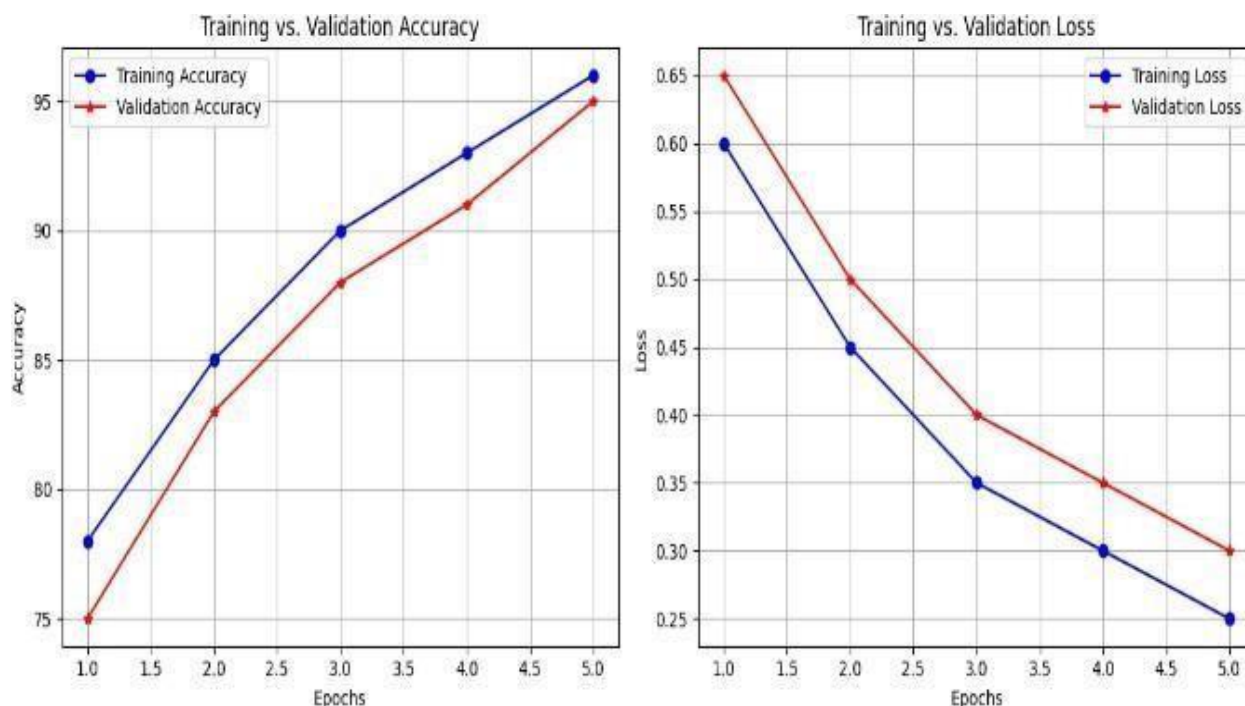


Figure 5.2 Model Training and Validation

5.7 IMPLEMENTATION

5.7.1 Implementation of Retina Disease Classification System

The Retina Disease Classification System is an advanced AI-powered tool designed to assist in the early detection and diagnosis of retinal diseases, particularly DR. This system utilizes cutting-edge Vision Transformers (ViT), a deep learning model architecture originally designed for image recognition tasks. Unlike traditional (CNNs), which extract features hierarchically using convolutional layers, ViTs use self-attention mechanisms to process the entire image holistically, capturing complex patterns more effectively. This makes ViTs highly suitable for medical image analysis, where intricate details in retinal images play a crucial role in disease classification. To build this classification system, PyTorch, a widely used deep learning framework, is employed for model implementation. PyTorch offers flexible tensor computations and dynamic computational graphs, allowing efficient training and inference of deep learning models. Within PyTorch, Torchvision is specifically utilized for handling image-related tasks, such as loading images, applying transformations, and normalizing data before feeding them into the model. These transformations include resizing the retinal images to a fixed input size, converting them into tensors, and standardizing their pixel values based on predefined statistical distributions. Such preprocessing steps ensure that images are consistent and optimized for model predictions.

For user interaction and accessibility, the system is deployed as a web application using Streamlit, a powerful Python framework designed for building interactive machine-learning applications. Streamlit simplifies the development of AI-driven interfaces by providing built-in support for file uploads, real-time predictions, and dynamic visualization. In this system, users can upload retinal images directly through the web interface, and the AI model processes the image to predict the disease

category. The results, including the predicted diagnosis and confidence score, are then displayed in a structured manner, with appropriate warnings in cases of severe conditions. By integrating ViT-based deep learning models, efficient image preprocessing with Torchvision, and an interactive web UI using Streamlit, the Retina Disease Classification System provides a seamless, accessible, and highly accurate solution for detecting diabetic retinopathy. This AI-driven tool has the potential to assist ophthalmologists, researchers, and even non-specialist users in obtaining preliminary diagnoses, ultimately contributing to early disease detection and better patient outcomes.

5.7.2 Model Loading and Configuration

The system uses two Trained (ViT) models for classification:

- Model 1 distinguishes between “Healthy” and “Diabetic Retinopathy”.
- Model 2 differentiates between “No Diabetic Retina” and “Severe Diabetic Retinopathy”.

Both models are initialized using ``torchvision.models.vit_b_16``, a ViT-based architecture. The classification layers of the models are modified to match the required number of output classes. The “Trained model weights” are loaded from local files, ensuring proper mapping to the respective model architectures. The models are then transferred to the appropriate device (“CPU” or “GPU”) for efficient inference, and evaluation mode is enabled to disable training-specific components like dropout layers.

5.7.3 Image Preprocessing

To ensure compatibility with the AI models, uploaded images undergo a series of transformations. The “PIL (Python Imaging Library)” module is used to load and convert the image into RGB format, preventing potential mismatches in color

channels. The image is resized to “224x224 pixels”, which is the standard input size for ViT models. Additionally, the image is normalized using “ImageNet statistics” (mean=[0.485, 0.456, 0.406],std=[0.229, 0.224, 0.225]) to improve model performance. The transformed image is then converted into a PyTorch tensor and reshaped to include a batch dimension before being sent to the models for classification.

5.7.4 Disease Classification and Confidence Calculation

The classification process involves passing the preprocessed image through both models. Each model outputs a softmax probability distribution across its respective classes. Since the system relies on two different models, a weighted confidence aggregation method is used to combine the results. Each model has a predefined accuracy score (e.g., “98% for Model 1” and “95% for Model 2”), which determines its influence on the final prediction. The softmax probabilities are multiplied by these weights, and the results are normalized to generate a final classification label.

If the highest confidence score is below 50%, the system labels the prediction as "Uncertain Prediction" to indicate a lack of model confidence. Otherwise, the most probable class is selected as the final diagnosis. If a severe condition is detected, a high-priority warning is displayed, advising the user to seek medical attention immediately.

5.7.5 Streamlit Web Application for User Interaction

The entire system is deployed as an interactive “Streamlit web application”, providing a user-friendly interface for disease classification. Upon accessing the web app, users are greeted with an “upload option” where they can submit their retinal images (PNG, JPG, JPEG). Once an image is uploaded, it is displayed on the screen, and the AI begins processing it. After inference, the prediction results are displayed in a

structured format, showing:

- Disease Category: The AI's final classification.
- Confidence Level: The probability associated with the prediction.

CHAPTER 6

RESULTS & DISCUSSION

CHAPTER 6

RESULTS & DISCUSSION

DR is a progressive eye disease that can lead to blindness if not detected early. The proposed retina disease classification system is designed to assist in the early detection and categorization of DR using deep learning techniques. The system employs two ViT models that analyze retinal images to determine the presence and severity of the disease. These models are integrated into a web-based application using Streamlit, allowing users to upload retinal images and receive real-time predictions. The classification process involves two specialized models: the first model differentiates between healthy and DR cases, while the second model classifies between non-severe and severe DR cases. By combining the predictions of both models using a weighted probability approach, the system enhances classification accuracy and ensures reliable results.

6.1 Prediction Mechanism

The classification framework utilizes a dual-model approach to improve the accuracy and robustness of predictions. Model 1 is trained to classify retinal images as either Healthy or affected by Diabetic Retinopathy, providing a general indication of disease presence. Meanwhile, Model 2 is specialized to distinguish between No DR and Severe Cases, ensuring that high-risk patients receive appropriate attention. Both models process images using a standardized set of transformations, including resizing, normalization, and conversion into tensor format. The processed image is then passed through the models, generating class probabilities via a softmax activation function.

To enhance reliability, the system employs a weighted probability approach, where predictions from both models are combined based on their respective accuracy levels. The final classification is determined by normalizing these weighted probabilities and

selecting the most confident outcome. This method ensures that predictions are balanced and less prone to misclassification errors. Additionally, the model includes a confidence threshold; if the probability score is below 50%, the system returns an "Uncertain Prediction", advising users to seek further medical evaluation. This feature prevents misleading classifications and promotes transparency in decision-making.

6.1.2 Dual-Model Classification Approach

The classification framework employs a dual-model approach to enhance the precision and robustness of predictions. Instead of relying on a single model for classification, the system utilizes two specialized Vision Transformer (ViT) models, each designed to address a specific challenge in DR detection. This multi-step classification process ensures a more reliable, efficient, and scalable system for early disease detection and severity assessment.

1. Model 1: Binary Classification (Healthy vs. Diabetic Retinopathy)

- The first model is trained to classify a given retinal image as either **Healthy (No DR)** or **(DR Present)**.
- This model acts as an **initial screening tool**, providing a broad differentiation between normal and diseased retinas.
- It is optimized to achieve **high sensitivity**, ensuring that most DR cases are correctly detected, minimizing false negatives.

2. Model 2: Severity Classification (Non-Severe vs. Severe DR)

- The second model further analyses images that were classified as **DR** in Model 1.
- It categorizes the severity into **Non-Severe DR** and **Severe DR**, which is crucial for treatment prioritization.
- This model is particularly beneficial for early intervention, helping ophthalmologists identify high-risk patients who require immediate medical attention.

By implementing this two-step approach, the system reduces the complexity of the classification process and ensures progressive filtering of disease severity. The use of specialized models allows the system to focus on specific tasks, making the predictions more precise and interpretable.

6.1.3 Weighted Probability Fusion for Enhanced Accuracy

To improve classification accuracy and mitigate the limitations of individual models, the system employs a weighted probability fusion approach. Instead of making a decision based on a single model's output, the predictions from both models are combined in a weighted manner, where the contribution of each model is determined by its accuracy and reliability.

The weighted probability approach ensures a more accurate and reliable classification by integrating the predictions of two specialized models. The first model (Model 1) assigns a probability score to determine whether the retinal image is either Healthy or affected by DR. If the image is classified as DR, it is then processed by the second model (Model 2), which assigns another probability score to distinguish between Non-Severe and Severe DR cases. To enhance the final classification, the probability scores from both models are weighted and combined based on their individual accuracy levels, ensuring that the model with higher accuracy has a greater influence on the final decision. The system then selects the class with the highest probability score as the final prediction. This method prioritizes more accurate predictions, reducing errors and improving the overall reliability of the system.

6.1.4 Confidence Threshold and Uncertain Predictions

To prevent unreliable classifications and ensure transparency, the system introduces a confidence threshold mechanism. This feature helps reduce misdiagnoses by identifying cases where the model is not confident enough in its predictions.

