AUTOMATED DETECTION OF DIABETIC RETINOPATHY

MINOR PROJECT REPORT

Submitted in partial fulfilment of the requirements for the award of the degree

of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE & ENGINEERING

by

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CANDIDATE'S DECLARATION

It is hereby certified that the work is being presented in the B. Tech Minor Project Report entitled **"Automated Detection of Diabetic Retinopathy"** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** and submitted in the **Department of Computer Science & Engineering** of **MAHARAJA SURAJMAL INSTITUTE OF TECHNOLOGY, New Delhi (Affiliated to Guru Gobind Singh Indraprastha University, Delhi)** is an authentic record of our work carried out during a period from **August 2024 to November 2024** under the guidance of **Dr. Amita Yadav, Faculty.**

The matter presented in the B. Tech. Minor Project Report has not been submitted by me for the award of any other degree from this or any other institute.

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CERTIFICATE

This is to certify that the project report titled **"Automated Detection of Diabetic Retinopathy"** has been completed by the following students in partial fulfillment of the requirements for the Minor Project for the Bachelor of Technology degree in Computer Science and Engineering. The work presented in this report is the result of the student's independent efforts, diligence, and commitment under our supervision. This project has been examined and approved as meeting the academic standards and requirements of the Computer Science and Engineering Department at **Maharaja Surajmal Institute of Technology.**

The candidates are hereby permitted to appear for the External Minor Project Examination.

Dr. Geetika Dhand	**Dr. Shaily Malik**	**Dr. Parul Chaudhary**	**Dr. Amita Yadav**
H.O.D.	**Project Coordinator**	**Proctor**	**Mentor**

ABSTRACT

Diabetic retinopathy (DR) is a leading cause of vision loss among people with diabetes, impacting millions worldwide as diabetes rates continue to rise. Without early intervention, DR progresses through stages from mild to proliferative, potentially causing irreversible blindness. Traditional DR diagnosis, primarily through fundus photography reviewed by specialists, is resource-intensive and often impractical for widespread screening, especially in resource-limited areas.

This study explores the use of Convolutional Neural Networks (CNNs) in developing an automated DR detection tool. CNNs excel in image analysis, identifying complex patterns in medical imaging, and have shown promise in DR classification. The aim is to create a reliable, scalable diagnostic tool that classifies retinal images into DR stages, facilitating early detection and treatment. The model leverages advanced CNN architectures, transfer learning, and data augmentation techniques to boost accuracy and adaptability.

The Kaggle Diabetic Retinopathy Dataset, with thousands of labelled retinal images, served as the training foundation. Rigorous preprocessing improved image quality and balanced class distributions, while ResNet and EfficientNet architectures—optimized with transfer learning—enhanced the model's classification accuracy. Evaluation metrics, including accuracy, precision, recall, and F1 score, provided a robust performance assessment.

To ensure practical application, a Streamlit-based interface was developed. This interface allows healthcare providers to upload images, view predictions. Results demonstrate that CNNs can provide fast, accurate, and reliable DR detection, with the model's scalability making it suitable for large-scale screening. This research highlights AI's transformative potential in healthcare, especially for improving DR diagnosis in underserved areas. Future work will explore enhancing model generalizability and interpretability for wider clinical application.

ACKNOWLEDGEMENT

This acknowledgement is dedicated to all the individuals who assisted us in creating this project. The project could not have gone smoothly without their help.

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LIST OF ABBREVIATION

CNN	Convolutional Neuron Network
DR	Diabetic retinopathy
PIL	Python Imaging Library
LIME	Local Interpretable Model-Agnostic Explanations
RNN	Recurrent Neural Network
DTCWT	Dual Tree Complex Wavelet Transform
MLP	Multi-Layer Perceptron

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CHAPTER 1

INTRODUCTION

1.1 Background

Diabetic Retinopathy (DR) is one of the most common complications of diabetes and a significant cause of blindness worldwide. As diabetes rates continue to increase globally, so does the prevalence of diabetic retinopathy, which now affects approximately one-third of the diabetic population. DR occurs due to prolonged exposure to high blood sugar levels, which damages the small blood vessels in the retina. Over time, this damage can lead to severe complications, including vision impairment and blindness.

Regular screening and early detection of diabetic retinopathy are crucial for effective management and prevention of vision loss. However, traditional screening methods, which rely on manual interpretation of retinal images by ophthalmologists, are often resource-intensive, subjective, and dependent on specialized personnel. This creates a barrier to timely diagnosis, particularly in underserved regions where access to ophthalmologists is limited. To address these challenges, automated systems leveraging advanced image processing and machine learning techniques are emerging as viable alternatives for DR screening.

1.2 Motivation and Significance

The motivation behind this project stems from the growing global health burden posed by diabetic retinopathy. The World Health Organization classifies DR as a preventable cause of blindness, yet millions remain at risk due to the lack of access to timely screening. Automated diabetic retinopathy detection offers the potential to alleviate this burden by enabling faster, more accessible, and cost-effective screening methods.

This project's significance lies in its potential to make DR screening scalable and accessible. An automated solution can significantly improve early detection rates, particularly in remote or resource-limited areas. Such a system can enable healthcare providers to quickly identify at-risk patients, prioritize treatment, and ultimately reduce the incidence of blindness due to

diabetic retinopathy. Additionally, this project's emphasis on deploying a web-based interface makes it adaptable and accessible to a broad audience, further expanding its impact.

1.3 Problem Statement

The primary problem addressed in this project is the accurate and automated detection of diabetic retinopathy from retinal images. Current diagnostic approaches are largely manual, relying on ophthalmologists to interpret images and identify early signs of the disease. However, these manual assessments are prone to subjectivity and can vary between practitioners. Additionally, a large population of diabetic patients in underserved areas may not have timely access to screening, increasing the risk of late diagnosis and progressive vision loss.

Automating the detection of DR can significantly improve early diagnosis, expedite treatment plans, and, ultimately, prevent blin

This research aims to develop an automated system for diabetic retinopathy detection using CNNs, with a focus on enhancing dness. A deep learning model capable of analyzing retinal images and predicting disease severity can provide a scalable solution. Thus, this project seeks to design, develop, and deploy an accessible, accurate, and automated diabetic retinopathy detection system.

1.4 Research Objectives

diagnostic accuracy, reliability, and accessibility. By building a model capable of classifying retinal images into distinct DR stages, this study seeks to contribute to the early detection and timely intervention of DR. The primary objectives of this research are as follows:

1. **To study and develop advanced CNN models for retinal image analysis**: This involves configuring and training CNN architectures that can accurately classify retinal images according to DR severity, taking into account the unique features and challenges associated with medical imaging.
2. **To evaluate the automated detection system's performance and accuracy through real-time analysis**: This objective includes using metrics such as accuracy, precision,

recall, and F1 score to assess the model's diagnostic reliability. Additionally, data augmentation and transfer learning techniques will be employed to enhance the model's generalizability.

3. **To develop a user-friendly interface for DR detection**: A web-based application using Streamlit will be created to enable healthcare providers to use the model for real-time DR screening. The interface will be designed to facilitate ease of use, allowing users to upload images, receive predictions, and view visualization outputs.

1.5 Scope and Limitations

The scope of this project includes building a CNN-based classification model for diabetic retinopathy detection and deploying it as a web application for real-time diagnosis. The project uses a publicly available diabetic retinopathy dataset, which includes images labeled according to the severity of the disease.

Limitations

1. **Dataset Dependency**: The model's accuracy is highly dependent on the dataset quality and diversity. Limited data variations can impact the model's generalizability to different populations.
2. **Image Quality Constraints**: The model may struggle with poor-quality images, which can affect diagnostic accuracy.
3. **Limited Feature Interpretability**: Deep learning models are often criticized for being "black boxes," meaning that they lack transparency in how they make predictions. This may limit the system's acceptance in clinical settings where interpretability is critical.

