Diabetic Retinopathy Detection

Submitted in the partial fulfillment of the requirements

for the degree of B.Tech in Computer Engineering

by

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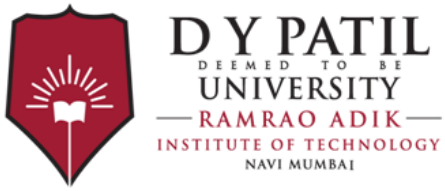

Department of Computer Engineering

Ramrao Adik Institute of Technology

Sector 7, Nerul, Navi Mumbai

(Under the ambit of D. Y. Patil Deemed to be University)

May 2025

Ramrao Adik Institute of Technology

(Under the ambit of D. Y. Patil Deemed to be University)

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CERTIFICATE

This is to certify that, the Mini Project-IV report entitled

Diabetic Retinopathy Detection

is a bonafide work done by

Yash Jadhav (22CE1217)

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and is submitted in the partial fulfillment of the requirement for the degree of

B.Tech in Computer Engineering

to the

D. Y. Patil Deemed to be University

Supervisor	Project Co-ordinator
(Mrs Apurva Shinde)	**(Mrs Shweta Ashtekar)**
Head of Department	Principal
(Dr. Amarsinh V. Vidhate)	**(Dr. Mukesh D. Patil)**

Mini Project Report - IV Approval

This is to certify that the Mini Project - IV entitled ***" Diabetic Retinopathy Detection "*** is a bonafide work done by ***Yash Jadhav (22CE1217)***, ***Sarthak Ghadge (22CE1228)***, ***Parag Khandare(22CE1230)***, and ***Anand Jha (22CE1244)*** under the supervision of ***Mrs Apurva Shinde***. This Mini Project is approved in the partial fulfillment of the requirement for the degree of ***B.tech in Computer Engineering***

Internal Examiner :

1. .....

2. .....

External Examiners :

1. .....

2. .....

Date : .../.../.....

Place : .....

DECLARATION

I declare that this written submission represents my ideas and does not invovle plagiarism. I have adequately cited and referenced the original sources wherever others' ideas or words have been included. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action against me by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Abstract

This project has constructed an automated system for detection and classification of Diabetic Retinopathy (DR) stages based on deep learning techniques. The primary objective of this system is to provide ophthalmologists with a rapid, reliable, and easy-to-utilize diagnostic measure. A Convolutional Neural Network (CNN) was trained on retinal fundus images to classify DR into five separate states, No DR, Mild DR, Moderate DR, Severe DR, Proliferative DR. As model building proceeded, a platform called TensorFlow/Keras was utilized for data preprocessing, normalization of images, model training and model evaluation. An easy-to-use web app front end was created using Streamlit allowing the user to upload retina images and receive predicted classifications in almost real time. The model produced high accuracy and confidence demonstrating the strength of medical imaging in deep learning techniques.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Overview

Diabetic Retinopathy (DR) is a pathological complication of diabetes that involves the eyes. DR occurs when excessive blood sugar levels destroy blood vessels in the retina leading to visual loss, and in severe cases complete loss of sight. As diabetes is now becoming more prevalent globally, especially in developing countries, the population susceptible to developing DR has also continued to increase.

Early detection of DR is critical to prevent the loss of vision, but manual evaluations of fundus images for DR are lengthy, and typically carried out by trained personnel who acquire specialized skill sets whilst in a health profession. To alleviate some of the burdens of DR diagnosis, advancements in Artificial Intelligence (AI) and Machine Learning (ML) are revolutionizing the field of medical image interpretation. Deep Learning (DL), a subset of ML, has shown great success in image classification tasks due to its ability to learn hierarchies of feature representations from the data. Among DL methods, Convolutional Neural Networks (CNNs) have had great success in many medical applications including skin lesion classification, pneumonia diagnosis, and diabetic retinopathy classification. In this project, we will identify a DT method using deep learning for automatic diabetic retinopathy classification from retinal images. Using transfer learning with a vigour of pre-trained model, we will create and assess classification models using retinal images which will be made publicly available.

1.1.1 AI & ML

Artificial Intelligence is a range of technologies that try to simulate human intelligence. Machine Learning in Artificial Intelligence means techniques for making computers learn from data somewhat or entirely beyond pre-programming. Deep Learning is a branch of Machine Learning that employs many-layered neural networks (thus ”deep”) for simulating and modeling sophisticated patterns in data.

We apply deep learning techniques, in the form of Convolutional Neural Networks (CNNs), to label retinal fundus images into various stages of diabetic retinopathy. CNNs are particularly suitable for this project since they are capable of learning spatial hierarchies of features adaptively and automatically from input images with optimization. The ResNet50 architecture or the deep residual network is nicely documented for learning extremely deep networks with efficiency with its application of skip connections. Since our project applies the ResNet50 architecture, it would enable us to utilize the strength of pretrained large models, such as ImageNet, and further boost performance when there is insufficient training data available.