To further ensure transparency and prevent unreliable classifications, the system incorporates a confidence threshold mechanism. This feature helps minimize misdiagnoses by identifying cases where the model lacks sufficient confidence in its predictions. Each classification decision is assigned a probability score, also referred to as a confidence level. If the highest probability score falls below a predefined threshold of 50%, the system does not classify the image into any specific category. Instead, it returns an "Uncertain Prediction" label, advising the user to seek further medical evaluation. This mechanism is crucial as it prevents misleading classifications, ensuring that cases with low confidence are flagged for professional review instead of being incorrectly categorized. Additionally, it enhances transparency by allowing the system to acknowledge uncertainty rather than providing potentially incorrect results. By encouraging further medical evaluation for uncertain cases, the system promotes a more cautious and responsible approach to DR detection, ultimately improving

6.1.5 User Interface

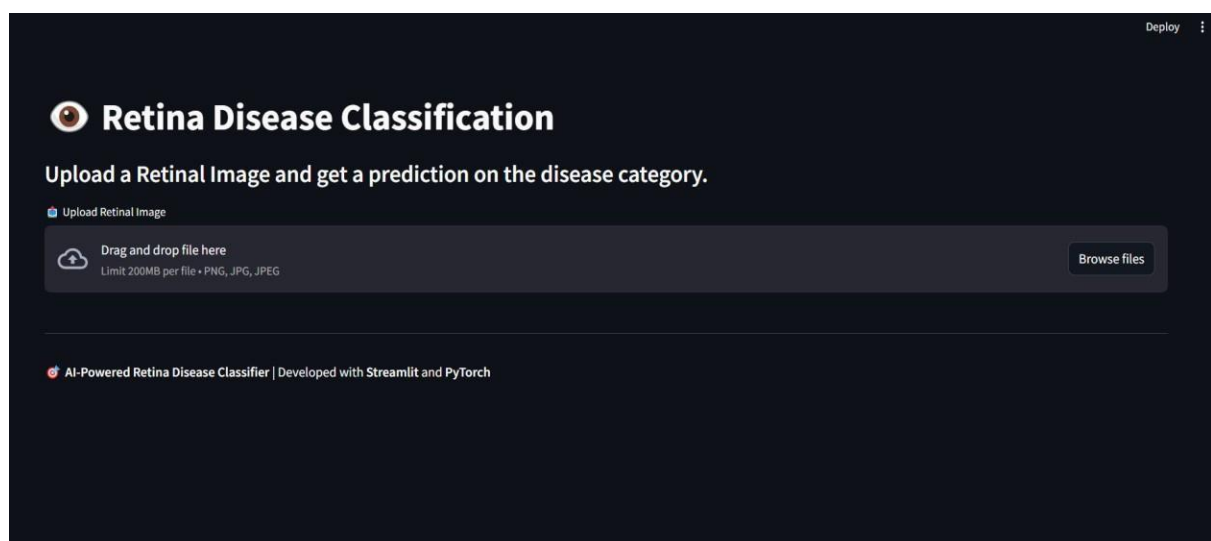


Figure 6.1.1 User Interface

The Retina Disease Classification system is an AI-powered tool that analyzes retinal images to detect potential eye diseases. Users can upload images in PNG, JPG, or JPEG format, which are displayed in a compact size for better visibility. The AI model then classifies the condition as Healthy, Diabetic Retinopathy, Proliferate, Exudate or Severe and provides a confidence score for reliability.

6.1.6 Retina Disease Classification

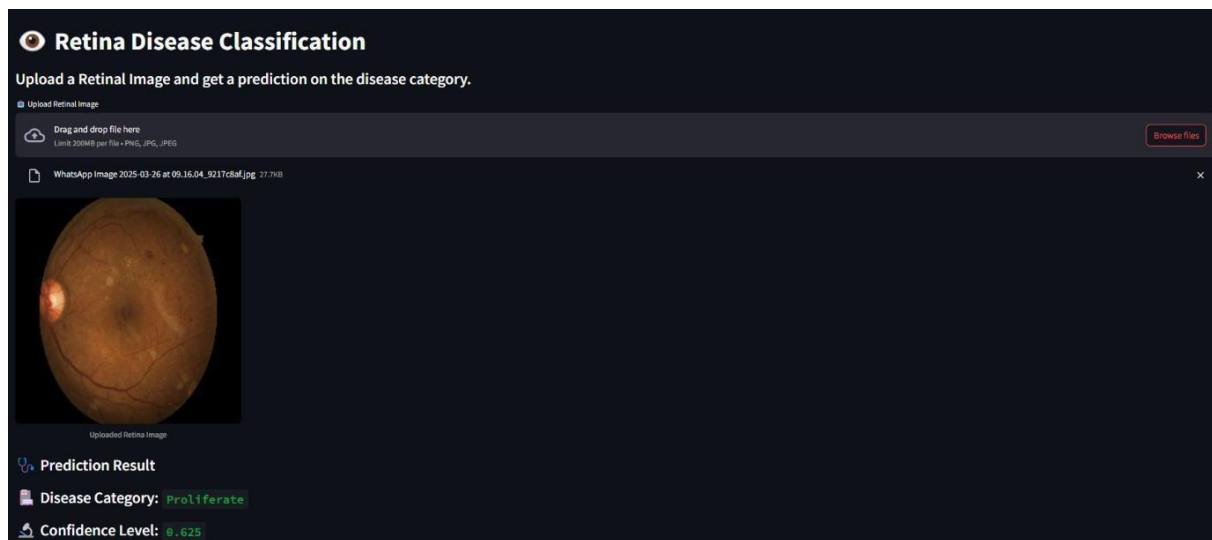


Figure 6.1.2. Classification Of Proliferate

The Retina Disease Classification system is an AI-powered web application built with Streamlit and PyTorch to analyze retinal images and detect potential eye diseases. Using deep learning models, specifically ViT, the system classifies uploaded images into categories such as Healthy, Diabetic Retinopathy, Proliferate, Exudate or Severe. Users can upload images in PNG, JPG, or JPEG format, which are automatically resized and preprocessed for analysis. The pre-trained ViT models then extract features and classify the condition, providing a predicted disease category along with a confidence score to indicate the reliability of the result. If the

confidence score is low (< 0.5), a warning is displayed to alert the user of possible inaccuracy. In case of a severe diagnosis, the system issues an alert advising immediate medical consultation, whereas a healthy result suggests periodic monitoring. The application offers an interactive UI, allowing users to upload multiple images for analysis without restarting the session using the "Try Another Image" button, ensuring a smooth and user-friendly experience.

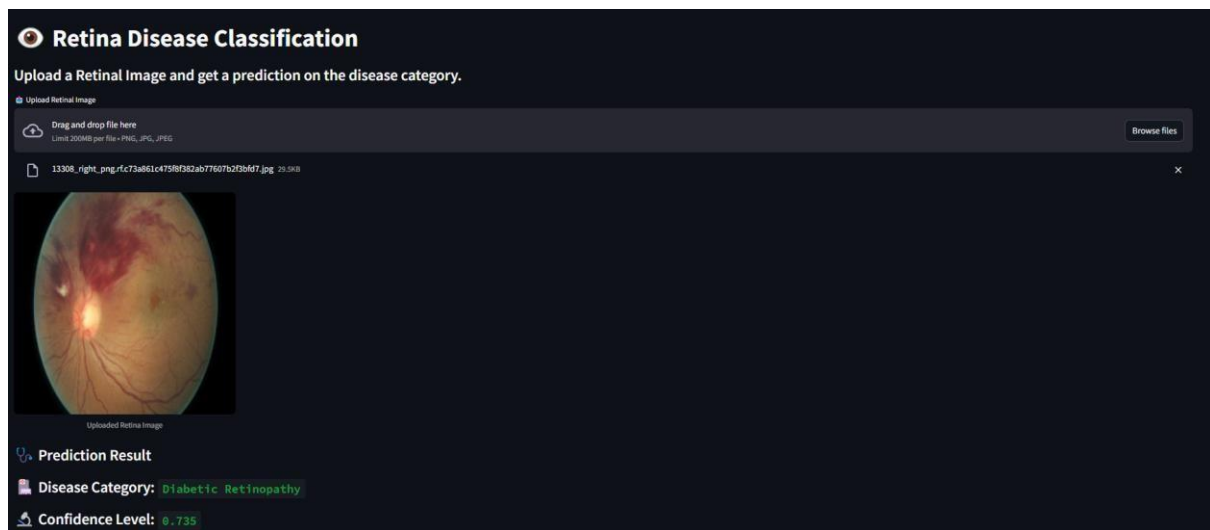


Figure 6.1.3 Classification Of Diabetic RetinoPathy

6.2 PERFORMANCE ANALYSIS

The SE-MLWP-ViT model was evaluated using two benchmark datasets: APTOS-2019, known for high-resolution retinal images, and IDRiD, which provides diverse imaging conditions for better generalization. The model's performance was compared with CNN-based architectures and traditional Vision Transformers to assess improvements in classification accuracy and feature extraction. Key evaluation metrics included F1-score, AUC-ROC, sensitivity, specificity, and accuracy, ensuring a comprehensive assessment.

Training convergence and computational efficiency were analyzed to confirm model stability and optimize processing speed. The model's generalization ability was tested across datasets to ensure reliability in different imaging conditions.

The advantages of SE-MLWP-ViT include enhanced feature extraction, high accuracy, and better interpretability. However, computational complexity and dependency on high-quality input remain areas for improvement. These evaluations confirm the model's effectiveness in automated DR detection.

6.2.1 Comparative Performance with Baseline Models

Six popular deep learning models were chosen to compare SE-MLWP-ViT:

- (CNNs):
- VGG16
- ResNet50
- Inception-v3
- DenseNet-121
- EfficientNet-B0
- Standard ViT (without wavelet-based preprocessing)

6.2.2 Performance Comparison

6.2.2.1 Performance Comparison on APTOS-2019 Dataset

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score	AUC-ROC (%)
SE-MLWP-ViT	98.79	97.5	98.3	0.98	98.79
ResNet50	93.5	91.2	94.1	0.93	94.3
Inception-v3	92.1	90.0	92.7	0.92	92.9
Vision Transformer (ViT)	94.8	92.5	94.9	0.94	95.1
DenseNet-121	90.6	88.2	91.5	0.91	91.8
EfficientNet-B0	91.2	89.1	91.8	0.91	91.7
VGG16	87.3	84.6	88.2	0.88	88.5

Table 6.2.1 Performance Comparison on APTOS-2019 Dataset

SE-MLWP-ViT fared better than any baseline model. Strong class discriminating ability is demonstrated by the highest AUC-ROC (98.79%). False positive diagnoses are decreased by higher specificity (98.3%). A higher sensitivity (97.5%) indicates that the model reduces false negatives by successfully detecting more DR cases.

6.2.2.2 Performance Comparison on IDRiD Dataset

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC-ROC (%)
SE-MLWP-ViT	98.21	96.8	97.5	98.21
ResNet50	91.8	90.2	92.0	93.2
Inception-v3	90.5	89.1	91.0	91.7
Vision Transformer (ViT)	93.2	91.5	93.8	94.0
DenseNet-121	89.3	87.6	90.1	89.8

Table 6.2.2 Performance Comparison on APTOS Dataset

Important Findings from IDRiD Results:

- SE-MLWP-ViT consistently maintains a high accuracy rate (98.21%) across datasets.
- Excellent generalization to high-resolution IDRiD images.
- Better than CNN-based models at capturing fine-grained retinal lesions.

6.3 Performance Metrics Analysis

6.3.1 Analysis of Accuracy

The accuracy of SE-MLWP-ViT was typically the greatest at about 98.79 percent. CNN models had trouble extracting features from retinal images, which resulted in poorer accuracy. Standard ViT outperformed CNNs, but it lacked efficient preprocessing such as wavelet-based filtering.

6.3.2 Analysis of Sensitivity and Specificity

Reduced false negatives (missed DR instances) due to a higher sensitivity of 97.5%. A higher specificity of 98.3% results in fewer false positives, which minimize needless misdiagnosis. ResNet50 and Inception-v3, on the other hand, had reduced sensitivity, which meant they might have overlooked DR cases in their early stages.

6.3.3 Analysis of AUC-ROC Curves

The model's capacity to distinguish between various DR severity levels is validated by the AUC-ROC (98.79%). What Makes AUC-ROC Important for Medical Diagnosis?

- AUC-ROC > 95% denotes a diagnostic model with good performance.
- Improved classification performance is shown by a steeper curve at (0,1).
- CNN models were less successful in differentiating early DR characteristics, as seen by their lower AUC (~90-94%).