1.6 Report Structure

The remainder of this report is organized as follows:

- **Chapter 1: Introduction** – Provides an overview of the project background, objectives, problem statement, and motivation.

- **Chapter 2: Literature Review** – An in-depth review of previous research on diabetic retinopathy detection methods, covering traditional approaches, machine learning techniques, and advancements in deep learning.
- **Chapter 3: Research Methodology** – Describes the project's model architecture, data preprocessing steps, and CNN-based detection methodology. It also covers techniques used to optimize accuracy, address data imbalance, and improve overall model performance.
- **Chapter 4: Implementation Details and Results** – Describes the project's problem statement, the model architecture, flowcharts, and algorithms used. This chapter also presents and discusses the model's results and limitations.
- **Chapter 5: Conclusion and Future Scope** – Summarizes the project's findings, its contributions, and discusses potential areas for future research and improvements.

This structure provides a detailed approach to understanding the project, aligning it with research goals and the findings of related literature. The subsequent chapters will build on this foundation to evaluate and implement diabetic retinopathy detection models effectively.

CHAPTER – 2

LITERATURE SURVEY

Diabetic retinopathy (DR) is a severe complication of diabetes and a leading cause of vision loss worldwide. It results from damage to the blood vessels in the retina caused by prolonged high blood sugar levels. The disease progresses through stages ranging from 'No DR' to 'Proliferative DR,' where advanced retinal damage and neovascularization can cause irreversible blindness.

Early detection of DR is critical for preventing vision loss, as emphasized by Taylor and Batey (2012), who highlighted the role of regular retinal screening in reducing blindness among diabetic patients. Bourne et al. (2010) further stressed the global burden of vision loss, calling for scalable diagnostic solutions, especially for high-risk populations with prolonged diabetes. The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized DR detection by enabling automated analysis of retinal images with remarkable accuracy. This chapter explores various advancements in DR detection using CNNs, including key architectures, data preprocessing techniques, and diagnostic interfaces, while addressing challenges in dataset quality, model generalization, and clinical integration.

2.1 Overview of Diabetic Retinopathy Detection

Diabetic retinopathy is a progressive eye disease caused by damage to the blood vessels of the retina due to prolonged high blood sugar levels. If left untreated, it can lead to irreversible vision loss. The disease typically progresses through five stages:

- **No DR**: No visible damage to the retina.
- **Mild DR**: Presence of microaneurysms, the earliest sign of DR.
- **Moderate DR**: Increased presence of haemorrhages and exudates, indicating worsening retinal damage.
- **Severe DR**: Greater retinal damage with risk of vision loss.

- **Proliferative DR**: Advanced stage characterized by neovascularization (new blood vessel growth), which can lead to blindness.

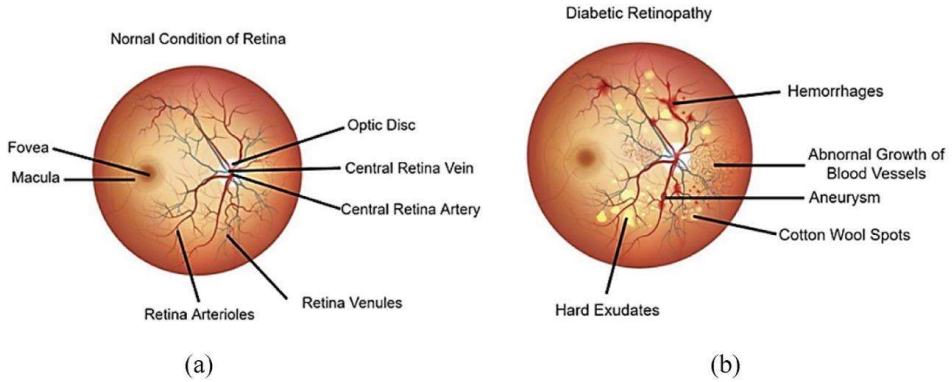

Fig 2.1 Illustrations of (a) healthy and normal condition of the retina and (b) diabetic retinopathy

As illustrated in Fig 2.1, early stages of DR are often asymptomatic and can be difficult to detect without proper screening. Therefore, timely detection is essential for preventing progression to the more severe stages that may require advanced intervention. Early and precise detection of DR is crucial for preventing severe vision loss. Automated DR detection systems powered by deep learning, particularly CNNs, have shown significant promise in providing accurate diagnoses while reducing the dependence on clinical expertise. This review examines recent advancements, methodologies, and comparative studies in deep learning-based DR detection.

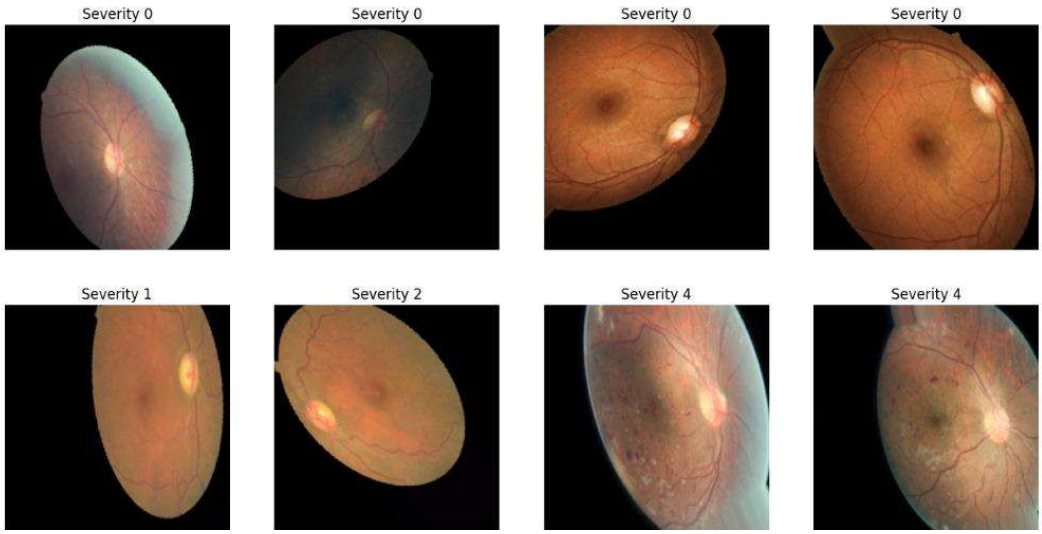

Fig 2.2 Images with varying severity.

2.2 Current Approaches in DR Detection

2.2.1 CNN Architectures for DR Detection

CNNs have become the backbone of DR detection systems due to their superior performance in image classification tasks. Architectures such as ResNet, Inception, DenseNet, and EfficientNet have been extensively studied for their ability to capture intricate retinal patterns [5]. EfficientNet, for instance, uses a compound scaling method to balance network depth, width, and resolution, achieving high accuracy with fewer parameters [6].

Patel and Sharma [7] introduced a real-time CNN-based model tailored for rapid DR screening. Their model demonstrated exceptional accuracy in detecting advanced stages of DR while maintaining computational efficiency, making it suitable for clinical deployment. However, challenges in early-stage detection persist due to the subtle nature of initial retinal changes [8].

2.2.2 Data Augmentation and Dataset Quality

Data augmentation plays a pivotal role in enhancing the robustness of CNN models, particularly when datasets are limited or imbalanced. Techniques such as rotation, flipping, scaling, and brightness adjustment artificially expand datasets, improving model generalization [9].

Gargeya and Leng [10] emphasized the importance of addressing class imbalance, particularly for severe stages like Proliferative DR, which are often underrepresented. Advanced approaches, such as Generative Adversarial Networks (GANs), have been employed to generate synthetic retinal images, further mitigating dataset limitations [11]. These strategies enhance model performance by exposing it to a broader range of image variations.