1.2 Motivation

The impetus of this project stems from a persistent need for reliable, scalable, and accurate ophthalmic diagnostic equipment. The standard manner of diagnosis of diabetic retinopathy to date is by having a specialist manually review, examine, and categorize retinal photos; a multi-tiered effort that often involved human error and variability, thus defeating the purpose of early diagnosis and treatment, while leaving you with unmet healthcare accessibility issues where eye care becomes unavailable.

AI-supported diagnosis would help for the delivery of healthcare services in remote and excluded communities. Using deep-learning algorithms we will be able to create systems that scan retinal images without difficulty and provide real-time screening support for doctors or act autonomously using telemedicine systems.

1.3 Problem Statement and Objectives

The primary issue given in this work is automatic identification and classification of diabetic retinopathy stages from retinal images. Perhaps there are some minor variations in the different

grades of diabetic retinopathy in retinal images that a professional person might fail to classify by hand. So, in this project we would like to build a model which will classify an image into one of five classes representing the degree of diabetic retinopathy. In order to address this problem, we identify the following goals:

We first desire to obtain and preprocess a known set of labeled retinal images. Next, we will create a deep learning model utilizing the ResNet50 structure via transfer learning techniques. We will train the model with respect to proper preprocessing, data augmentation, and class balancing to maximize the generalization capacity of the model. Third, we will use several of the commonly-used classification metrics to test model performance such as; accuracy, precision, recall, F1-score, confusion matrices, etc. Last, we will graph results and examine misclassifications in order to have an understanding of the reliability, and robustness of the model. Also, to depict model performance we will have confusion matrices and ROC curves.

1.4 Organization of the report

This report is divided into five key chapters. Chapter 2 has a detailed literature review of currently available diabetic retinopathy detection systems, with focus on strengths and weaknesses of previous work. Chapter 3 outlines the system proposed, i.e. data preprocessing, architecture of the model, and strategies for training. Chapter 4 has the discussion of implementation and experimental results along with analysis from evaluation metrics. Lastly, Chapter 5 summarizes the report and presents possible areas for future upgrades of the project.

Chapter 2

Literature Survey

2.1 Survey of Existing System

Over the past decade, medical imaging has seen tremendous advancement due to deep learning technologies that have developed extremely fast. Diabetic retinopathy, for example, has been one of the specific areas of interest to researchers keen on automating early disease diagnosis. Over the last decade, medical imaging has expanded extremely quickly with deep learning technologies. Diabetic retinopathy has been a particular region of interest for scientists who are concerned with automating early disease detection. Probably the most important initiative in this area was the Kaggle Diabetic Retinopathy Detection Challenge, which made available a large, labeled dataset of retinal fundus images to the research community. This made rapid innovation possible through access to the dataset and utilization of machine learning and deep learning techniques for computer-aided diagnosis of diabetic retinopathy.

The majority of the early systems employed traditional image processing methods with handcrafted feature extraction, such as blood vessel detection, lesion segmentation, or texture analysis. The drawback with these methods was that they were not able to generalize to larger, more diverse datasets, as they were based on handcrafted features. Following the advent of convolutional neural networks (CNNs), researchers started shifting to end-to-end learning models where hierarchical representations were automatically learned from raw images.

Various CNN architectures have been tested for DR classification. For example, VGG16 with its shallow yet deep architecture was okay but was associated with lengthy training times and weak feature reuse. InceptionV3 and Xception , using depth wise separable convolutions and multi-scale processing, showed improved accuracy and efficiency. The models, though, still

consumed a lot of computational power and fine-tuning to excel with imbalanced data such as medical applications.

One of the more robust and commonly used architectures utilized in existing research is ResNet50, which is favored for utilizing residual blocks that facilitate deeper network training by the prevention of the vanishing gradient issue. The majority of research has shown that ResNet-based models can outperform earlier CNNs both in performance and stability, especially when pretrained on large datasets such as ImageNet and fine-tuned for medical use.

Moreover, transfer learning has also become a routine procedure to handle the limited size of medical data. Instead of training models from the ground up, scientists employ pre-trained models and then fine-tune them on the DR dataset. This is quicker in terms of training, but also improves accuracy because the model can leverage all of the learned features from a generic image set.

Despite this, it is not a mundane task to put diabetic retinopathy into five categories - no DR to proliferative DR - since adjacent classes look very much alike and medical data are noisy.

2.2 Limitations of Existing System or Research Gap

Even though existing deep learning-based methods have shown encouraging performance, several of their limitations and areas of study remain to be tackled in order to enable their large-scale clinical deployment. The most important among these is perhaps dataset distribution imbalance. Typically, retinal image datasets contain predominantly samples with no or mild DR, and images for more advanced cases are sparse. This imbalance results in biased models with good performance on the dominant class but poor performance on minority classes, which are clinically most valuable to detect.