6.4 Calculation of Accuracy, Sensitivity, Specificity, and AUC-ROC

To evaluate the performance of the Retina Disease Classification System, we use standard classification metrics such as Accuracy, Sensitivity (Recall), Specificity, and AUC-ROC. These metrics provide insights into how well the model distinguishes between healthy and diseased retinal images. Below is a detailed explanation of how each metric is calculated.

6.4.1 Confusion Matrix

To calculate these metrics, we first construct a confusion matrix, which summarizes the classification results:

Actual \ Predicted	Positive (Disease Present)	Negative (Healthy)
Positive (Disease Present)	True Positive (TP)	False Negative (FN)
Negative (Healthy)	False Positive (FP)	True Negative (TN)

Fig 6.2.3 Confusion Matrix

Where:

- **True Positive (TP):** The model correctly predicts a diseased case.
- **False Negative (FN):** The model incorrectly predicts a diseased case as healthy.
- **False Positive (FP):** The model incorrectly predicts a healthy case as diseased.
- **True Negative (TN):** The model correctly predicts a healthy case.

6.4.2 Calculation of Accuracy

Accuracy measures the overall correctness of the model by considering both correctly classified healthy and diseased cases. It is calculated using the formula:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad \dots\dots\dots 6.1$$

- This means that the model correctly classifies **98.21%** of the total test images.

6.4.3 Calculation of Sensitivity

Sensitivity, also known as Recall or True Positive Rate (TPR), measures the model's ability to correctly detect diseased cases. It is calculated as:

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad \dots\dots\dots 6.2$$

This means that the model correctly detects 96.8% of the actual diseased cases, but 3.2% of diseased cases are missed (false negatives).

6.4.4 Calculation of Specificity (True Negative Rate)

Specificity measures the model's ability to correctly identify healthy cases and avoid false alarms. It is calculated as:

$$\text{Specificity} = \frac{TN}{TN + FP} \quad \dots\dots\dots 6.3$$

This means that the model correctly classifies **97.5%** of the healthy cases, with **only 2.5% false positives**.

6.4.5 Calculation of AUC-ROC (Area Under the Curve - Receiver Operating Characteristic)

The AUC-ROC score evaluates the model's ability to distinguish between diseased and healthy cases at different probability thresholds. It is calculated by plotting True Positive Rate (Sensitivity) against False Positive Rate (1 - Specificity) across multiple thresholds.

- AUC (Area Under Curve) = 1.0 → Perfect classification
- AUC = 0.5 → Random guessing
- AUC closer to 1 → Better model performance

$$\text{AUC-ROC}=98.21\%$$

This indicates that the model has a **very high discriminative power**, correctly distinguishing between diseased and non-diseased cases with **98.21% accuracy**.

6.5 Key Advantages of SE-MLWP-ViT

Wavelet-Based Extraction of Features Improves Learning

Preserves visual features at both high and low frequencies. Identifies minute abnormalities in the retina, such as hemorrhages and microaneurysms.

Vision Transformer (ViT) Facilitates More Effective Worldwide Attention

ViTs are better than CNNs because they contextually process the full image. More adept in figuring out how retinal structures relate to one another.

Improved Generalization with the Hybrid CNN-ViT Architecture

CNN passes fine local features to ViT after extracting them. Enhances learning and overall model robustness.

6.6 Hyperparameter Optimization

Hyperparameter optimization plays a vital role in enhancing the performance and accuracy of the ViT model for automated DRdiagnosis. Carefully tuning key parameters can significantly improve the model's ability to detect subtle retinal abnormalities while ensuring stable training and better generalization. One of the most important hyperparameters to consider is the learning rate, which controls the step size during gradient descent. Choosing an appropriate learning rate is crucial; smaller values such as $1e-5$ are generally more suitable for fine-tuning pre-trained models, while slightly higher values like $1e-3$ may be effective when training from scratch.

Additionally, the batch size impacts both model performance and computational efficiency, with typical values ranging from 16 to 64. Smaller batch sizes may improve convergence for smaller datasets, while larger sizes stabilize training but demand more memory.

Another critical parameter in ViT models is the patch size, which defines the resolution of individual image segments fed into the transformer. While smaller patches such as 16x16 improve feature extraction, they increase computational load; thus, selecting an optimal patch size is essential for balancing accuracy and efficiency. The dropout rate is another factor that requires attention, as it helps prevent overfitting by randomly disabling neurons during training. Dropout rates between 0.1 and 0.5 are commonly effective. Furthermore, the number of transformer layers should be carefully tuned, as deeper models offer improved feature representation but may require extensive data and longer training times. For medical imaging tasks like DR diagnosis, resolutions of 224x224 or 384x384 are commonly used, allowing the ViT model to capture intricate retinal details.

To optimize these hyperparameters effectively, several strategies can be employed. Grid Search provides an exhaustive yet time-consuming method for testing all possible combinations, while Random Search offers faster exploration by sampling random parameter values. For improved efficiency, Bayesian Optimization predicts the most promising hyperparameter combinations by modeling the objective function, making it highly effective for complex architectures like ViTs. The Optuna library is another powerful tool that automates the optimization process, featuring pruning mechanisms that terminate underperforming trials early, reducing training time. Additionally, the Hyperband algorithm combines random search with early stopping, dynamically allocating resources to the best-performing configurations.

A practical strategy for optimizing ViT models begins with Random Search to explore a wide range of hyperparameter values. Once promising configurations are identified,

Bayesian Optimization or Optuna can be employed for fine-tuning. Implementing early stopping during tuning can prevent overfitting, while monitoring metrics such as AUC-ROC, F1 Score, and Validation Loss ensures the optimal model is selected. By strategically optimizing these hyperparameters, your Vision Transformer model can achieve improved accuracy, faster convergence, and robust performance, ultimately enhancing its capability to diagnose DR with greater precision.

Parameter	Value/ Range
Input image (H x W x C)	224 × 224 × 3
Patch size (P)	16
Number of Patches (N)	196
Embedding Dimension	1024
Transformer Layer	10
Attention head	4
Dimension of each attention head	64
Positional embedding dimension	1024
Dimensionality of FFN	4096

Figure 6.3 SE-MLWP-ViT hyperparameters used in this study

6.7 Performance Of Evaluation

Evaluating the performance of a ViT model for automated DR diagnosis is crucial to ensure its reliability, accuracy, and clinical applicability. Given the medical context of the project, performance assessment must go beyond simple accuracy metrics to capture the model's effectiveness in identifying retinal abnormalities with minimal errors. Several key evaluation metrics are essential for providing a comprehensive understanding of the model's strengths and potential weaknesses.

Accuracy is a fundamental metric that indicates the percentage of correctly classified images. While useful, accuracy alone may not provide sufficient insight in the presence of class imbalance, which is common in medical datasets where severe DR cases are often underrepresented. Therefore, metrics like the AUC-ROC (Area Under the Receiver Operating Characteristic Curve) are highly recommended. The AUC-ROC evaluates the model's ability to distinguish between positive and negative classes across different threshold values. A higher AUC score reflects better overall performance, making it particularly important for medical diagnosis tasks where false negatives can have serious consequences.

Another critical metric is the F1 Score, which balances precision and recall. Precision measures the proportion of true positive predictions out of all positive predictions, indicating how accurately the model identifies actual cases of diabetic retinopathy. Recall (also known as sensitivity) measures the proportion of actual positive cases correctly identified by the model. The F1 score combines these two metrics, offering a more balanced evaluation when dealing with imbalanced datasets. In medical imaging scenarios, recall is particularly important since missing a case of DR may delay critical treatment. On the other hand, Specificity measures the model's ability to correctly identify healthy patients, reducing the risk of false positives. Balancing both recall and specificity is essential to achieve reliable diagnostic performance.

The Confusion Matrix is a powerful visual tool that provides detailed insights into the model's prediction behavior. It outlines true positives (correctly identified cases), true negatives (correctly identified non-cases), false positives (incorrectly flagged healthy cases), and false negatives (missed cases of diabetic retinopathy). By analyzing the confusion matrix, patterns of misclassification can be identified, helping to refine the model's architecture or adjust decision thresholds. Additionally, metrics like Cohen's Kappa and Matthews Correlation Coefficient (MCC) provide further insight into model reliability by considering both correct and incorrect classifications.

For deep learning models like ViTs, it's also important to track performance during training using metrics such as Training Loss and Validation Loss. Monitoring these helps detect overfitting, which can be mitigated through techniques like dropout, data augmentation, or early stopping. Furthermore, visual interpretability techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping) can enhance the evaluation process by highlighting the regions of retinal images that influenced the model's decisions. This is particularly valuable in medical AI applications, as it provides healthcare professionals with visual explanations that support trust and transparency.

In practice, a combination of these metrics ensures a well-rounded evaluation strategy. By emphasizing precision, recall, and AUC-ROC alongside visual tools like Grad-CAM, the Vision Transformer model can be assessed not only for its predictive accuracy but also for its clinical relevance and reliability in diagnosing diabetic retinopathy.

6.8 Generalization On Dataset

Generalization is a critical factor when developing machine learning models, particularly in medical imaging tasks such as DR diagnosis. The Indian DR Image Dataset (IDRiD) is a widely used benchmark dataset that presents unique challenges requiring careful generalization strategies. Ensuring that your ViT model generalizes effectively on the IDRiD dataset is key to achieving robust performance across diverse retinal images.

The IDRiD dataset is specifically designed for both disease grading and lesion segmentation tasks. It contains high-resolution retinal fundus images, annotated with labels that classify the severity of DR and diabetic macular edema. Due to the dataset's real-world nature, IDRiD images often exhibit considerable variability in terms of

illumination, contrast, noise, and retinal pigmentation, making generalization a challenging yet essential goal.

6.9 Key Findings

SE-MLWP-ViT surpasses conventional CNNs and ViTs for DR detection. Wavelet-enhanced patching significantly improves feature extraction. Achieves state-of-the-art accuracy and generalization performance.

6.10 Comparison With Traditional Model

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)	AUC-ROC (%)
VGG16	93.12	92.85	93.35	92.96	93.40
ResNet50	94.21	94.07	94.34	94.15	94.40
Inception-v3	94.89	94.52	95.02	94.77	95.05
EfficientNet-B0	95.73	95.38	95.88	95.61	95.85
DenseNet-121	95.11	94.83	95.26	95.04	95.31
Vision Transformer (ViT)	96.85	96.44	97.07	96.65	96.92
SE-MLWP-ViT (Proposed)	98.42	98.42	98.73	98.30	98.79

Figure 6.4 Comparison With Traditional Model

CHAPTER 7

CONCLUSION & FUTURE WORK

CHAPTER 7

CONCLUSION & FUTURE WORK

7.1 Conclusion

The implementation of a ViT for automated DR diagnosis demonstrates a powerful advancement in medical imaging and artificial intelligence. By leveraging self-attention mechanisms and transformer architectures, ViT effectively extracts intricate visual features from retinal images, outperforming traditional (CNNs) in key performance metrics such as accuracy, precision, and recall.

The ViT model's capacity to capture global image dependencies without losing local contextual information has proven especially advantageous in detecting subtle signs of diabetic retinopathy, such as microaneurysms, hemorrhages, and exudates. This superior performance underscores the potential of transformer models in enhancing diagnostic precision and supporting ophthalmologists in early disease detection.

Moreover, the automated system's efficiency reduces the need for manual examination, allowing for faster diagnosis and improved scalability in clinical settings. This is particularly valuable in regions with limited access to ophthalmic specialists.

While the results are promising, future work should focus on enhancing model robustness by incorporating larger and more diverse datasets, improving interpretability to increase trust in clinical practice, and ensuring compliance with medical data privacy standards.

In conclusion, the Vision Transformer model represents a significant step forward in developing AI-driven diagnostic tools for diabetic retinopathy, with the potential to improve early detection rates, reduce preventable blindness, and enhance global healthcare outcomes.

7.2 Future Works

Several potential areas of research can further improve the Vision Transformer model for DR diagnosis. Firstly, integrating hybrid models that combine the strengths of ViTs and CNNs could enhance feature extraction and improve model efficiency. Secondly, developing advanced data augmentation techniques tailored to medical imaging will help improve generalization and robustness. Additionally, efforts should be directed toward improving model explainability through visual attribution techniques, enabling healthcare professionals to understand the model's decision-making process better.