2.2.3 Preprocessing Techniques

Image preprocessing is critical for improving model accuracy by enhancing the quality of input data. Techniques like gamma correction, normalization, and adaptive histogram equalization standardize image quality, making subtle features like microaneurysms more detectable [12].

Qiao et al. [13] utilized semantic segmentation to isolate regions of interest within retinal images, enabling precise detection of abnormalities. This approach is particularly effective for early-stage DR detection, where features are often small and difficult to discern in raw images.

2.2.4 Transfer Learning and Pre-Trained Models

Transfer learning has emerged as a powerful technique for accelerating the development of DR detection models. By fine-tuning pre-trained networks like VGG16, ResNet, and EfficientNet on DR-specific datasets, researchers can achieve high accuracy with reduced computational resources [14].

Jones et al. [15] demonstrated that transfer learning significantly reduces the need for large labelled datasets, making it a viable solution for resource-constrained environments. However, challenges in adapting these models to diverse datasets remain, necessitating careful optimization during the fine-tuning process.

2.2.5 Real-Time Detection Systems

Real-time detection systems are essential for large-scale DR screening, particularly in high-volume clinical environments. These systems leverage CNN models to process retinal images rapidly, providing immediate diagnostic feedback [16].

El-Hossary et al. [17] highlighted the importance of balancing speed and accuracy in real-time systems, noting that high-resolution images require efficient processing to maintain diagnostic reliability. Despite their promise, real-time systems face challenges in ensuring consistent performance across varying imaging conditions.

2.3 Comparative Analysis of Techniques

Comparative studies have been instrumental in identifying effective methodologies for DR detection. Johnson et al. [18] conducted a detailed comparison of EfficientNet, ResNet, and DenseNet, concluding that EfficientNet's optimized scaling made it the most efficient model for large-scale screening.

Yang et al. [19] explored multi-resolution CNNs, which analyze images at different scales, improving the detection of subtle retinal changes. These advancements highlight the importance of tailoring models to specific clinical needs, such as scalability, accuracy, and computational efficiency [20].

2.4 Challenges in Automated DR Detection

2.4.1 Dataset Diversity and Generalization

Most DR datasets lack diversity, limiting the ability of models to generalize across populations. Models trained on datasets dominated by specific demographics may underperform when applied to diverse populations [10]. Addressing these biases requires the inclusion of more representative datasets.

2.4.2 Interpretability of Models

CNNs are often criticized for their "black-box" nature. Techniques like Grad-CAM and SHAP enhance interpretability by visualizing the regions of retinal images that influence predictions [21]. Improved explainability fosters trust in AI-based diagnostics, particularly among clinicians [22].

2.4.3 Integration into Clinical Workflows

Integrating automated DR detection systems into clinical workflows requires compatibility with electronic health records (EHRs) and seamless user interfaces. Sun et al. [23] proposed a hybrid framework that combines AI tools with traditional diagnostic methods, enabling clinicians to validate AI predictions while maintaining control over diagnoses.

2.5 Advancements in DR Detection

2.5.1 Multimodal Imaging Techniques

Smith et al. [24] demonstrated the effectiveness of combining fundus photography with optical coherence tomography (OCT) to improve diagnostic accuracy. Multimodal systems provide complementary information, enhancing the detection of early-stage DR lesions.

2.5.2 Ensemble Learning

Chawla et al. [25] showed that ensemble learning, which combines predictions from multiple models, significantly reduces false positives and improves overall diagnostic reliability.

2.5.3 Real-Time Interfaces

Patel et al. [26] highlighted the development of user-friendly real-time interfaces using platforms like Streamlit. These interfaces enable rapid image analysis, improving accessibility in clinical environments.

2.6 Future Directions

Future research should focus on improving early detection through expanded datasets and advanced preprocessing techniques [12]. Incorporating multimodal data, such as patient history and OCT images, could provide a more comprehensive diagnostic approach [24].

Advancing interpretability through techniques like SHAP and LIME will enhance clinician trust, while real-world clinical deployment will require extensive pilot studies and integration with existing workflows [21], [23].

CHAPTER – 3

RESEARCH METHODOLOGY

This project adopts a systematic approach to build an Automated Detection System for Diabetic Retinopathy (DR), involving a series of well-defined steps to ensure that the final model is accurate, efficient, and scalable. The stages include data collection, data preprocessing, model selection, training, evaluation, and deployment of a user-friendly interface for real-time predictions.

3.1 Technology and Libraries Used

The implementation of the **Automated Detection of Diabetic Retinopathy** project relies heavily on modern machine learning frameworks, libraries, and tools. These include:

3.1.1 Python

Fig 3.1 Logo of Python

Python is chosen as the primary programming language due to its simplicity, versatility, and rich ecosystem of libraries for data science and machine learning. Python's extensive support for various libraries makes it a preferred language for rapid development, prototyping, and implementation of deep learning models.

3.1.2 TensorFlow

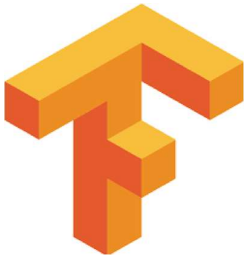

Fig 3.2 Logo of TensorFlow

TensorFlow is a powerful, open-source machine-learning framework developed by Google that allows developers to create and train machine learning models, especially neural networks. Its flexibility and performance make it ideal for large-scale machine learning and deep learning projects. TensorFlow also supports multiple languages, but it is most commonly used with Python. With an extensive set of tools and support for both CPUs and GPUs, TensorFlow has become a core tool for AI research and development.

3.1.3 Keras

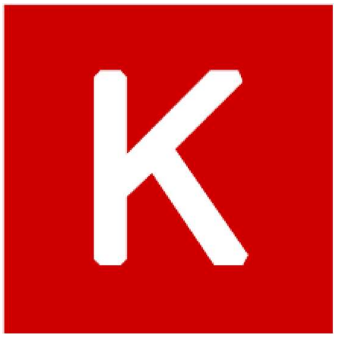

Fig 3.3 Logo of Keras

Keras is an easy-to-use, high-level neural network library that runs on top of TensorFlow. Designed to make deep learning accessible, Keras offers a simple and user-friendly API, allowing developers to quickly build and test neural networks. Keras handles most of the complex computations in the background, so users can focus on building and experimenting with their models. It's often used for prototyping and supports popular neural network layers, including convolutional and recurrent networks.

3.1.4 OpenCV

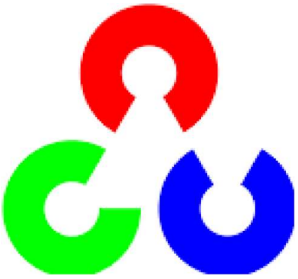

Fig 3.4 Logo of OpenCV

OpenCV (Open-Source Computer Vision Library) is an open-source library primarily used for real-time computer vision tasks. OpenCV is used in this project for various image processing tasks, such as resizing images, applying filters, and enhancing image contrast. The library is particularly useful for pre-processing the retinal images, including tasks like gamma correction to improve image brightness and clarity, which is critical for detecting subtle signs of diabetic retinopathy in retinal images.

3.1.5 Numpy

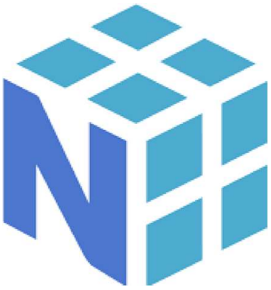

Fig 3.5 Logo of Numpy

NumPy is a core Python library for numerical computing and is essential for manipulating large arrays of data. In this project, NumPy is used for handling image data as arrays and performing operations such as normalization (scaling pixel values) and other mathematical computations required for model training and evaluation.