Another main limitation is non-interpretability. Deep learning models have been widely criticized for being ”black boxes,” where decisions are made without any knowledge of the involved rationale. In clinical practice, transparency and trust are crucial. Doctors are less likely to trust an automated system except when it presents some sort of visual explanation or evidence to validate its predictions. Though methods like Grad-CAM and saliency maps have been put forward, these remain in their infancy stage of being incorporated into useful diagnostic tools.

Second, and more critically, overfitting is a chronic issue in deep learning for medical

imaging. Since datasets are usually small and highly variable, models learn to memorize training data rather than generalize to new, unseen cases well. This is especially true when preprocessing methods such as augmentation and normalization are not always executed.

Computational complexity is also a limitation. High-performance models have been reported to consume considerable GPU usage when training and making predictions. As such, they are not suitable for deployment in lower-resource or rural healthcare settings, which are usually in greatest need of automatic diagnostic functionality.

Lastly, while numerous models can perform adequately on benchmark data sets, they are tested for real-world deployment. The models need to be tested on a diverse patient population, under varied imaging conditions, and with electronic health records, to then be acceptable in real-world applications.

These problems serve as justification for the rationale for this project in developing a better interpretable, properly balanced, and computationally effective diabetic retinopathy diagnostic system that can be clinically and practically used in real-world environments.

Chapter 3

Proposed System

3.1 Problem Statement

Diabetic retinopathy can lead to irreversible blindness if not diagnosed, but retinal imaging capability to detect cases early can greatly enhance patient outcomes. The primary difficulty for manual detection is that it is inefficient, high variability and acceptable performance depends heavily on the expertise of ophthalmologists. There is also limited access particularly in rural and under-served communities. Consequently, there exists a keen demand for an automated system that was designed to interpret retinal fundus images and determine the severity of diabetic retinopathy accurately and reliably.

The suggested system assists in solving this issue by using deep learning methods like convolutional neural networks to build a strong model trained to recognize and classify the five diabetic retinopathy stages. Through automated classification, the system will deliver an aid tool for clinicians to accelerate screening and enhance access to eye care.

3.2 Proposed Methodology/Techniques

For addressing the issue efficiently, we suggest using a deep learning technique with transfer learning from a pre-trained ResNet50 model. ResNet50 is a 50-layer deep convolutional neural network whose feature extraction ability is strong and whose training is effective by employing residual blocks. The reason to use ResNet50 is that it offers the potential to retain informative features at various levels (layers) and significantly enhance performance even with very small data sets.

Description of the techniques is explained in several steps:

Preprocessing and collection of data; this dataset (younger patients) are retinal images classified into five DR classes. Resizing images to fixed dimensions, normalization, and used to create data augmentation using horizontal flips, rotation, and zooms as augmentations to enhance generalization and minimize overfitting.

Transfer Learning and Fine-Tuning; our pre-trained ResNet50 is trained across ImageNet layers that have been altered with our own classification head on top, designed to be compatible with our five output labels classes. The deeper layers of the model are frozen only at initial training stages so as to preserve ImageNet's general features. At later periods, specially chosen layers are fine-tuned on our retinal dataset for domain-specific patterns acquisition.

Training and Testing: Training is performed based on a categorical cross-entropy loss function optimized using the Adam optimizer. During training, class weights are used to handle class imbalance in the dataset. Training is measured in terms of accuracy, precision, recall, and F1-score and the confusion matrix to measure class-wise performance.

Model Validation: Performance of the model is verified upon training using a clean-cut test set to confirm whether the system can generalize over unseen data. Visualization tools of Grad-CAM may further be incorporated for interpretability.

The above strategy achieves a trade-off between performance and computational complexity and is hence appropriate to apply in practical usage where both speed as well as accuracy is required.

3.3 System Design

The proposed system has a modular and lightweight design, so it can be extended with new functionality and improved performance. The system architecture consists of various modules:

Input module: For acceptable input formats of retinal images. The usable images change before entering the model by the preprocessing module.

Preprocessing Module: Normalization, data augmentation, and resizing take place in this module. The images will be a consistent input size to allow feature extraction, therefore learning robust features.

Model Module: The CNN architecture which is based on ResNet50 is represented in this module. It is in the model module where feature extraction and classification will happen.

Output module: This module will present a predicted class label for the diabetic retinopathy stage. The class label can be extended with visual explanations to the user such as a heatmap or attention map.

Evaluation Module: This module will calculate or report metrics of the evaluation including accuracy, loss, confusion matrix, and classification report. Any of those components can be updated for detailed analysis of model performance.

The system has a modular architecture which allows for easy debugging, monitoring performance, and the ability to integrate into a broad clinical decision support system.