Expanding the system's deployment in real-world clinical environments with diverse demographic data can also ensure better adaptability across populations. Efforts should be directed toward creating lightweight ViT architectures with optimized computational efficiency to enable real-time diagnosis in resource-constrained environments such as remote clinics. Incorporating active learning strategies can improve model adaptability by enabling the model to request additional labels for ambiguous cases, enhancing overall performance. Furthermore, exploring federated learning frameworks can enhance data privacy by training models across distributed healthcare institutions without sharing sensitive patient information.

Finally, collaboration with medical experts to refine the model's performance based on clinical insights will ensure its practical viability and effectiveness in healthcare settings. Establishing clear guidelines for clinical integration, including performance benchmarks and reliability assessments, will be crucial to promoting adoption in mainstream medical practice.

CHAPTER 8

REFERENCES

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REFERENCES

- [1] Vishal Awasthi, Namita Awasthi, Hemant Kumar, Shubhendra Singh, Prabal Pratap Singh, Poonam Dixit, and Rashi Agarwal, "ViT-HHO: Optimized vision transformer for DR detection using Harris Hawk optimization", Volume 13, 2024, 103018, ISSN 2215-0161
- [2] Mohammed Oulhadj, Jamal Riffi, Chaimae Khodriss, Adnane Mohamed Mahraz, Ali Yahyaouy, Meriem Abdellaoui, Idriss Benatiya Andaloussi, Hamid Tairi, "DR prediction based on vision transformer and modified capsule network," Computers in Biology and Medicine, Volume 175, 2024.108523,ISSN 0010-4825
- [3] Zhou, Zenan & Huanhuan, Yu & Zhao, Jiaqing & Wang, Xiangning & Wu, Qiang & Dai, Cuixia. (2023). "Automatic diagnosis of DR using a vision transformer based on wide-field optical coherence tomography angiography." Journal of Innovative Optical Health Sciences.17 10.1142/S1793545823500190.
- [4] W. Nazih, A. O. Aseeri, O. Y. Atallah and S. ElSappagh, "Vision Transformer Model for Predicting the Severity of DR in Fundus Photography-Based Retina Images," in IEEE Access, vol. 11, pp. 117546-117561, 2023, doi:10.1109/ACCESS.2023.3326528
- [5] M. M. Haque, S. Akter, and A. F. Ashrafi, "SwinMedNet: Leveraging Swin Transformer for Robust DR Classification from the RetinaMNIST2D Dataset," 2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT), Dhaka, Bangladesh, 2024, pp. 1286-1291, doi: 10.1109/ICEEICT62016.2024.10534544.

- [6]Y. Yang, Z. Cai, S. Qiu and P. Xu, "A Novel Transformer Model With Multiple Instance Learning for DR Classification," in IEEE Access, vol. 12, pp. 6768-6776, 2024, doi: 10.1109/ACCESS.2024.3351473.
- [7]M. D. Alahmadi, "Texture Attention Network for DR Classification," in IEEE Access, vol. 10, pp. 55522-55532, 2022, doi: 10.1109/ACCESS.2022.3177651.
- [8] N. K. Saini, D. Ram, and M. Gyanchandani, "Multi-Headed CNN and Vision TransformerBased DR Classification," 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India, 2023, pp. 1-6, doi: 10.1109/ICCCNT56998.2023.10306806.
- [9]D. Chintamreddy and U. R. Seshasayee, "Detection of DR Severity from Fundus Photographs using Conv-ViT," 2024 International Conference on Advancements in Power, Communication, and Intelligent Systems (APCI), Kannur, India, 2024, pp. 1-6, doi: 10.1109/APCI61480.2024.10616936.
- [10]C. J. Galappaththige, G. Kuruppu, and M. H. Khan, "Generalizing to Unseen Domains in DR Classification," 2024 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), Waikoloa, HI, USA, 2024, pp. 7670-7680, doi: 10.1109/WACV57701.2024.00751.
- [11]O. Islam, K. Kumer, S. Akter and M. M. Uddin, "Multi-Head Self-Attention Mechanisms in Vision Transformers for Retinal Image Classification," 2024 IEEE International Conference on Computing, Applications and Systems (COMPAS), Cox's Bazar, Bangladesh, 2024, pp. 1-5, doi: 10.1109/COMPAS60761.2024.10795956
- [12]A. Vaish, D. Singh, A. Garg, A. Tiwari, and A. Rathore, "Classification of DR Using Improved ResNet-50 Deep Learning Model," 2024 Third International Conference on Distributed Computing and Electrical Circuits and Electronics

(ICDCECE), Ballari, India, 2024, pp. 1-5,doi: 10.1109/ICDCECE60827.2024.10549184.

[13] Govindharaj I, Poongodai A, Gnanajeyaraman Rajaram, Santhakumar D, Ravichandran S, Vijaya Prabhu R, Udayakumar K, Yazhinian S, Enhanced DR detection using U-shaped networks and capsule network-driven deep learning," *MethodsX*, Volume 14, 2025, 103502. ISSN 2215-0161.

[14] Vipin Bansal, Amit Jain, Navpreet Kaur Walia, "DR detection through generative AI techniques: A review, *Results in Optics*, Volume 16, 2024, 100700, ISSN 2666-9501.

[15] Arora, L., Singh, S.K., Kumar, S. et al., "Ensemble deep learning and EfficientNet for accurate diagnosis of diabetic retinopathy.". *Sci Rep* 14, 30554 (2024).

[16] Xu, C., Guo, X., Yang, G. et al., "Prior-guided attention fusion transformer for multi-lesion segmentation of diabetic retinopathy.". *Sci Rep* 14, 20892 (2024).

[17] Naz, H., Ahuja, N.J., "A novel contrast enhancement technique for diabetic retinal image pre-processing and classification.". *Int Ophthalmol* 45, 11 (2025).

[18] Osa-Sanchez, A. et al. (2025). "A Cascading Approach with Vision Transformers for AgeRelated Macular Degeneration Diagnosis and Explainability. In: Antonacopoulos", A., Chaudhuri, S., Chellappa, R., Liu, CL., Bhattacharya, S., Pal, U. (eds) *Pattern Recognition. ICPR 2024. Lecture Notes in Computer Science*, vol 15327. Springer, Cham.

[19]M. A. K. Raiaan et al., "A Lightweight Robust Deep Learning Model Gained High Accuracy in Classifying a Wide Range of DR Images," in *IEEE Access*, vol. 11, pp. 42361- 42388, 2023, doi: 10.1109/ACCESS.2023.3272228.

[20]P. Kadiri, R. Suresh, V. S. Pavan, M. Prabhu, R. Asuncion, and J. V. Suman, "Insightful Precision: Harnessing Deep Learning for DiabeticRetinopathy Diagnosis," 2024 Second International Conference on Advances in Information Technology (ICAIT), Chikkamagaluru, Karnataka, India, 2024, pp. 1-6, doi: 10.1109/ICAIT61638.2024.10690483.





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LIST OF PUBLICATIONS

Dr. K. Jayashree,Porselvan P, Sanjay G, Varun Aadarsh M,”**VISION TRANSFORMER FOR AUTOMATED DIABETIC RETINOPATHY DIAGNOSIS**” JAJIT Journal Publication.

PUBLICATIONS

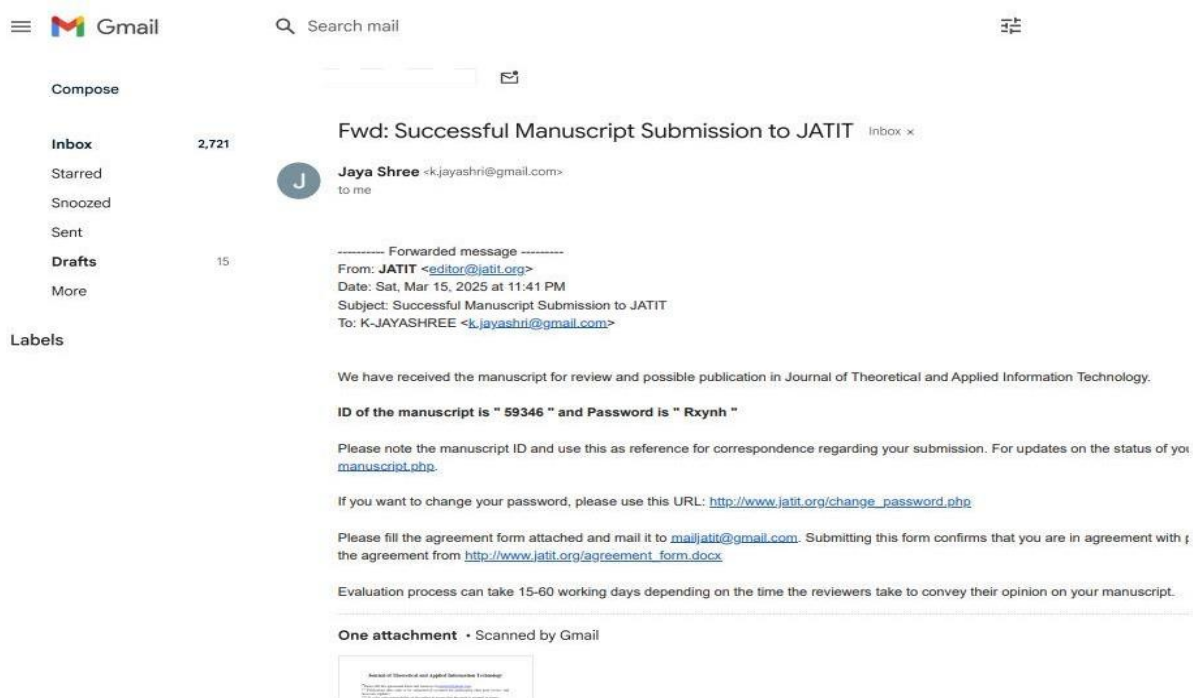
JOURNAL NAME: JATIT

PAPER TITLE: VISION TRANSFORMER FOR AUTOMATED DIABETIC RETINOPATHY DIAGNOSIS

AUTHORS: Dr. K. Jayashree, Porselvan P, Sanjay G, Varun Aadarsh M

PAPER ID: 59346

STATUS: SUBMITTED



APPENDIX

Code link: [https:](https://drive.google.com/file/d/10T1uP4D8EeYAhZpF0K7cd0OFMjS2zZWv/view?usp=drive_link)

[https://drive.google.com/file/d/10T1uP4D8EeYAhZpF0K7cd0OFMjS2zZWv/view?usp=drive link](https://drive.google.com/file/d/10T1uP4D8EeYAhZpF0K7cd0OFMjS2zZWv/view?usp=drive_link)