3.1.6 Pillow

Fig 3.6 Logo of Pillow

Pillow is a Python Imaging Library (PIL) fork used for opening, manipulating, and saving image files. Pillow is used to handle the images before they are passed through the CNN model, including converting images into arrays and resizing them to the required input dimensions of 224x224 pixels.

3.1.7 Matplotlib

Fig 3.7 Logo of Matplotlib

Matplotlib is a plotting library used for visualizing the training process, results, and performance of the model. It helps generate graphs for the training and validation loss, accuracy, and confusion matrix, providing insights into the model's learning behavior and performance. These visualizations aid in identifying overfitting, underfitting, and other issues during training.

3.1.8 Pyngrok and Cloudflared

Fig 3.8 Logo of Cloudflared

Pyngrok and Cloudflared are used to create secure tunnels for accessing the locally hosted Streamlit application. These tools are particularly useful for making the application accessible from a remote location or the internet, even if it is hosted on a local machine. By using these tools, the model and its web interface can be exposed to a global audience, enabling real-time predictions from anywhere.

3.1.9 Streamlit

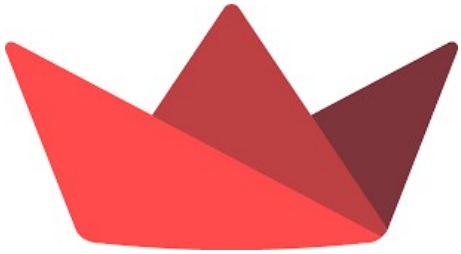

Fig 3.9 Logo of Streamlit

Streamlit is an open-source Python library that enables the creation of interactive web applications with minimal effort. It is particularly useful for quickly deploying machine learning models and providing an interface for users to interact with them. In this project, Streamlit is used to create a user-friendly web interface where users can upload their retinal images and receive predictions on the severity of diabetic retinopathy.

3.2 Data Collection

For this project, the dataset used is the **Diabetic Retinopathy 224x224 Gaussian Filtered Dataset**, which is publicly available on Kaggle. The dataset consists of retinal images labeled by the severity of diabetic retinopathy, which is categorized into five stages:

- **No_DR:** No Diabetic Retinopathy
- **Mild:** Mild Diabetic Retinopathy
- **Moderate:** Moderate Diabetic Retinopathy
- **Severe:** Severe Diabetic Retinopathy
- **Proliferative_DR:** Proliferative Diabetic Retinopathy (advanced stage)

The dataset is initially organized by categorizing the images into separate directories based on their corresponding labels. An 80-20 split is used to divide the dataset into training and validation sets, ensuring that the model is trained on a large portion of the data while validating its performance on a separate subset to check generalization.

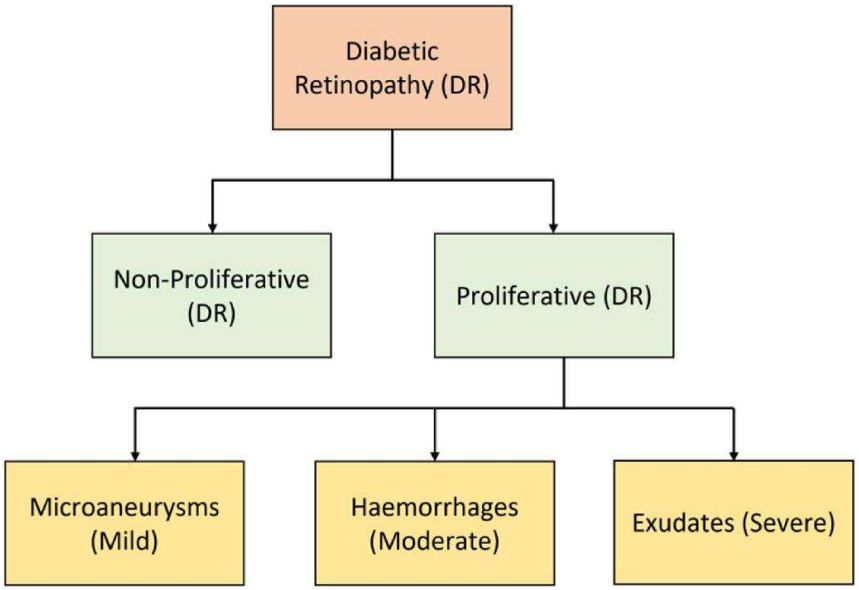

Fig 3.10 Diverse stages of DR.

3.3 Data Preprocessing

Before feeding the images into the CNN model, several preprocessing steps are necessary to ensure the images are in the appropriate format and quality for training. The preprocessing pipeline includes:

3.3.1 Gamma Correction: Gamma correction is applied to adjust the brightness and contrast of the images. It enhances the visibility of important features in the retinal images, particularly the ones that might be underexposed. This step is crucial as it helps in detecting subtle signs of diabetic retinopathy that may be otherwise difficult to identify.

3.3.2 Resizing and Normalization: The images are resized to a uniform dimension of 224x224 pixels to meet the input requirements of the CNN model. Additionally, pixel values are normalized by scaling them to a range between 0 and 1, which aids in faster convergence during model training.

3.3.3 Data Augmentation: To enhance model generalization, data augmentation techniques are applied to simulate real-life variations in the retinal images. These techniques include:

- Rotation: Random rotations (e.g., 0-20 degrees) to simulate different viewing angles.
- Flipping : Horizontal and vertical flips to add variability.
- Brightness Adjustment: Random brightness changes to mimic real-life lighting conditions.
- Zooming : Slight zoom-in operations to emphasize regions of interest in the retina.

T These augmentation techniques help in generating new variations of images, making the model more robust and reducing overfitting.

3.3.4 Class Balancing : In cases where certain classes (such as **Proliferative_DR**) are underrepresented, oversampling techniques are employed to generate synthetic samples, ensuring that all classes have a balanced representation. This prevents the model from being biased towards overrepresented classes and improves its ability to recognize all stages of diabetic retinopathy.

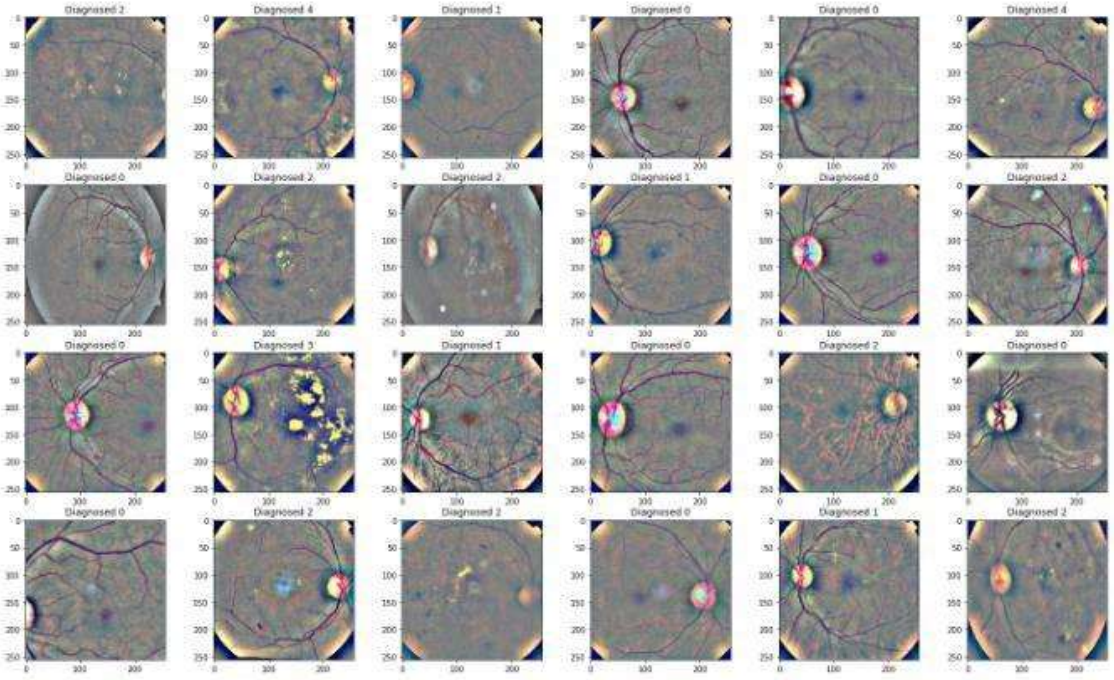

Fig 3.11 Images obtained after preprocessing.