3.4 Details of Hardware/Software Requirement

The system was implemented with Python and Jupyter Notebook as development environment. The following tools and libraries have been employed:

Programming Language: Python 3.x

Deep Learning Framework: TensorFlow 2.x with Keras API

Libraries for Image and Data Manipulation: NumPy, Pandas

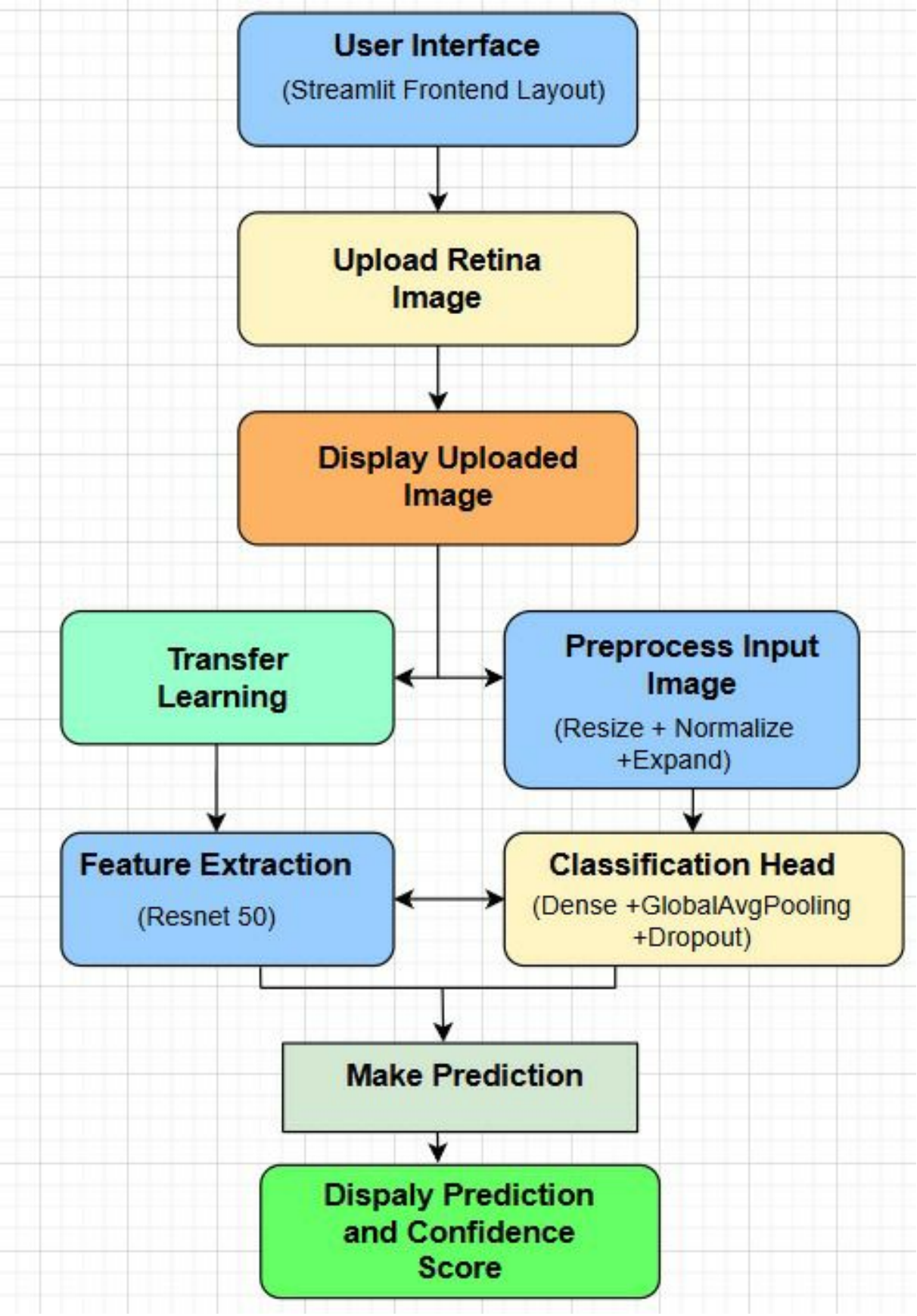
Libraries for Data Processing and Visualization: Matplotlib, Seaborn

Libraries for Image Processing: OpenCV, PIL

Model Training Platform: Google Co later with access to NVIDIA Tesla T4 GPU for speedy training

The bare minimum hardware to train the model would typically be an 8GB RAM machine with a GPU local or cloud-based to support the computational requirements of training a deep learning model.

For deployment into the real world, the model can be exported and deployed in web-based applications using Streamlit through formats like TensorFlow Lite optimized for edge device inference.