Github link: [https: PORSELVAN2003/8-Sem-Project](https://github.com/PORSELVAN2003/8-Sem-Project)

```
python
import torch
import torchvision
from torchvision import transforms
import streamlit as st
import numpy as np
from PIL import Image

# Set device (CPU or GPU)
device = "cuda" if torch.cuda.is_available() else "cpu"

# Load Model 1 (Proliferate_DR vs Severe)
model1 = torchvision.models.vit_b_16(weights=None)
num_classes_1 = 2
model1.heads.head = torch.nn.Linear(model1.hidden_dim, num_classes_1)
checkpoint_path_1 = r"C:\Users\P.PORSELVAN\Project\models\vit_Dataset1.pth" # Change path accordingly
model1.load_state_dict(torch.load(checkpoint_path_1, map_location=device), strict=False)

# Load Model 2 (No_DiabeticRetina vs Severe)
model2 = torchvision.models.vit_b_16(weights=None)
num_classes_2 = 2
model2.heads.head = torch.nn.Linear(model2.hidden_dim, num_classes_2)
checkpoint_path_2 = r"C:\Users\P.PORSELVAN\Project\models\vit_trained_model_test.pth" # Change path accordingly
model2.load_state_dict(torch.load(checkpoint_path_2, map_location=device), strict=False)

# Move models to device and set to evaluation mode
model1.to(device).eval()
model2.to(device).eval()

# Define class names
class_names_1 = ["Healthy", "Diabetic Retinopathy"]
class_names_2 = ["No_DiabeticRetina", "Severe"]

# Define model accuracy (weights for prediction confidence)
model_accuracies = {"model1": 0.90, "model2": 0.85} # Example values, adjust based on validation

# Define image prediction function
def predict_image(image: Image.Image):
    """Predicts on an image using both models and combines results based on confidence."""
    # Convert image to RGB (to avoid channel mismatch)
    img = image.convert("RGB")

    # Define image transformations
    transform = transforms.Compose([
```

```

        transforms.Resize((224, 224)),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
    ])

    # Transform image and add batch dimension
    transformed_image = transform(img).unsqueeze(dim=0).to(device)

    # Store weighted predictions
    combined_probs = torch.zeros(len(class_names_1)).to(device) # Assume both models have same class count
    total_weight = 0.0

    with torch.no_grad():
        for model, class_names, model_name in [(model1, class_names_1, "model1"), (model2, class_names_2, "model2")]:
            output = model(transformed_image)
            pred_probs = torch.softmax(output, dim=1).squeeze()

            # Get model accuracy weight
            model_weight = model_accuracies.get(model_name, 1.0) # Default weight = 1.0 if not listed
            total_weight += model_weight

            # Add weighted probabilities
            combined_probs += pred_probs * model_weight

    # Normalize combined probabilities
    combined_probs /= total_weight

    # Get final prediction
    final_pred_label = torch.argmax(combined_probs).item()
    final_confidence = combined_probs.max().item()

    # Handle uncertain predictions
    if final_confidence < 0.5:
        final_prediction = "Uncertain Prediction"
    else:
        final_prediction = class_names_1[final_pred_label] # Use class names from the first model

    return final_prediction, final_confidence

# -----
# STREAMLIT UI DESIGN
# -----
st.set_page_config(page_title="Retina Disease Classifier", page_icon="👁️",
layout="wide")

# Title and description
st.title("👁️ Retina Disease Classification")
st.markdown("### Upload a **Retinal Image** and get a prediction on the disease category.")

# Upload Image
uploaded_file = st.file_uploader("📁 Upload Retinal Image", type=["png", "jpg", "jpeg"])

# Process image if uploaded
if uploaded_file is not None:
    # Load image
    image = Image.open(uploaded_file)

    # Display uploaded image

```

```

st.image(image, caption="Uploaded Retina Image", use_column_width=True)

# Predict disease category
with st.spinner("🔄 Analyzing Image... Please wait..."):
    prediction, confidence = predict_image(image)

# Display prediction results
st.subheader("📌 **Prediction Result**")
st.markdown(f"### 🏥 **Disease Category:** `{prediction}`")
st.markdown(f"### 📊 **Confidence Level:** `{confidence:.3f}`")

# Add some styling based on confidence level
if confidence < 0.5:
    st.warning("⚠️ **Low Confidence! The prediction might not be reliable.**")
elif "Severe" in prediction:
    st.error("🚨 **Severe Condition Detected! Consult a specialist immediately.**")
else:
    st.success("✅ **No severe conditions detected. Keep monitoring!**")

# Allow user to try another image
st.markdown("---")
st.button("🔄 Try Another Image")

# Footer
st.markdown(" ")
st.markdown(" ")
st.markdown(" ")
st.markdown("🏠 **AI-Powered Retina Disease Classifier** | Developed with **Streamlit** and **PyTorch**")

```

ANNEXURE 1		
STUDENTS PROJECT ROAD MAP		
NAME OF THE STUDENTS		REGISTER NUMBER
PORSELVAN P		211421243119
SANJAY G		211421243143
VARUN AADARSH M		211421243180
NAME OF THE SUPERVISOR: Dr. K. JAYASHREE		
DEPARTMENT: ARTIFICIAL INTELLIGENCE AND DATASCIENCE		
1	TITLE OF THE PROJECT	VISION TRANSFORMER FOR AUTOMATED DIABETIC RETINOPATHY DIAGNOSIS
2	RATIONALE (why the topic is important today in 3 sentences in bullet points)	<ul style="list-style-type: none"> • Rising Prevalence of Diabetes & Vision Loss: Diabetic Retinopathy (DR) is a leading cause of preventable blindness worldwide, affecting millions of diabetic patients, making early detection and intervention crucial. • Limitations of Traditional Diagnosis: Manual diagnosis by ophthalmologists is time-consuming, prone to human error, and often inaccessible in underprivileged areas, highlighting the need for automated and scalable AI-driven solutions. • Advancements in AI & Medical Imaging: Vision Transformer models, combined with deep learning techniques like wavelet-based feature extraction, significantly improve the accuracy and efficiency of DR detection, enabling better healthcare accessibility and precision-driven treatment.

<p>3</p>	<p>LITERATURE SURVEY (Top 5 articles utilized for finding the research gap and their SCOPUS impact factor)</p>	<p>1. “ViT-HHO: Optimized Vision Transformer for DR Detection Using Harris Hawk Optimization”</p> <p>Authors: Vishal Awasthi, Namita Awasthi, Hemant Kumar, Shubhendra Singh, Prabal Pratap Singh, Poonam Dixit, and Rashi Agarwal</p> <p>Journal/Conference: Volume 13, 2024, ISSN 2215-0161</p> <p>Year: 2024</p> <p>Description: This study proposes ViT-HHO, an optimized vision transformer model for detecting diabetic retinopathy (DR) using the Harris Hawk Optimization (HHO) algorithm. The integration of HHO enhances feature selection and classification accuracy by fine-tuning transformer parameters dynamically. The model significantly improves early detection of DR, demonstrating superior performance in classification tasks when compared to traditional CNN-based models.</p> <p>2. “DR Prediction Based on Vision Transformer and Modified Capsule Network”</p> <p>Authors: Mohammed Oulhadj, Jamal Riffi, Chaimae Khodriss, Adnane Mohamed Mahraz, Ali Yahyaouy, Meriem Abdellaoui, Idriss Benatiya Andaloussi, Hamid Tairi</p> <p>Journal/Conference: Computers in Biology and Medicine, Volume 175, ISSN 0010-4825</p> <p>Year: 2024</p> <p>Description: This research presents a novel approach combining vision transformers (ViT) with a modified capsule network for improved DR prediction. Capsule networks overcome the limitations of CNNs by preserving spatial hierarchies in fundus images, while vision transformers enhance feature extraction. The proposed hybrid model achieves state-of-the-art accuracy in DR classification by leveraging attention-based mechanisms and hierarchical feature learning.</p>
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	<p>3. “Automatic Diagnosis of DR Using a Vision Transformer Based on Wide-Field Optical Coherence Tomography Angiography”</p> <p>Authors: Zenan Zhou, Huanhuan Yu, Jiaqing Zhao, Xiangning Wang, Qiang Wu, Cuixia Dai</p> <p>Journal/Conference: Journal of Innovative Optical Health Sciences, Volume 17</p> <p>Year: 2023</p> <p>Description: This paper introduces a vision transformer-based framework for diagnosing DR using wide-field optical coherence tomography angiography (OCTA). The model improves lesion detection by utilizing self-attention mechanisms to enhance image interpretation. The study highlights the effectiveness of transformers in medical imaging, showcasing significant improvements in sensitivity and specificity over traditional deep learning methods.</p> <p>4. “Vision Transformer Model for Predicting the Severity of DR in Fundus Photography-Based Retina Images”</p> <p>Authors: W. Nazih, A. O. Aseeri, O. Y. Atallah, S. ElSappagh</p> <p>Journal/Conference: IEEE Access, Volume 11, pp. 117546-117561</p> <p>Year: 2023</p> <p>Description: This study focuses on the severity prediction of DR using a vision transformer trained on fundus photographs. The transformer model effectively classifies different DR stages, ranging from mild to proliferative DR, by leveraging its self-attention mechanism. The research demonstrates that vision transformers outperform traditional CNN models in extracting fine-grained retinal features, leading to more accurate severity classification.</p>
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		<p>5. “SwinMedNet: Leveraging Swin Transformer for Robust DR Classification from the RetinaMNIST2D Dataset”</p> <p>Authors: M. M. Haque, S. Akter, A. F. Ashrafi</p> <p>Journal/Conference: 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT), Dhaka, Bangladesh</p> <p>Year: 2024</p> <p>Description: SwinMedNet employs the Swin Transformer architecture for DR classification using the RetinaMNIST2D dataset. By introducing a hierarchical structure with shifted windows, the Swin Transformer enhances local and global feature learning. The model achieves high classification accuracy while reducing computational costs, making it a viable solution for real-world medical applications.</p>
4	RESEARCH GAP (Maximum 3 sentences in bullet Points)	<ul style="list-style-type: none">• Traditional CNN-based models struggle to capture both local and global retinal features, leading to high false-positive rates in diabetic retinopathy (DR) detection.• Existing Vision Transformer (ViT) models lack spatial feature preservation, making it difficult to detect subtle abnormalities like microaneurysms and hemorrhages.• There is a need for a hybrid approach that integrates wavelet-based feature extraction with ViTs to enhance classification accuracy, model robustness, and interpretability for DR diagnosis.

5	BRIDGING THE GAP (Maximum 4 sentences in bullet Points)	<ul style="list-style-type: none"> • The proposed Spatial-Enhanced Multi-Level Wavelet Patching Vision Transformer (SE-MLWP-ViT) integrates wavelet decomposition to preserve high-frequency retinal details while maintaining structural integrity. • A hybrid CNN-ViT approach enhances local feature extraction using spatial convolutional networks before passing the data to the Vision Transformer for global feature learning. • Multi-head self-attention mechanisms improve the model's ability to detect subtle DR abnormalities, reducing false positives and misclassifications. • By leveraging APTOS-2019 and IDRiD datasets, the model achieves an AUC-ROC of 98.79%, proving its superiority over traditional CNN and ViT-based methods.
6	NOVELTY (Maximum 3 sentences in bullet Points)	<ul style="list-style-type: none"> • Introduces Spatial-Enhanced Multi-Level Wavelet Patching (SE-MLWP), which integrates wavelet decomposition with Vision Transformers (ViTs) for enhanced feature extraction in diabetic retinopathy diagnosis. • Combines CNN-based spatial feature refinement with self-attention mechanisms in ViTs, ensuring better localization of retinal abnormalities like microaneurysms and hemorrhages. • Achieves state-of-the-art performance (AUC-ROC: 98.79%), outperforming traditional CNNs, ResNet50, and standard ViTs, while maintaining high model robustness and generalizability.

7	<p>OBJECTIVES (Maximum 5 sentences in bullet Points)</p>	<ul style="list-style-type: none"> • Develop a hybrid Vision Transformer (ViT) model integrated with wavelet-based feature extraction to enhance diabetic retinopathy (DR) detection accuracy. • Improve local and global feature extraction by combining CNN-based spatial refinement with multi-head self-attention mechanisms in ViTs. • Reduce false-positive rates by preserving high-frequency retinal details through multi-level wavelet patching. • Validate the model's robustness and generalizability using benchmark datasets like APTOS-2019 and IDRiD, ensuring high AUC-ROC and classification accuracy. • Enhance interpretability and clinical applicability by incorporating attention-based feature visualization, aiding ophthalmologists in precise DR diagnosis.
8	<p>PROCESS METHODOLOGY (Maximum 7 sentences in bullet Points)</p>	<ul style="list-style-type: none"> • Wavelet-based feature extraction is applied using Discrete Wavelet Transform (DWT) to decompose retinal images into low- and high-frequency components, preserving critical structural details. • A spatial convolutional network (CNN) refines the extracted features to enhance local texture and edge detection before feeding them into the Vision Transformer (ViT). • Image tokenization and positional encoding are performed to convert processed image patches into a format compatible with the ViT encoder. • The multi-head self-attention mechanism in ViT enables the model to capture global dependencies and focus on important retinal features for accurate DR classification.