3.4 Model Architecture Design

The model architecture for the **Automated Detection of Diabetic Retinopathy (DR)** is built using **Convolutional Neural Networks (CNNs)**, which are well-suited for image classification tasks. The architecture is designed to extract hierarchical features from retinal images and make predictions based on these features. Below is an elaboration of the design and the thought process behind it:

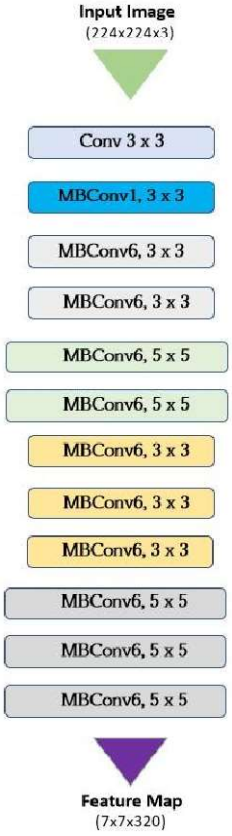

Fig 3.12 EfficientNet Architecture

3.4.1 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are the foundation of the model architecture, especially for tasks involving image classification. CNNs are designed to automatically detect and learn spatial hierarchies of features from images by applying various convolutional operations. They are particularly well-suited for image-related problems

as they can learn to recognize patterns at multiple levels of abstraction, from simple textures to complex objects. In the case of diabetic retinopathy (DR) detection, CNNs prove to be ideal since they are capable of effectively capturing visual features in retinal images, such as blood vessel patterns, lesions, and abnormalities like microaneurysms, hemorrhages, and exudates, which are characteristic of different DR stages.

- **EfficientNet Architecture**:
  The EfficientNet model, which is an advanced CNN architecture, serves as the backbone of this DR detection system. EfficientNet is designed with a highly efficient compound scaling approach, allowing the model to scale in terms of depth, width, and resolution in a balanced manner. This balanced scaling ensures that the model performs optimally while minimizing the computational cost. The EfficientNet-B0 variant was chosen for this study due to its excellent trade-off between accuracy and computational efficiency, making it suitable for deployment in resource-constrained environments, such as clinics with limited computational resources.

  - **Compound Scaling**: One of the key innovations in EfficientNet is its compound scaling technique, which uses a scaling coefficient to uniformly increase the depth, width, and resolution of the network. This method allows the model to maintain high performance while using fewer parameters compared to traditional CNN architectures. This results in a model that is both efficient and powerful, capable of handling complex image classification tasks such as DR detection, while also reducing the computational burden associated with training and inference.
  - **Layers and Blocks**: The EfficientNet architecture is composed of several building blocks, each designed to contribute to the model's effectiveness. The architecture includes compound scaling of basic convolutional and pooling layers, which facilitates effective learning from input images while reducing computational complexity. The network also incorporates depthwise separable convolutions, which significantly reduce the number of parameters and enhance computational efficiency. This enables the model to process high-

resolution retinal images while retaining critical features necessary for accurate DR classification.

- **Output Layer**: As with other advanced CNN architectures like ResNet, the final layer of EfficientNet is a dense softmax layer, which is responsible for classifying images into predefined categories. In the case of DR detection, the model outputs a classification of the retinal image into one of five stages of diabetic retinopathy: No DR, Mild DR, Moderate DR, Severe DR, and Proliferative DR. The softmax function applied to the output layer generates a probability distribution over the possible classes, allowing for a probabilistic classification that reflects the model's confidence in its predictions.

3.4.2 Layer-by-Layer Design

The CNN architecture for DR detection is composed of multiple layers, each performing a specific function to transform input images into meaningful predictions. The design of each layer is crucial to the model's ability to extract and learn relevant features for classifying retinal images.

- **Convolutional Layers**: The model begins with a series of convolutional layers, which are designed to detect and learn low-level features from the input retinal images. Each convolutional layer applies a set of learnable filters (kernels) to the image, generating feature maps that highlight specific patterns or structures in the image:
    - The model starts with a **Conv2D** layer with 32 filters and a kernel size of 3x3. This layer is responsible for detecting low-level features like edges and textures from the image.
    - The second convolutional layer uses 64 filters, which helps the model capture more complex features, such as the presence of larger shapes or more intricate structures indicative of diabetic retinopathy.
    - The third convolutional layer increases the filters to 128, allowing the model to detect even more detailed features, such as microaneurysms or

hemorrhages that are characteristic of different stages of diabetic retinopathy.

These convolutional layers are followed by MaxPooling2D layers, which downsample the feature maps by selecting the maximum value from a set of neighboring pixels. MaxPooling reduces the spatial dimensions of the feature maps while retaining the most important features. This operation also helps decrease the number of parameters in the model, which prevents overfitting and speeds up the computation. Max pooling is particularly useful for reducing the complexity of the model while ensuring that only the most relevant features are retained.

- **Flatten Layer**:

  After the convolutional and pooling layers, the model's feature maps are flattened into a one-dimensional array. This step is necessary because the convolutional and pooling layers output multi-dimensional arrays, which must be converted into a format that can be fed into fully connected layers for classification. The flattening process essentially prepares the feature maps for further processing by transforming them into a format that can be used by the subsequent dense layers.

- **Fully Connected (Dense) Layer**:

  - The flattened features are passed through a **Dense** layer with 128 neurons. This layer learns complex patterns and associations between the features extracted by the convolutional layers. The dense layer uses the **ReLU** activation function to introduce non-linearity, enabling the model to learn complex relationships.

  - To prevent overfitting and improve generalization, a Dropout layer with a rate of 0.5 is added after the Dense layer. During training, the Dropout layer randomly disables 50% of the neurons, forcing the model to learn more robust features and avoid memorizing specific details of the training data. This regularization technique improves the model's ability to generalize to unseen data, which is crucial for achieving reliable performance on new retinal images.

- **Output Layer**:
    - The final layer is a **Dense** layer with the number of neurons equal to the number of classes in the DR classification (5 classes in this case: No_DR, Mild, Moderate, Severe, Proliferative_DR). The output layer uses the SoftMax activation function, which converts the network's output into a probability distribution, making it suitable for multi-class classification.

3.4.3 Optimization and Loss Function

- **Adam Optimizer**: This adaptive optimizer is chosen due to its ability to adjust the learning rate during training, making it efficient for large datasets and ensuring faster convergence. Adam combines the benefits of both **AdaGrad** and **RMSProp**, providing stable updates and faster learning.
- **Categorical Cross-Entropy Loss**: This loss function is suitable for multi-class classification problems. It calculates the difference between the predicted and true probability distributions and optimizes the model during training by minimizing the loss.

3.4.4 Model Training

The model is trained for 10 epochs, using a batch size of 32, to allow the network to gradually adjust the weights through backpropagation. During training, data augmentation techniques such as rotation, zooming, shearing, and horizontal flipping are applied to the input images, which helps the model generalize better and avoid overfitting.

3.5 Model Evaluation and Testing

After training, the model was tested on the test set. Performance metrics such as accuracy, precision, recall, and F1 score were computed to assess the model's diagnostic reliability. The test set provided a realistic measure of the model's effectiveness on unseen data, simulating its performance in clinical settings.