User Interface
(Streamlit Frontend Layout)
Upload Retina Image
Display Uploaded Image
Transfer Learning
Preprocess Input Image
(Resize + Normalize +Expand)
Feature Extraction
(Resnet 50)
Classification Head
(Dense +GlobalAvgPooling +Dropout)
Make Prediction
Dispaly Prediction and Confidence Score

Chapter 4

Results and Discussion

4.1 Implementation Details

The proposed system was able to be implemented in a reproducible and modular manner through using Python code in a Jupyter Notebook environment. Firstly, the range of images in the dataset was loaded and explored (considering a total of 50 images were annotated in regards to five stages of diabetic retinopathy as follows; 0 (No DR), 1 (Mild, 2 (Moderate), 3 (Severe), and 4 (Proliferative DR).The dataset was split into training and testing, ensuring both that the split was stratified and balanced; this was done in order to test the model uniformly with all classes represented.

Each image of the dataset was resized to the same shape of 224×224 pixels, which is the required shape to feed into the ResNet50 model. For image preprocessing, pixel intensity normalization was performed, as well as the execution of data augmentation including random rotations, flipping vertically about the x-axis, zooms (uniform scaling), and variations in brightness. This set of transformations allowed the model to generalize better simulating different conditions under which images were taken.

The ResNet50 model was also initialized with ImageNet pretrained weights. The last fully connected layers were replaced by a newly-created classification head that had five-class output. Initially, all pretrained layers were frozen in order to retain the general features, and only the top layers were fine-tuned. Some layers were later unfrozen and fine-tuned on the diabetic retinopathy data to maximize task-specific learning.

The model was trained using the Adam optimizer and the loss function categorical cross-entropy. The model was trained over several epochs and incorporating early stopping in order

to minimize the risk of overfitting. The learning rate scheduler ensured convergence was stable, and learning rates were adapted to the current model parameters. Class imbalance was dealt with using class weights, giving a higher weight to each minority class.

4.2 Result Analysis

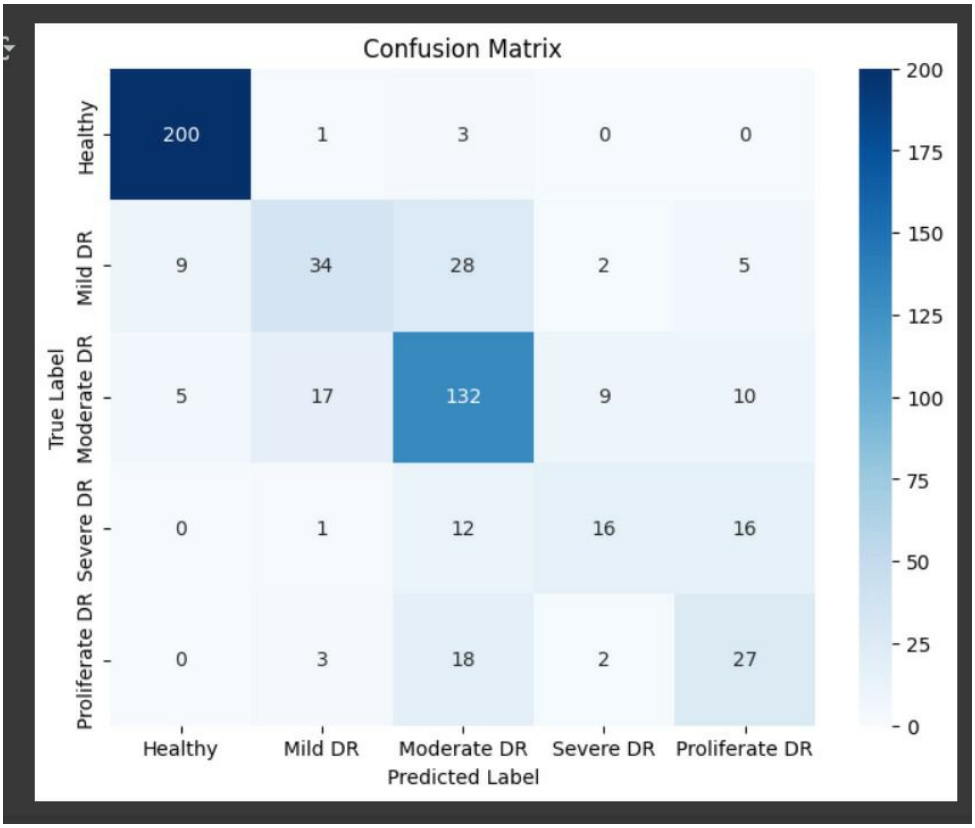
The model was subsequently assessed on the test set, with its performance evaluated using metrics such as accuracy, precision, recall, and F1-score. The overall classification accuracy of the model was impressive given the subjective visual nature of some of the DR stages, as well as class imbalance across the dataset.