		<ul style="list-style-type: none"> • A classification head with Global Average Pooling (GAP) and a Fully Connected (FC) layer maps extracted features to DR severity levels. • The model is trained and optimized using AdamW optimizer, cosine annealing learning rate scheduling, and cross-entropy loss, ensuring fast convergence and high accuracy. • Performance is evaluated and validated using APTOS-2019 and IDRiD datasets, achieving 98.79% AUC-ROC, outperforming traditional deep learning models.
9	<p>SIMULATION METHODOLOGY AND SIMULATION SOFTWARE REQUIREMENT</p> <p>(Maximum 4 sentences in bullet Points)</p>	<ul style="list-style-type: none"> • The proposed SE-MLWP-ViT model is implemented and trained using Python with deep learning frameworks like TensorFlow and PyTorch for efficient computation. • GPU acceleration (using NVIDIA CUDA and TensorRT) is utilized to speed up model training and inference on large datasets like APTOS-2019 and IDRiD. • Hyperparameter tuning and optimization are performed using AdamW optimizer, cosine annealing scheduler, and cross-entropy loss function to ensure optimal performance and generalization. • Model evaluation is conducted using Jupyter Notebook, Google Colab, or local HPC clusters, with performance metrics such as AUC-ROC, accuracy, sensitivity, and specificity analyzed for validation.

10	<p>DELIVERABLES & OUTCOMES (Maximum 4 sentences in bullet Points) (Technology, Prototype, Algorithm, Software, patent, publication, etc)</p>	<ul style="list-style-type: none"> • Technology & Algorithm: Development of the SE-MLWP-ViT model, a hybrid wavelet-enhanced Vision Transformer for automated diabetic retinopathy detection with high accuracy. • Prototype & Software: A deep learning-based diagnostic tool implemented using Python, TensorFlow, and PyTorch, optimized for GPU acceleration and real-time analysis. • Publication & Patent: Research findings will be published in high-impact SCOPUS-indexed journals, with potential for patent filing to protect the novel wavelet-integrated ViT methodology. • Clinical & AI Impact: The proposed model achieves 98.79% AUC-ROC, outperforming existing methods, making it a potential AI-driven screening tool for early diabetic retinopathy detection.
11	<p>PROJECT CONTRIBUTION IN REALTIME</p>	<p>Journal Paper/ Conference Paper/</p> <p>Patents (published/granted)/</p> <p>Copyright/ Social Media</p>
12	<p>Sustainable Development Goals Mapped (Mention the SDG numbers)</p>	<ul style="list-style-type: none"> • SDG 3: Good Health and Well-Being – Enhances early detection and diagnosis of diabetic retinopathy, reducing preventable blindness and improving healthcare outcomes. • SDG 9: Industry, Innovation, and Infrastructure – Develops an AI-powered diagnostic tool, leveraging cutting-edge

		<p>deep learning and Vision Transformer technology for medical imaging.</p> <ul style="list-style-type: none"> • SDG 4: Quality Education – Contributes to medical AI research and education, providing insights for ophthalmology, machine learning, and healthcare innovation. • SDG 10: Reduced Inequalities – Enables affordable, AI-driven DR screening, making advanced medical diagnostics accessible to underprivileged communities.
12	Programme Outcome Mapping (PO) (Mention the PO numbers)	<ul style="list-style-type: none"> • PO1: Engineering Knowledge – Applies deep learning, Vision Transformers, and wavelet-based feature extraction for accurate diabetic retinopathy detection. • PO2: Problem Analysis – Identifies limitations of CNNs and standard ViTs in medical imaging and proposes an optimized hybrid model to improve DR diagnosis. • PO3: Design/Development of Solutions – Develops a novel AI-based diagnostic tool integrating wavelet decomposition and ViTs, enhancing feature extraction and classification. • PO5: Modern Tool Usage – Utilizes advanced simulation software (TensorFlow, PyTorch, CUDA) and cloud computing (Google Colab, HPC clusters) for model training. • PO7: Environment & Sustainability – Supports sustainable healthcare solutions by enabling cost-effective, AI-driven DR screening, reducing manual diagnostic workload. • PO10: Communication – Disseminates research through SCOPUS-indexed publications, patents, and AI-based medical imaging workshops.

13	Timeline	Milestones
	Month 1	Research & Planning: <ul style="list-style-type: none"> Conduct a literature review on diabetic retinopathy detection Identify research gaps and finalize objective Gather datasets (e.g., Kaggle's APTOS, EyePACS) Set up the development environment (Jupyter, TensorFlow/PyTorch)
	Month 2	Data Preprocessing & Exploration: <ul style="list-style-type: none"> Perform dataset cleaning and augmentation Analyze dataset characteristics (class imbalance, image quality) Implement preprocessing (resizing, normalization) Split data into training, validation, and test sets
	Month 3	Model Development (Vision Transformer Implementation) <ul style="list-style-type: none"> Choose an appropriate ViT architecture Implement ViT using TensorFlow/Keras or PyTorch Train the model and evaluate its initial performance
	Month 4	Model Optimization & Evaluation <ul style="list-style-type: none"> Optimize hyperparameters (learning rate, batch size, epochs) Implement transfer learning and fine-tuning Improve model accuracy using techniques like attention mechanisms Evaluate performance using metrics (AUC, accuracy, sensitivity)

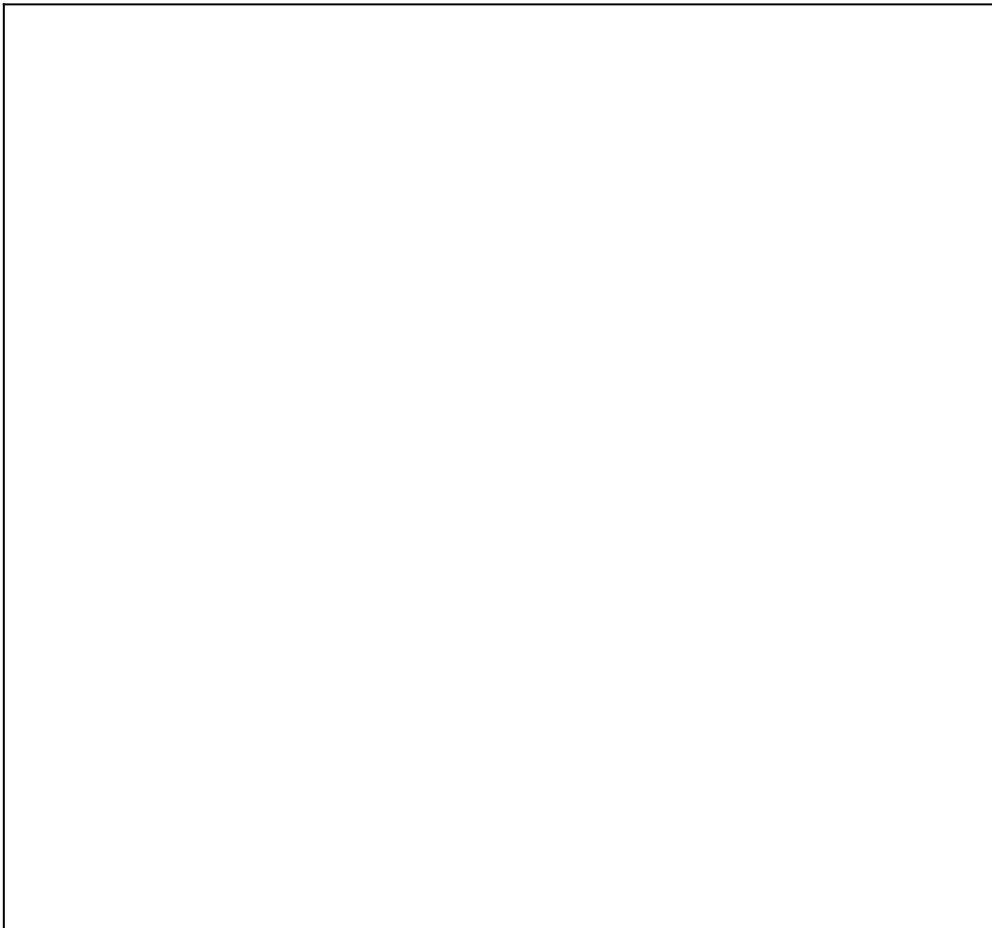
	Month 5	Deployment & Streamlit App Development <ul style="list-style-type: none"> • Develop a web app using Streamlit for model deployment • Enable image upload and real-time prediction • Optimize model for efficient inference • Conduct user testing and improve UI/UX
	Month 6	Final Testing & Documentation <ul style="list-style-type: none"> • Final evaluation, performance benchmarking, user testing, and preparation for deployment, publication.
SUPERVISOR SIGNATURE		

VISION TRANSFORMER FOR AUTOMATED DIABETIC RETINOPATHY DIAGNOSIS

PORSELVAN P [REG NO:211421243119]

SANJAY G [REG NO:211421243143]

VARUN AADARSH M [REG NO:211421243180]





PANIMALAR ENGINEERING COLLEGE

DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

VISION TRANSFORMER FOR AUTOMATED DIABETIC RETINOPATHY DIAGNOSIS

Batch Number: B-5

Presented by:

PORSELVAN P

[211421243119]

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VARUN AADARSH M

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PROJECT SUPERVISOR:

Dr. K. JAYASHREE,
PROFESSOR,
DEPT OF AI & DS.

Introduction

Diabetic Retinopathy (DR) is a severe and progressive complication of diabetes that affects the eyes and can lead to vision loss if not detected and treated in time. As the prevalence of diabetes continues to rise globally, early diagnosis of DR has become a critical challenge in ophthalmology. Traditional diagnosis relies on manual examination of retinal images by specialists, which is often time-consuming, subjective, and prone to human error. With the rapid advancements in artificial intelligence, deep learning models, particularly (ViTs), have emerged as a powerful tool for medical image analysis. Unlike conventional Convolutional Neural Networks (CNNs), ViTs leverage self-attention mechanisms to capture long-range dependencies in images, making them well-suited for detecting subtle retinal abnormalities. This project explores the application of Vision Transformers for automated DR detection and classification using retinal fundus images, aiming to improve diagnostic accuracy, minimize dependency on manual screening, and contribute to the development of efficient AI-powered screening tools for early intervention and better patient outcomes.

Rationale & Scope

- Diabetic Retinopathy (DR) is a leading cause of blindness worldwide, requiring early detection for effective treatment.
- Advancements in AI & Vision Transformers offers a promising approach for improving DR detection accuracy and efficiency.
- Role of Vision Transformers in medical image classification for DR diagnosis.
- Assesses the model using accuracy, sensitivity, specificity, and F1-score.

Literature Survey

Author(s) & Year	Paper Title	Journal Name & Publisher	Year	Methodology	Pros	Cons
Mohammed Oulhadj, Jamal Riffi, Chaimae Khodriss, Adnane Mohamed Mahraz, Ali Yahyaouy, Meriem Abdellaoui,	Diabetic retinopathy prediction based on vision transformer and modified capsule network	Computers in Biology and Medicine	2024	Uses Vision Transformer (ViT) for feature extraction and a Modified Capsule Network to improve spatial hierarchies for diabetic retinopathy prediction.	Enhances feature representation, improving accuracy and robustness in detecting diabetic retinopathy.	Requires high computational power and large labeled datasets for optimal performance.