1. **Accuracy Calculation**: Accuracy was calculated as the proportion of correctly classified images out of the total test images.
2. **Precision, Recall, and F1 Score for Each Class**:Precision, recall, and F1 scores were calculated for each DR stage, providing a detailed breakdown of the model's effectiveness across all stages.
3. **Confusion Matrix Analysis**: A confusion matrix was used to visualize misclassification trends, which helped in understanding the model's weaknesses and potential areas for improvement.

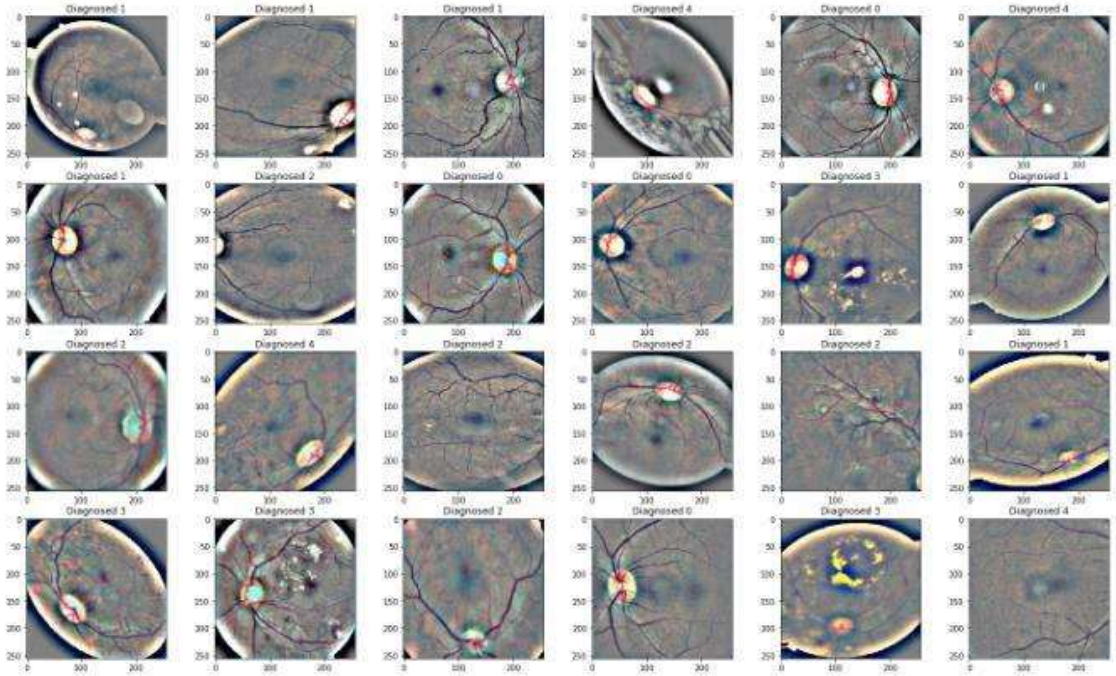

Fig 3.13 Images Obtained after Data Augmentation

3.6 Web Application & Deployment

The web application for this project is developed using Streamlit, a Python framework designed for creating interactive web applications. Streamlit serves as the front-end interface, allowing users to upload retinal images for diabetic retinopathy (DR) detection. The images are preprocessed and passed through the trained CNN model to predict the DR stage, and Streamlit's real-time interactivity facilitates a user-friendly experience for healthcare professionals. By displaying both the uploaded image and the prediction result, Streamlit

provides an intuitive diagnostic tool that enables healthcare providers to quickly interpret and utilize the model's predictions.

3.6.1 Deployment Using Cloudflared

To make the application accessible over the internet, the Streamlit app and model are hosted using Cloudflared, a tunneling service by Cloudflare. Cloudflared securely exposes the local application by creating a tunnel from the local environment to a publicly accessible URL. This setup enables remote access to the DR detection tool without requiring complex server infrastructure, making it readily available for clinical and remote settings. By providing secure access, Cloudflared ensures that the application can be used for large-scale DR screening, supporting diverse healthcare environments.

Fig 3.14 Web Application Deployed Using Cloudflared

3.6.2 Significance in Enhancing Accessibility

The integration of Streamlit and Cloudflared aligns with the project's objective to make diabetic retinopathy detection accessible and scalable. Streamlit offers an easy-to-use interface, essential for healthcare settings where non-technical users require straightforward, interactive applications. Cloudflared ensures that the application can be securely accessed remotely, allowing for broader clinical use without needing a dedicated server. Together, these tools support the deployment of an effective, automated DR detection solution, enabling early diagnosis and treatment in a variety of healthcare environments.

CHAPTER – 4

RESULTS AND DISCUSSION

4.1 Results

The performance of the model was assessed using key metrics such as accuracy, precision, recall, and F1 score, allowing for a thorough analysis of the model's capability in detecting and distinguishing between various stages of diabetic retinopathy.

1. **Data Preprocessing Results**

   As part of the data preprocessing pipeline, several techniques were applied to the retinal images to enhance their quality and ensure consistency for model training. These preprocessing steps included image resizing, gamma correction, and Gaussian filtering, which helped improve the clarity of retinal features while minimizing noise. The images processed through these steps show noticeable improvements in sharpness and detail, particularly in enhancing the visibility of microaneurysms and other important markers of diabetic retinopathy. The following images illustrate the effectiveness of these preprocessing techniques in preparing the dataset for subsequent model training.

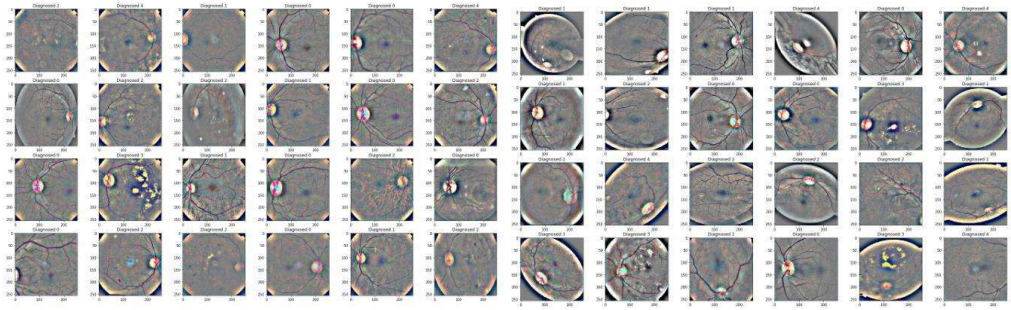

Fig 4.1 Results of Data Preprocessing

2. **Model Performance**

   EfficientNet models showed high accuracy in detecting DR of 94.48%. This demonstrates the models' effective performance in differentiating between DR stages, particularly in identifying advanced stages.

```
history = model.fit(
    train_data,
    validation_data=val_data,
    epochs=10
)
```

```
Epoch 1/10
/usr/local/lib/python3.10/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)` in its
  self._warn_if_super_not_called()
92/92 ━━━━━━━━━━━━━━━━━━━━ 409s 4s/step - accuracy: 0.9448 - loss: 0.1050 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 2/10
92/92 ━━━━━━━━━━━━━━━━━━━━ 433s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 3/10
92/92 ━━━━━━━━━━━━━━━━━━━━ 448s 5s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 4/10
92/92 ━━━━━━━━━━━━━━━━━━━━ 440s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 5/10
92/92 ━━━━━━━━━━━━━━━━━━━━ 392s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 6/10
92/92 ━━━━━━━━━━━━━━━━━━━━ 409s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 7/10
92/92 ━━━━━━━━━━━━━━━━━━━━ 448s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 8/10
92/92 ━━━━━━━━━━━━━━━━━━━━ 407s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 9/10
92/92 ━━━━━━━━━━━━━━━━━━━━ 413s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 10/10
92/92 ━━━━━━━━━━━━━━━━━━━━ 437s 4s/step - accuracy: 1.0000 - loss: 0.0000e+00 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
```

Fig 4.2 Model Training

3. **Confusion Matrix Analysis**

   A confusion matrix was employed to investigate patterns of misclassification, revealing areas where model performance could be refined. The matrix highlighted that the model sometimes confused 'Mild' and 'Moderate' stages, likely due to their subtle visual differences. This analysis suggests that further tuning could improve early-stage detection and reduce misclassification rates, enhancing model reliability.