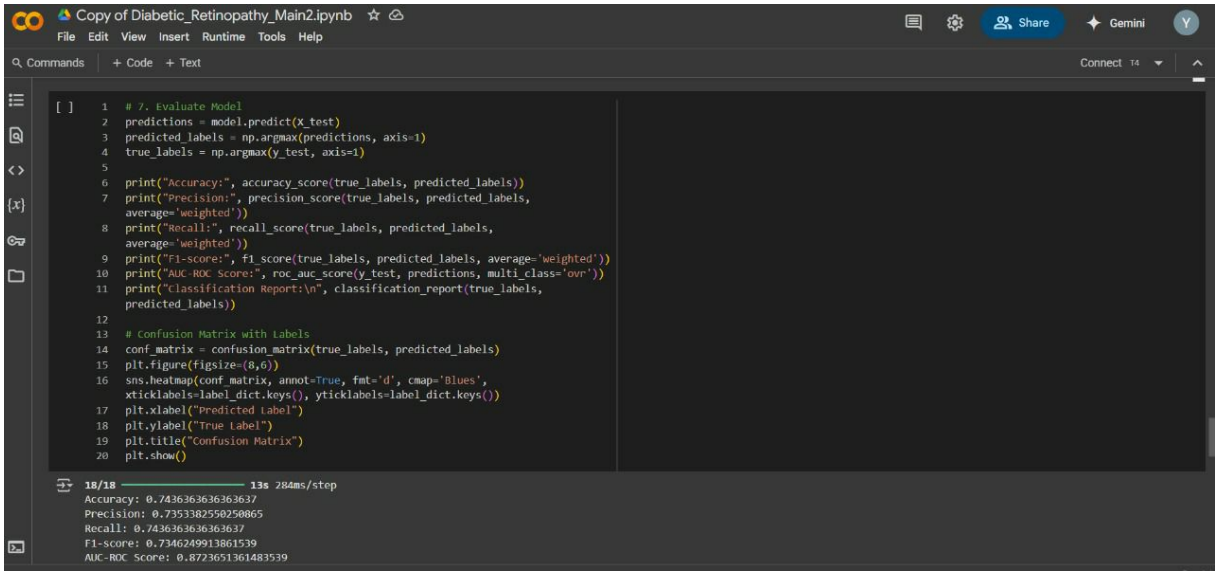
We also created a confusion matrix to better understand how the classification performance differed between each individual class. It appears the model did a good job of classifying between 'No DR' and 'Proliferative DR,' as there was enough distinguishable features. The model misclassified a few examples of the more intermediate classes such as 'Moderate' and 'Severe', which to be fair can be more challenging as differences in lesion patterns in that spectrum are more nuanced.

In order to get a better sense of where the model was drawing its decisions from, Grad-CAM (Gradient-weighted Class Activation Mapping) visualizations were used to show the areas of the retinal images, which contributed to the model's prediction. In Grad-CAM examples, the model focused on clinically important areas such as microaneurysms, hemorrhages and neovascularization. These factors of the model further confirmed that the model was actually learning important features.

Despite the model achieving high performance at classification, some limitations were also identified. Lower accuracy for the underrepresented classes was reported, demonstrating that synthetic augmentation or balancing of data should be considered in future work. Also, an addition could be to include other preprocessing, specific to a domain (e.g., removal of vessels, removal of optic disc). Such action can be anticipated to augment the concentration on features disease-specific within the model.

Overall, the model showed excellent promise for deployment as a diagnostic aid for detecting diabetic retinopathy. With further calibration and validation on larger real-world datasets, it can be implemented as part of an assistive screening system within hospitals or telemedicine platforms.