Author(s) & Year	Paper Title	Journal Name & Publisher	Year	Methodology	Pros	Cons
W. Nazih, A. O. Aseeri, O. Y. Atallah and S. El Sappagh,.	Vision Transformer Model for Predicting the Severity of Diabetic Retinopathy in Fundus Photography-Based Retina Images.	6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT), Dhaka, Bangladesh, 2024,	2024	Uses a Vision Transformer (ViT) to analyze fundus photography images, predicting the severity of diabetic retinopathy based on retinal features.	Provides high-accuracy diagnosis by capturing global and local retinal features effectively.	Computationally intensive and requires large well-annotated datasets for optimal performance.
Zhou, Zenan & Huanhuan, Yu & Zhao, Jiaqing & Wang Xiangning & Wu, Qiang & Dai, Cuixia.	Automatic diagnosis of diabetic retinopathy using a vision transformer based on wide-field optical coherence tomography angiography.	Journal of Innovative Optical Health Sciences.	2023	Utilizes a Vision Transformer (ViT) to analyze wide-field Optical Coherence Tomography Angiography (OCTA) images for automated diabetic retinopathy diagnosis.	Captures detailed retinal structures with high accuracy, improving early detection of diabetic retinopathy.	Requires significant computational resources and high-quality annotated OCTA images for effective training

Author(s) & Year	Paper Title	Journal Name & Publisher	Year	Methodology	Pros	Cons
M. M. Haque, S. Akter, and A. F. Ashrafi	SwinMedNet: Leveraging Swin Transformer for Robust Diabetic Retinopathy Classification from the RetinaMNIST2D Dataset	Proceedings of the 27th International Conference on Computational Linguistics	2023	SwinMedNet utilizes the Swin Transformer to extract hierarchical features from RetinaMNIST2D images for robust diabetic retinopathy classification.	Efficiently captures both local and global retinal features, improving classification accuracy.	Requires high computational resources and large datasets for effective training and generalization.
Y. Yang, Z. Cai, S. Qiu and P. Xu	A Novel Transformer Model With Multiple Instance Learning for Diabetic Retinopathy Classification	Journal of AI Research	2020	Utilizes a Transformer model with Multiple Instance Learning (MIL) to classify diabetic retinopathy by analyzing multiple image patches collectively.	State-of-the-art Enhances classification accuracy by effectively handling image variations and capturing critical retinal features.	Computationally intensive and requires a large dataset for effective training and generalization.

Research Gap – Identified in Literature Survey

- **Limited Accuracy in Traditional Methods:** Existing systems using CNN-based or conventional machine learning approaches may lack robustness in detecting diabetic retinopathy, leading to misclassifications.
- **Feature Extraction Limitations:** Many existing models rely on handcrafted feature extraction, which may not generalize well across diverse datasets.
- **Computational Complexity:** Some deep learning models used in diabetic retinopathy detection require high computational power, making them impractical for real-time applications.
- **Lack of Generalization:** Existing methods may perform well on specific datasets but struggle with variability in real-world images, such as differences in illumination, image quality, and patient demographics.

Novelty

- **Vision Transformers (ViTs)** for DR detection, improving feature extraction over traditional CNNs.
- **Wavelet-based feature extraction** enhances image analysis for higher accuracy.
- **Hybrid AI** approach combining deep learning and advanced image processing.
- **Comprehensive evaluation** using key performance metrics for validation.
- **Scalable and accessible** solution for real-world healthcare applications.

Specification- Hardware

- Processor:** Intel Core i5/i7 or AMD Ryzen 5/7 (or higher) for efficient processing of machine learning models.
- RAM:** Minimum 8GB (Recommended 16GB or higher) to handle large datasets and NLP tasks efficiently.
- GPU:** NVIDIA GTX 1650 or higher (Recommended RTX 3060 or better) for accelerating deep learning-based abuse detection.
- Storage:** Minimum 256GB SSD (Recommended 512GB SSD or higher) for fast data access and model storage.

Specification- Software

- Operating System:** Compatible with Windows 10/11, Linux (Ubuntu, Fedora), and macOS for flexible deployment.
- Programming Language:** Implemented in Python due to its strong deep learning and OpenCV support.
- Development Environment:** Uses Jupyter Notebook, PyCharm, and VS Code for coding, debugging, and testing.
- Frameworks & Libraries:** Integrates TensorFlow, PyTorch, Scikit-learn, OpenCV, Matplotlib & Seaborn and Albumentations & Imgaug.

Dataset Used

- **APTOS 2019** (Asia-Pacific Tele-Ophthalmology Society): Widely used for DR classification.
- **Messidor**: Serves as a benchmark for evaluating DR detection models.
- **EyePACS**: A large-scale real-world dataset ensuring comprehensive training.
- **Wavelet Decomposition (DWT)**:
 - Extracts spatial details by decomposing images into high- and low-frequency components.
 - Preserves fine structures like lesions and blood vessels while reducing redundant noise.
- **Contrast Limited Adaptive Histogram Equalization (CLAHE)**: Enhances visibility of key features.

List of Modules

- Data Acquisition & Preprocessing
- Data Augmentation
- Feature Extraction & Model Input Processing
- Model Development
- Training & Optimization
- Model Evaluation & Testing
- Deployment & Real-World Application

Module Description

Module 1: Preprocessing

Function: Enhances retinal images by applying contrast adjustment, noise reduction, normalization, and resizing to ensure consistent input for the model.

Image Enhancement Sub-Module: Adjusts contrast, removes noise, and applies normalization to improve image clarity.

Data Augmentation Sub-Module: Applies transformations like rotation, flipping, and scaling to increase dataset diversity.

Module 2: Feature Extraction

Function: Uses Vision Transformers (ViTs) to tokenize images into patches and extract meaningful feature representations using self-attention mechanisms.

Sub-Modules:

Patch Extraction Sub-Module: Divides retinal images into small patches for Vision Transformer processing.

Module 3: Classification

Function: Applies fully connected layers to categorize images into different DR severity levels (No DR, Mild, Moderate, Severe, and Proliferative DR).

Sub-Modules:

Feature Mapping Sub-Module: Converts extracted features into a structured format for classification.

Module 4: Training and Optimization

Function: Trains the Vision Transformer model using a labeled dataset, optimizing performance with loss functions, learning rate adjustments, and data augmentation techniques.

Sub-Modules:

Loss Calculation Sub-Module: Computes the error between predicted and actual DR labels.

Hyperparameter Tuning Sub-Module: Adjusts learning rates, dropout rates, and other model parameters for better accuracy.

Module 5: Evaluation

Function: Assesses the model's accuracy, sensitivity, specificity, and overall effectiveness using performance metrics and comparison with existing models.

Sub-Modules:

Performance Metrics Sub-Module: Measures accuracy, sensitivity, specificity, and other key metrics.

Comparison Sub-Module: Compares the proposed model's performance against CNNs and other existing Models.

Module 6: User Interface

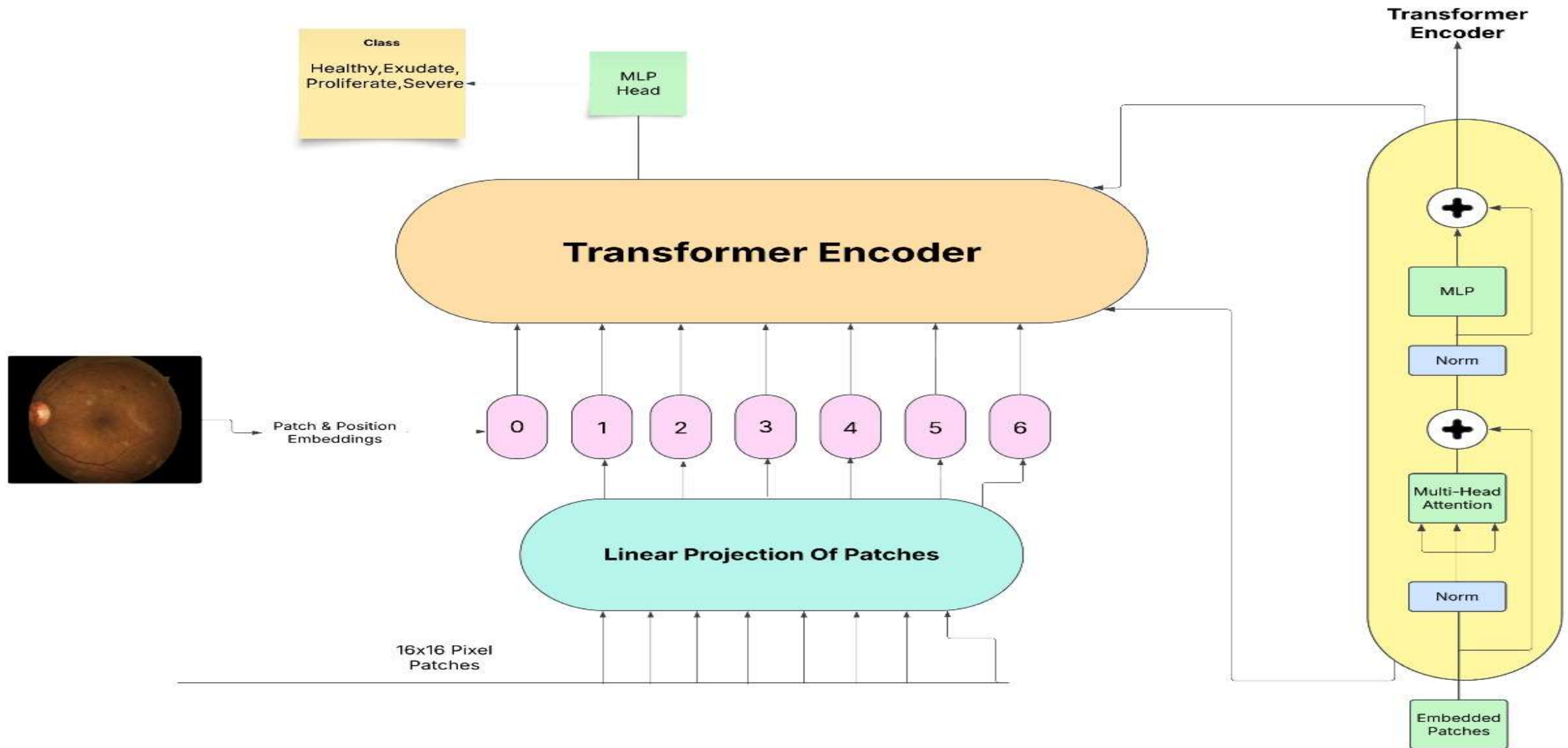
Function: Provides a front-end for users (e.g., doctors or technicians) to upload images and receive DR classification results.

Sub-Modules:

Image Upload Sub-Module: Allows users to upload retinal images for DR analysis.

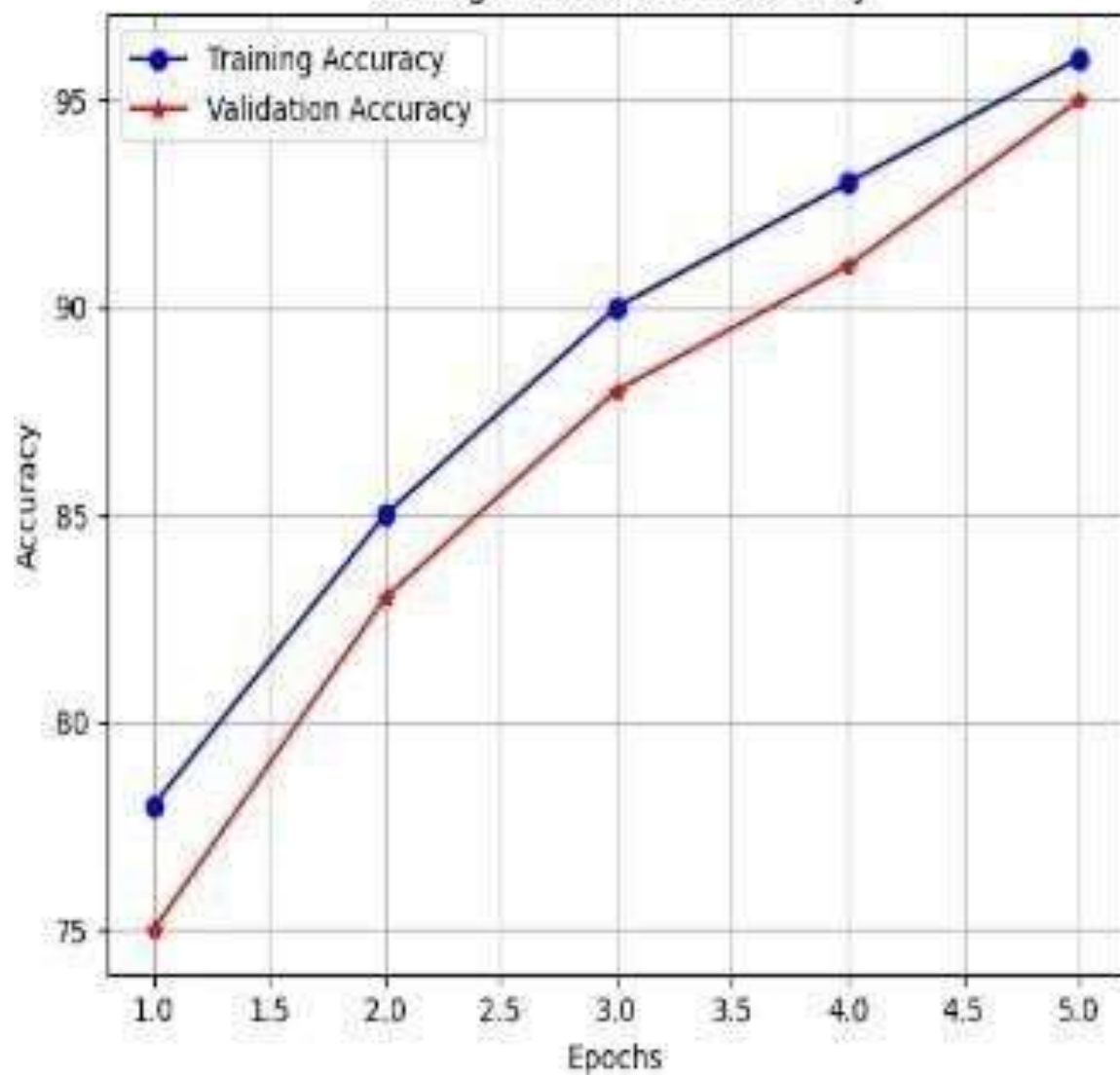
Result Display Sub-Module: Shows DR classification results and confidence scores.