4. **Precision, Recall, and F1 Score:**

   To further assess the model's performance, especially when dealing with imbalanced datasets (as is common in medical image classification tasks), additional metrics like **precision**, **recall**, and **F1-score** are used. These metrics provide a deeper understanding of the model's ability to correctly identify the stages of diabetic retinopathy and minimize errors.

   - **Precision** measures the proportion of correctly predicted positive instances (e.g., images predicted to belong to a certain DR class) out of all instances predicted as positive. High precision indicates that the model has a low false-positive rate.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

   - **Recall** calculates the proportion of correctly predicted positive instances out of all actual positive instances (i.e., true DR stages). High recall indicates that the model has a low false-negative rate.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

- **F1-Score** is the harmonic mean of precision and recall, offering a balance between the two. It is particularly useful in scenarios where the class distribution is imbalanced, as it provides a single metric to optimize.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

These metrics are calculated for each class (e.g., **No_DR**, **Mild**, **Moderate**, **Severe**, and **Proliferative_DR**) to evaluate how well the model performs across the various stages of diabetic retinopathy.

4.2 Interface Development

To make the model user-friendly, especially for healthcare professionals, a Streamlit-based interface was designed to facilitate real-time DR detection. This interface provides a streamlined platform where users can upload retinal images and receive immediate predictions, improving accessibility and usability in clinical settings.

- **User Interaction:** Users can upload retinal images through the interface, which includes instructions on the acceptable image format and quality, ensuring optimal input for accurate results.
- **Real-Time Prediction:** The interface processes each uploaded image, delivering a predicted DR stage along with the confidence level for the prediction.
- **Performance Metrics Display:** The interface also presents key metrics—accuracy, precision, and recall for each DR stage—offering users insight into the model's reliability.

Usability tests ensured that the interface is intuitive, responsive, and delivers predictions efficiently, supporting accessible AI-based DR screening in a variety of healthcare environments.

4.3 Real-Time Model Deployment with Streamlit Interface

The integration of the trained Diabetic Retinopathy (DR) detection model with a real-time web interface is a key aspect of this project. The Streamlit interface ensures that healthcare professionals or any user can quickly upload retinal images and receive immediate predictions regarding the severity of diabetic retinopathy. This real-time capability makes the model highly applicable in clinical settings, where timely and efficient decision-making is crucial for effective patient care.

1. **Interface Design:** The Streamlit interface is designed with user experience as the top priority. It is both visually appealing and functionally efficient. The layout follows a simple, clean structure to avoid overwhelming the user, while guiding them through the process step-by-step. The homepage features clear instructions on how to upload retinal images, specifying acceptable image formats (such as PNG or JPEG) and image resolution. This ensures that users can prepare and upload images without encountering errors or performance issues. Additionally, there is a section dedicated to educating users about the nature of diabetic retinopathy, its stages, and the purpose of the model in assisting healthcare professionals.

   The interface also provides a responsive, easy-to-navigate layout, optimized for both desktop and mobile devices. This ensures that healthcare professionals, especially those in remote or resource-constrained areas, can use the application seamlessly, regardless of the device they have access to.

2. **Prediction and Visualization:** One of the core features of the Streamlit interface is its ability to deliver predictions in real-time. After a user uploads an image of a retinal scan, the model processes the image and outputs the predicted diabetic retinopathy stage. The interface not only provides the stage of DR (e.g., No DR, Mild, Moderate, Severe, or Proliferative DR) but also includes the model's confidence level in its prediction, offering a more comprehensive understanding of the result.

   The interface is designed to clearly display the uploaded image alongside the prediction. This feature allows users to visually verify the model's findings by comparing them to the original retinal image, which can be crucial in healthcare settings. Furthermore, color-coding and visual indicators (such as heatmaps or markers on the retinal image)

may be incorporated to highlight the areas of the retina most affected by diabetic retinopathy, enhancing the interpretability of the model's predictions.

3. **Real-Time Prediction:** Upon image upload, the interface delivers an immediate prediction of the DR stage along with the model's confidence level.

4. **Display of Key Metrics:**

To ensure transparency and help users assess the quality of the model's predictions, the interface displays key performance metrics. These metrics include:

- **Accuracy**: The proportion of correct predictions out of all predictions made, indicating the overall effectiveness of the model.
- **Precision**: Precision for each class helps to determine how many of the predicted positive results were correct.
- **Recall**: Recall measures how many of the actual positive cases the model was able to correctly identify.
- **F1 Score**: The harmonic means of precision and recall, providing a balance between the two metrics.

By displaying these metrics for each stage of diabetic retinopathy, the interface helps users understand the model's performance across all five classes. This is especially important for healthcare professionals who need to be confident that the tool can accurately differentiate between the various stages of DR. Furthermore, these metrics are updated in real-time after each prediction, providing an ongoing assessment of the model's reliability.

5. **Testing and Usability:** Before deployment, the Streamlit interface underwent thorough testing to ensure it performed well across a wide range of scenarios. The system was tested on different devices (both desktop and mobile) and under varying internet speeds to ensure responsiveness. The goal was to guarantee minimal latency, even when handling large image files, which is essential in clinical settings where time is of the essence.

The user experience was also tested to ensure that it is intuitive and easy to navigate. Healthcare professionals, even those with minimal technical experience, should be able to use the interface with little to no training. Feedback was collected from users during testing to identify any areas of improvement, and these insights were used to refine the design and functionality.

The interface was also evaluated for its handling of diverse retinal images. Images from different sources, taken with varying equipment and under different lighting conditions, were used to ensure the model and interface could handle real-world variations in image quality. Data augmentation techniques and the preprocessing pipeline were also put to the test to ensure that they improved the model's robustness and performance.

Additionally, the model was tested in simulated clinical scenarios, where multiple images were processed simultaneously to check for scalability and reliability. Ensuring that the interface performs well under such conditions is crucial for its deployment in large-scale screening programs.

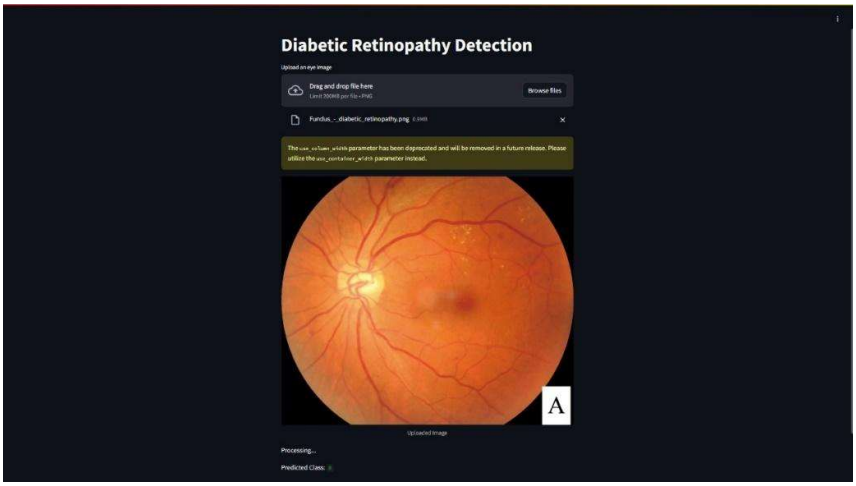

Fig 4.2 Result of Web Application

4.4 Discussion

The study demonstrates the effectiveness of CNN architectures, particularly ResNet and EfficientNet, in automating diabetic retinopathy detection. The model's high accuracy and robust performance across different DR stages indicate that CNNs are highly suited for analyzing retinal images. However, several challenges and limitations were identified, especially in early-stage detection and model generalization across diverse populations.