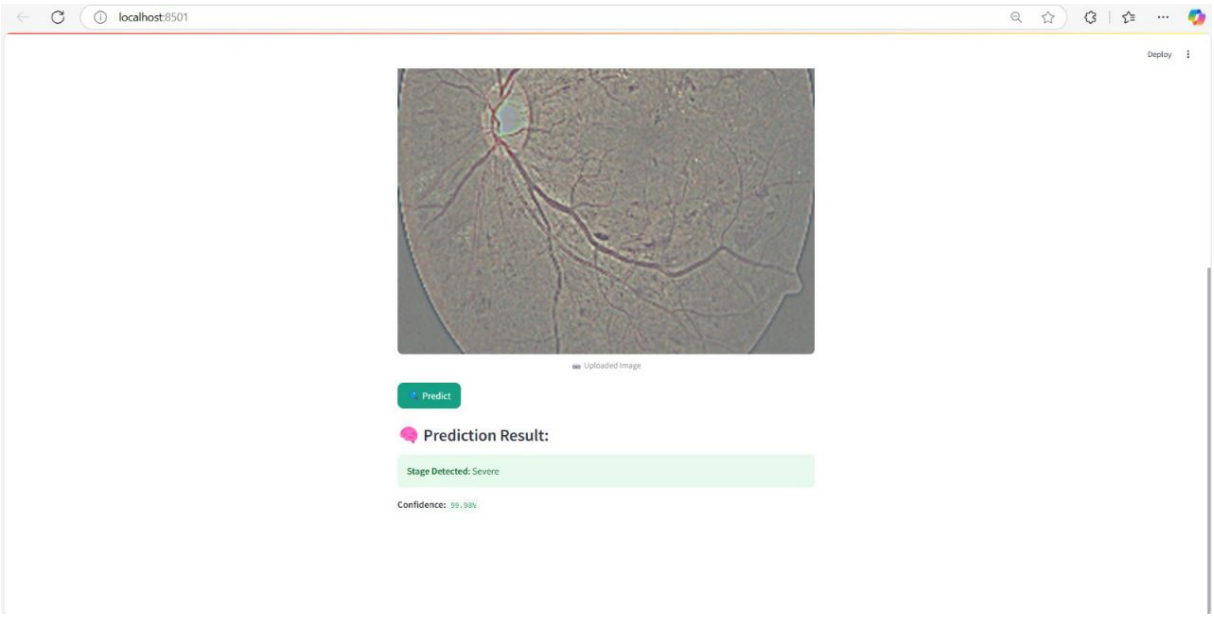

Confusion Matrix
Healthy
Mild DR
Moderate DR
Severe DR
Proliferate DR
True Label
200 1 3 0 0
9 34 28 2 5
5 17 132 9 10
0 1 12 16 16
0 3 18 2 27
Healthy
Mild DR
Moderate DR
Severe DR
Proliferate DR
Predicted Label
200
175
150
125
100
75
50
25
0