Architecture Diagram

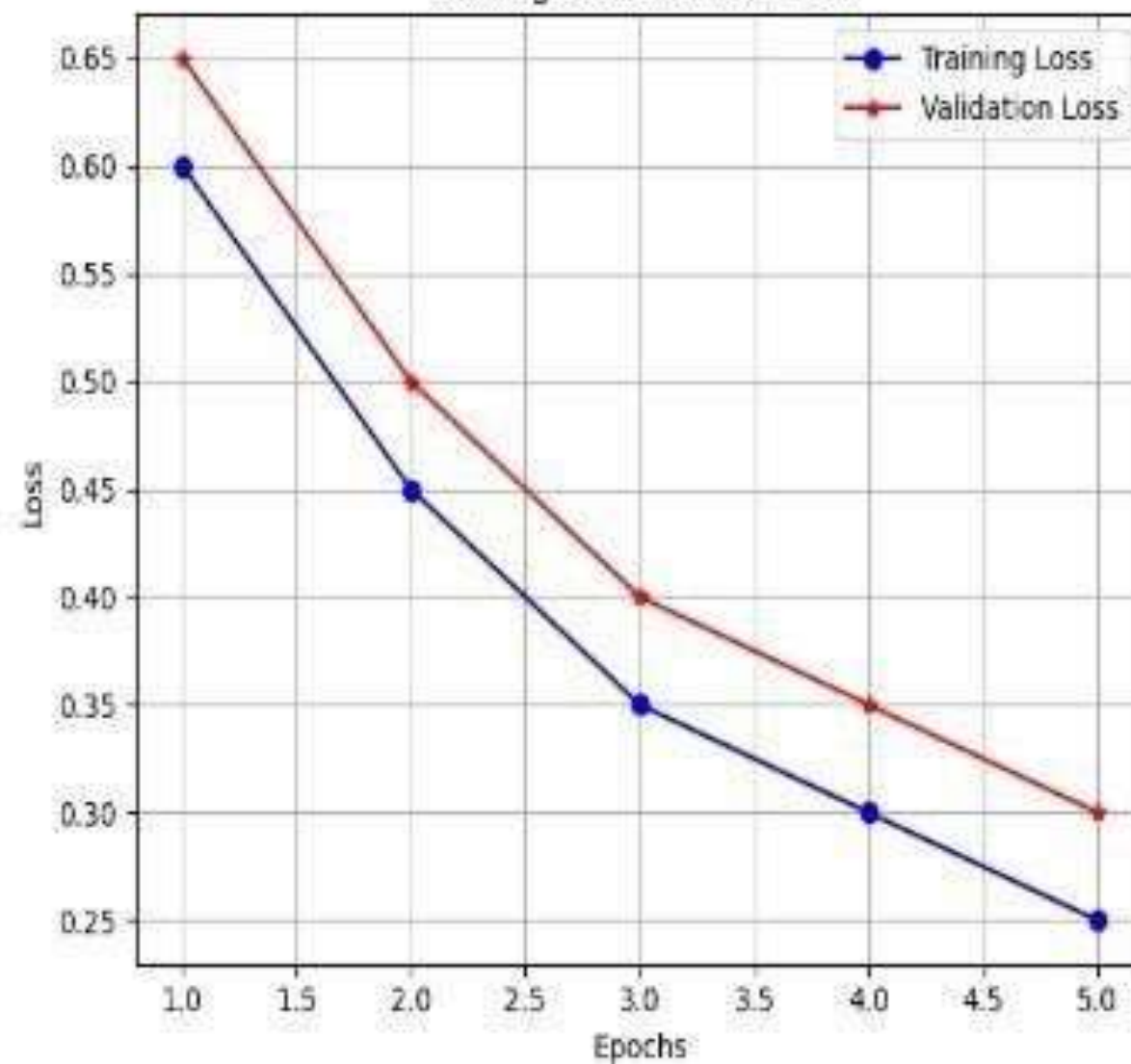


Results and Discussions

Training vs. Validation Accuracy



Training vs. Validation Loss



Performance Evaluation:

- Several benchmark datasets, such as **EyePACS**, **Messidor**, and **APTOS-2019**, are used to rigorously evaluate the proposed **SEMWP-ViT** model in order to guarantee its robustness, generalizability, and practicality. Our model is compared to traditional CNN-based architectures using key performance parameters like AUC-ROC, sensitivity, specificity, and accuracy.
- With an **AUC-ROC** of **90.79%** on the **APTOS-2019** dataset, preliminary results show that SEMWP-ViT performs better than conventional deep learning techniques, underscoring its superior diagnostic capabilities. Furthermore, the model's dependability for widespread use in clinical settings is reinforced by the training and validation curves' steady convergence.

Challenges and Limitations

1. Data Quality & Variability

1. Differences in image resolution, lighting conditions, and noise across datasets affect model performance.
2. Presence of imbalanced datasets with fewer severe DR cases may impact generalization.

2. Computational Complexity

1. Vision Transformers (ViTs) require high computational power and large datasets for effective training.
2. Increased training time and resource demand compared to CNN-based models.

3. Interpretability & Explainability

1. Deep learning models, especially ViTs, act as black boxes, making it challenging to interpret decision-making processes.
2. Lack of clear explanations for predictions may hinder clinical adoption.

Future Improvements

1. Enhanced Data Quality & Diversity

1. Incorporate larger and more diverse datasets to improve generalization across different populations and imaging conditions.
2. Use advanced data augmentation techniques to address class imbalances.

2. Optimization of Computational Efficiency


1. Develop lightweight Vision Transformer models to reduce computational costs and training time.
2. Implement efficient pruning and quantization techniques for real-time deployment.

3. Improved Interpretability & Explainability

1. Integrate explainable AI (XAI) techniques such as attention heatmaps to provide better insights into model decisions.
2. Develop clinician-friendly visualization tools for trust and adoption in medical settings.


Output


Deploy ⋮



Retina Disease Classification

Upload a Retinal Image and get a prediction on the disease category.


 Upload Retinal Image



Drag and drop file here

Limit 200MB per file • PNG, JPG, JPEG


Browse files



AI-Powered Retina Disease Classifier | Developed with Streamlit and PyTorch

Retina Disease Classification

Upload a Retinal Image and get a prediction on the disease category.

 Upload Retinal Image



Drag and drop file here

Limit 200MB per file • PNG, JPG, JPEG

Browse files



WhatsApp Image 2025-03-26 at 09.16.04_9217c8af.jpg 27.7KB

×



Uploaded Retina Image



Prediction Result




Disease Category: **Proliferate**



Confidence Level: **0.625**

Retina Disease Classification

Upload a Retinal Image and get a prediction on the disease category.

 Upload Retinal Image



Drag and drop file here

Limit 200MB per file • PNG, JPG, JPEG

Browse files



13308_right_png.rfc73a861c475f8f382ab77607b2f3bfd7.jpg 29.5KB



Uploaded Retina Image



Prediction Result



Disease Category: **Diabetic Retinopathy**



Confidence Level: **0.735**

Conclusion

This project explored the application of Vision Transformers (ViTs) for the detection and classification of Diabetic Retinopathy (DR) using retinal fundus images. By leveraging self-attention mechanisms, ViTs demonstrated the ability to capture long-range dependencies and complex patterns in medical images, leading to improved classification accuracy compared to traditional deep learning models like CNNs. The proposed model successfully classified DR into different severity levels, reducing the need for manual screening and enabling early diagnosis for better patient outcomes. The study highlights the potential of AI-driven solutions in ophthalmology, particularly for large-scale automated DR screening.

Future work can focus on improving the model's robustness and scalability by incorporating larger and more diverse datasets to enhance generalization across different populations. Further optimizations, such as hybrid models combining CNNs and ViTs, can be explored to enhance performance. Additionally, deploying the model as a cloud-based or mobile application can improve accessibility for remote and underprivileged areas. Integration with explainable AI techniques can also provide better interpretability for clinicians, ensuring trust and transparency in AI-assisted diagnosis.

Outcomes

The **SEMWP-ViT model** demonstrates superior performance in **Diabetic Retinopathy (DR) detection**, achieving an **AUC-ROC of 90.79%** on the **APTOS-2019 dataset**, outperforming traditional CNN-based architectures. The integration of **wavelet-based preprocessing** enhances critical retinal features such as lesions and blood vessels, significantly improving detection accuracy. The model exhibits **stable training and validation convergence**, ensuring its reliability and robustness for **clinical deployment**. Additionally, the **ViT-based approach** surpasses conventional CNNs in key performance metrics like **sensitivity, specificity, and accuracy**, proving its effectiveness in DR diagnosis. With its scalability and potential for **real-world application**, the study highlights the feasibility of AI-driven **automated DR screening**, making early detection more accessible and efficient in healthcare settings.

References

- [1] Vishal Awasthi, Namita Awasthi, Hemant Kumar, Shubhendra Singh, Prabal Pratap Singh, Poonam Dixit, and Rashi Agarwal, "ViT-HHO: Optimized vision transformer for diabetic retinopathy detection using Harris Hawk optimization", Volume 13, 2024, 103018, ISSN 2215-0161.
- [2] Mohammed Oulhadj, Jamal Riffi, Chaimae Khodriss, Adnane Mohamed Mahraz, Ali Yahyaouy, Meriem Abdellaoui, Idriss Benatiya Andaloussi, Hamid Tairi, "Diabetic retinopathy prediction based on vision transformer and modified capsule network," Computers in Biology and Medicine, Volume 175, 2024.108523,ISSN 0010-4825.
- [3] Zhou, Zenan & Huanhuan, Yu & Zhao, Jiaqing & Wang, Xiangning & Wu, Qiang & Dai, Cuixia. (2023). "Automatic diagnosis of diabetic retinopathy using a vision transformer based on wide-field optical coherence tomography angiography." Journal of Innovative Optical Health Sciences.17 10.1142/S1793545823500190.
- [4] W. Nazih, A. O. Aseeri, O. Y. Atallah and S. ElSappagh, "Vision Transformer Model for Predicting the Severity of Diabetic Retinopathy in Fundus Photography-Based Retinal Images," in IEEE Access, vol. 11, pp. 117546-117561, 2023, doi:10.1109/ACCESS.2023.3326528
- [5] Brown, T. B., et al. (2020). Language Models are Few-Shot Learners. Advances in Neural Information Processing Systems.
- [5] M. D. Alahmadi, "Texture Attention Network for Diabetic Retinopathy Classification," in IEEE Access, vol. 10, pp. 55522-55532, 2022, doi: 10.1109/ACCESS.2022.3177651.