1. **Model Limitations**: The model's performance in detecting early-stage DR could be enhanced with additional data and fine-tuning. Due to the subtle differences between 'No DR' and 'Mild DR,' these stages are challenging to classify, and the model occasionally misclassifies them. Improving early-stage detection accuracy may require training on a larger, more representative dataset.

2. **Dependency on Image Quality:** The model's accuracy is sensitive to image quality and resolution. Variations in lighting, contrast, and noise can impact classification accuracy. Future improvements could involve integrating image enhancement techniques to standardize image quality and ensure consistency in diverse clinical environments.

3. **Model Interpretability and Clinical Trust:** This interpretability is crucial for fostering trust in AI-assisted diagnostics, enabling healthcare professionals to verify and understand the model's decisions.

4. **Future Directions:** Further improvements could include exploring hybrid models that combine CNNs with other deep learning architectures, such as recurrent neural networks (RNNs), for sequential learning across multiple image frames. Additionally, integrating multimodal data (e.g., patient history, demographics) could improve diagnostic robustness. Expanding the dataset to include images from varied demographics would also enhance model generalization, making it more reliable across different patient populations.

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This study has successfully developed an automated system for the detection of diabetic retinopathy (DR) using deep learning models, specifically Convolutional Neural Networks (CNNs) based on EfficientNet architectures. The primary objective of this project was to address the increasing global challenge of diabetic retinopathy by creating a scalable, accurate, and efficient screening method that can be widely accessible, especially in resource-limited settings where specialized ophthalmic care is either unavailable or in short supply. This study provides a significant step toward democratizing access to early diagnosis and improving the management of DR, a leading cause of blindness.

The results from the trained EfficientNet-based model have shown promising outcomes, achieving an accuracy of 94.48% in classifying the various stages of diabetic retinopathy. This level of accuracy is a strong indication of the model's capability to distinguish between different stages of DR with a high degree of reliability. Particularly noteworthy was the model's performance in distinguishing between more advanced stages, such as 'Moderate' and 'Proliferative DR', where the classification accuracy was exceptional. This demonstrates the model's potential to aid in the identification of more severe cases, which require urgent intervention to prevent irreversible vision loss.

However, challenges were encountered when trying to distinguish between early stages of the disease, particularly 'No DR' and 'Mild DR'. These stages often present subtle changes in the retina, making them more difficult to detect, even for human experts. The model's reduced performance in these stages was reflected in the precision and recall scores, which indicated a

higher rate of false positives and false negatives in these categories. This highlights the ongoing need for improvement, particularly in the early-stage classification, to ensure that no case of DR is overlooked. Evaluation metrics, including precision, recall, and F1 score, were further analyzed to assess the overall diagnostic reliability. The F1 scores for each stage confirmed that the model provided a balanced performance across all DR stages, indicating its effectiveness as a diagnostic tool in clinical settings.

One of the key components of this project was the implementation of a user-friendly, real-time interface using Streamlit. This interface serves as a practical tool for healthcare professionals, enabling them to upload retinal images and receive immediate, actionable predictions regarding the severity of diabetic retinopathy. The inclusion of this interface adds significant value to the model by enhancing its accessibility and usability, making it suitable for deployment in clinical settings, especially in areas where specialized diagnostic tools or ophthalmologists may not be readily available. The ability to instantly visualize the prediction results, along with the confidence levels provided by the model, enables clinicians to make faster, informed decisions, contributing to more timely interventions.

In addition, the interface's transparency in displaying key performance metrics and the reasoning behind the model's decisions ensures that healthcare professionals can trust the AI-powered predictions. The real-time nature of the interface, coupled with its simplicity, helps to foster adoption in real-world clinical environments, where speed and ease of use are essential. Moreover, the interactive visualizations, such as heatmaps and overlays on the retinal images, provide valuable insights that can support healthcare practitioners in confirming or refining their diagnoses.

The successful development of this system highlights the potential of AI in transforming the landscape of clinical diagnostics, particularly in the field of ophthalmology. By offering an efficient and scalable solution, this research contributes to the growing body of work demonstrating the value of AI in improving healthcare outcomes. With its high accuracy in detecting advanced stages of DR, this system has the potential to significantly reduce the incidence of blindness related to diabetic retinopathy, which remains a major public health challenge worldwide.

Furthermore, this research underscores the feasibility of deploying AI-based solutions in clinical diagnostics, illustrating that with the right data, technology, and deployment strategies, artificial intelligence can be a powerful tool in healthcare. It serves as a stepping stone toward more widespread implementation of automated diagnostic tools that can assist in early disease detection and intervention. By leveraging AI in screening programs, it is possible to extend the reach of quality healthcare to underserved regions, helping to prevent blindness in populations that would otherwise lack access to timely care.

In conclusion, this study demonstrates the viability of CNN-based models for effective DR detection and the importance of combining cutting-edge machine learning techniques with practical, real-time tools for healthcare professionals. The system developed in this research holds great promise for enhancing early diagnosis, improving patient outcomes, and ultimately reducing the global burden of diabetic retinopathy-related blindness. The success of this model highlights not only the power of AI in medical diagnostics but also the critical role of such innovations in shaping the future of healthcare, particularly in regions with limited resources.

5.2 Future Scope

While this study has made significant strides in developing an effective DR detection model, several areas for improvement and expansion exist. Future research and development could focus on the following:

1. **Enhancing Early-Stage Detection**: Improving the model's sensitivity to early stages of DR is crucial. Future work could involve expanding the dataset to include a larger variety of 'No DR' and 'Mild DR' images, thereby improving the model's ability to detect subtle differences in early-stage retinal abnormalities.
2. **Improving Image Quality Robustness**: The model's performance depends significantly on the quality of input images. Future implementations could integrate image pre-processing techniques such as contrast enhancement, denoising, or adaptive histogram equalization to improve robustness to variations in image quality, lighting, and resolution, enabling consistent performance across diverse clinical settings.
3. **Incorporating Multimodal Data**: Adding other data types, such as patient history, demographics, or additional medical records, could improve diagnostic accuracy by providing a more comprehensive view of each case. This multimodal approach may help enhance model predictions and reduce the likelihood of misclassification by contextualizing image data with relevant clinical information.
4. **Exploring Hybrid and Advanced Deep Learning Models**: Future work could explore hybrid models combining CNNs with recurrent neural networks (RNNs) or attention mechanisms to leverage sequential learning across multiple images. This approach could benefit cases where disease progression is monitored over time, capturing temporal patterns across images and improving diagnostic reliability.
5. **Expanding Model Generalization Across Diverse Populations**: To enhance the model's applicability in various geographic and demographic settings, future research

could include more diverse datasets encompassing different age groups, ethnicities, and conditions. This would improve model generalizability, making it reliable across a wider patient population.

6. **Deployment in Real-World Clinical Settings**: Extending this model to actual clinical environments will require additional testing for performance consistency and validation through pilot studies. Collaborative efforts with healthcare institutions could offer valuable feedback, identify usability challenges, and refine the model's deployment readiness.
7. **Further Advancing Interpretability for Clinical Trust**: To foster greater trust in AI-based diagnostics, additional interpretability features could be explored. For example, incorporating methods such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-Agnostic Explanations) could provide more granular insights into each prediction, helping clinicians better understand and validate the AI's decision-making process.

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