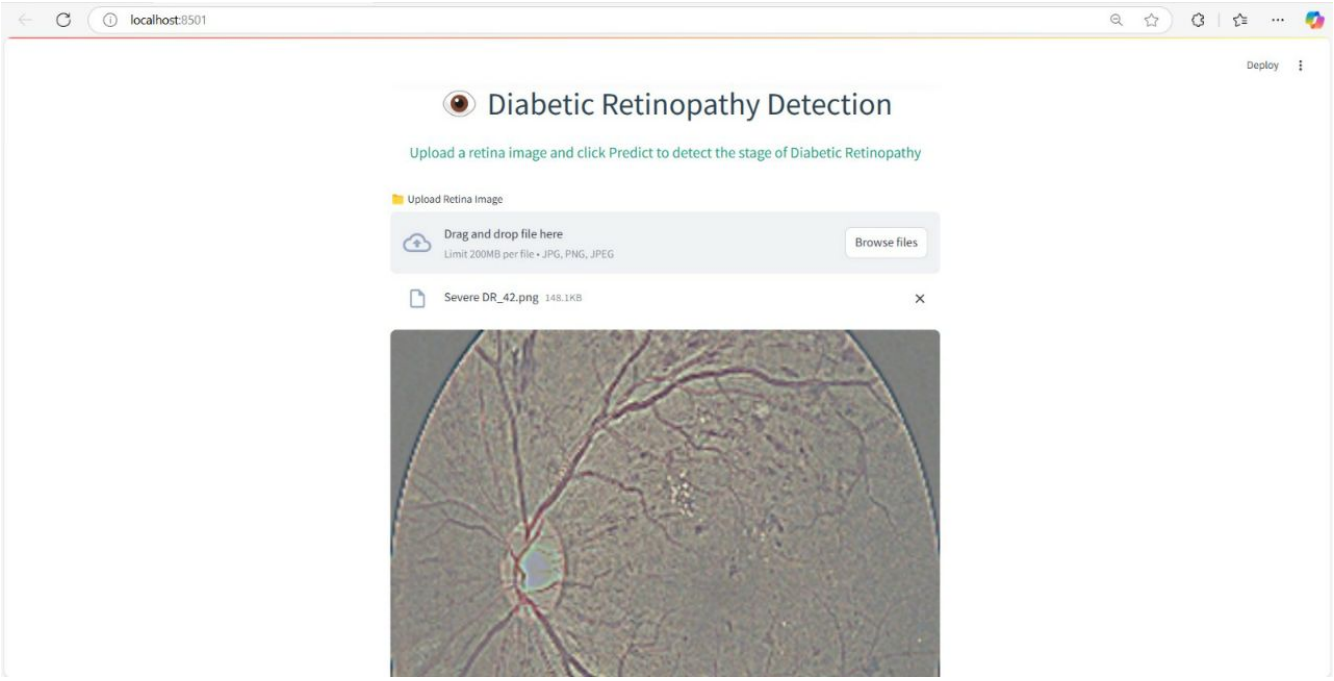

Copy of Diabetic_Retinopathy_Main2.ipynb
File Edit View Insert Runtime Tools Help
Share
Gemini
Commands
+ Code
+ Text
Connect
# 7. Evaluate Model
predictions = model.predict(x_test)
predicted_labels = np.argmax(predictions, axis=1)
true_labels = np.argmax(y_test, axis=1)
print("Accuracy:", accuracy_score(true_labels, predicted_labels))
print("Precision:", precision_score(true_labels, predicted_labels, average='weighted'))
print("Recall:", recall_score(true_labels, predicted_labels, average='weighted'))
print("F1-score:", f1_score(true_labels, predicted_labels, average='weighted'))
print("AUC-ROC Score:", roc_auc_score(y_test, predictions, multi_class='ovr'))
print("Classification Report:\n", classification_report(true_labels, predicted_labels))
# Confusion Matrix with Labels
conf_matrix = confusion_matrix(true_labels, predicted_labels)
plt.figure(figsize=(8,6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=label_dict.keys(), yticklabels=label_dict.keys())
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()
18/18 13s 284ms/step
Accuracy: 0.7436363636363637
Precision: 0.7353382550250865
Recall: 0.7436363636363637
F1-score: 0.7346249913861539
AUC-ROC Score: 0.8723651361483539

```
18/18 ━━━━━━━━━━━━━━━━━━━━ 13s 284ms/step
Accuracy: 0.7436363636363637
Precision: 0.7353382550250865
Recall: 0.7436363636363637
F1-score: 0.7346249913861539
AUC-ROC Score: 0.8723651361483539
Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.98      0.96       204
           1       0.61      0.44      0.51        78
           2       0.68      0.76      0.72       173
           3       0.55      0.36      0.43        45
           4       0.47      0.54      0.50        50

    accuracy                           0.74       550
   macro avg       0.65      0.61      0.62       550
weighted avg       0.74      0.74      0.73       550
```




localhost:8501
Deploy
Diabetic Retinopathy Detection
Upload a retina image and click Predict to detect the stage of Diabetic Retinopathy
Upload Retina Image
Drag and drop file here
Limit 200MB per file • JPG, PNG, JPEG
Browse files
Severe DR_42.png 148.1KB

Chapter 5

Conclusion and Further Work

While recent deep learning-based methods have shown encouraging performance, various limitations and areas of research remain to be overcome to enable their large-scale clinical application. Maybe the most serious issue is imbalance in dataset distribution. Typically, retinal image datasets contain the majority of samples with no or mild DR, and images of more severe cases are few. This imbalance produces unfair models with excellent performance on the majority class but poor performance on minority classes, which are most clinically significant to detect.

The other main limitation is non-interpretability. Deep learning models have been greatly criticized for being ”black boxes,” where decisions are made without knowing the underlying rationale. Trust and transparency are needed in clinical practice. Doctors are less likely to believe an automated system unless it presents some form of visual explanation or proof to support its predictions. Although techniques like Grad-CAM and saliency maps have been suggested, these are still in their infancy of being incorporated into useful diagnostic tools.

Second, and more critically, overfitting is a chronic issue in deep learning for medical imaging. Since datasets tend to be small and highly variable, models learn to memorize training data rather than generalize to new, unseen instances well. This is especially true when preprocessing methods such as augmentation and normalization are not adhered to strictly.

Computational complexity is also a limitation. High-performance models will use a great deal of GPU resources during training and inference. This makes them not deployable in low-resource or rural health settings, which are the ones that most urgently require automated diagnostic capabilities.

Lastly, while many models are highly accurate on benchmark data sets, real-world deployment and validation are restricted. Models need to be tested on heterogeneous patient popula-

tions, varied imaging conditions, and include electronic health records for them to be feasible in real-world use.

These concerns are the driving force behind the motivation of this project to develop a more interpretable, balanced, and computationally efficient system for diabetic retinopathy detection that is of clinical interest and practical for real-world application.

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Appendix A

Weekly Progress Report

RAMRAO ADIK INSTITUTE OF TECHNOLOGY
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Department of Computer Engineering
TE Mini-Project- IV Weekly Project Performance Report Even Sem 2024-2025

Project Title: _____ Group No:

Name of Students 1: Name of Students 2:

Name of Students 3: Name of Students 4:

Week No.	Topics to be Covered	Progress Status	Student 1 Sign	Progress Status	Student 2 Sign	Progress Status	Student 3 Sign	Progress Status	Student 4 Sign	Remark & Suggestions
1.	Abstract and Introduction									
2.	Literature Review									
3.	Problem Statement									
4.	Proposed system									
5.	System Design									
6.	Implementation Details Module wise									
7.	Implementation Details Module wise									
8.	Full Implementation Details									
9.	Result Analysis									
10.	Report Writing									
11.	Report Writing/Paper Publication/Copyright/Patents etc.									
12.	Conclusion / Future Work									

A: Satisfactory B: Average C: Needs Improvement

Project Guide Name and Sign:

Figure A.1: Weekly Progress Report

Appendix B

Plagiarism Report

Appendix C

Publication Details / Copyright / Project Competitions

1.

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