Deep Learning Based Diabetic Retinopathy Detection Model

DECLARATION

This is hereby declared that the project-work titled "DEEP LEARNING BASED DIABETIC RETINOPATHY DETECTION MODEL" is the outcome of report writing carried out by me under the supervision of Dr. Mithun Mazumdar, in the Department of Data Analytics, Institute of Management Studies, Kolkata, West Bengal, India. It is also declared that this report or any part of it has not been submitted elsewhere for the award of any degree or diploma.

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Thank you,

Sumedha Banerjee

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CERTIFICATE

This is certify that the Dissertation entitled “Deep Learning Based Diabetic Retinopathy Detection Model”, submitted by Sumedha Banerjee is a record of bonafide work carried out by her, in the fulfilment of the requirement for the final(4^{th} semester) Examination of M.Sc in Data Analytics at Institute of Management Study, Affiliated to Maulana Abul Kalam Azad University of Technology. This work is done during year 2023-24, under the guidance **Prof. Mithun Mazumdar.**

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Course Coordinator	***Principle***
Date:	

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DEEP LEARNING BASED DIABETIC RETINOPATHY DETECTION MODEL

Abstract

Diabetic Retinopathy (DR) is a medical condition that affects the eye for people who are diabetic. It weakens and damages the blood vessels in tissues of the retina. This condition highly affects people who do not manage their blood sugar and pressure level properly. The damaged blood vessels leak and cause dark spots in the vision of those who are affected. Early detection and timely intervention are crucial to prevent severe vision loss. So, this is done manually by the doctor by placing drops in the patient's eyes to dilate the pupil so that they get a better view of the inside and it will help them take a better look. This is where Deep Learning comes into play. This report presents a deep learning-based model for the automated detection and classification of diabetic retinopathy from retinal images. Leveraging convolutional neural networks (CNNs), the proposed model analyses fundus photographs to identify the presence and absence of DR. One thousand Healthy retinal images and another 1000 of DR-affected images taken from the dataset of Kaggle are utilized for this project. The model achieves high accuracy in distinguishing between the Healthy retinal images and the DR affected ones, demonstrating its potential as a reliable assistive tool for ophthalmologists in screening and diagnosis. The proposed method also uses ResNet50 (Residual Network that is 50 layers deep) model. Due to its depth and better transfer learning capabilities, the proposed model with ResNet50 achieved 97.16% classification accuracy. Performance metrics such as accuracy, sensitivity, specificity, and the area under the receiver operating characteristic curve (AUC-ROC) are discussed to evaluate the model's efficacy. The implementation details, data preprocessing techniques, and model architecture are elaborated upon, highlighting the advancements in deep learning that enable improved diagnostic capabilities for diabetic retinopathy.

Keywords: *Diabetic Retinopathy, Deep Learning, Convolutional Neural Networks, Retinal Images, Transfer Learning, ResNet50.*

Deep Learning Based Diabetic Retinopathy Detection Model

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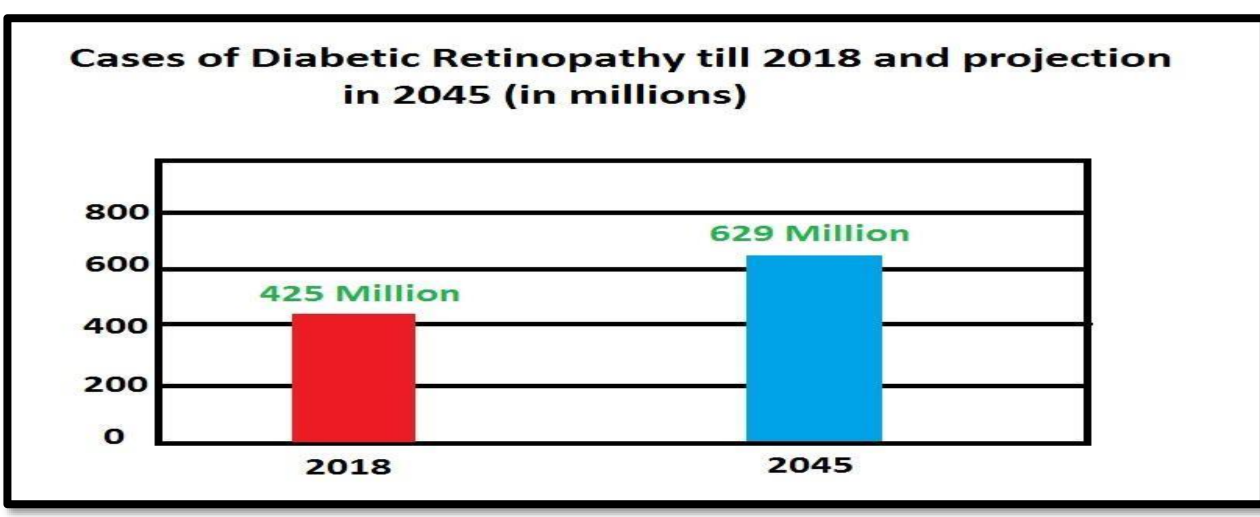
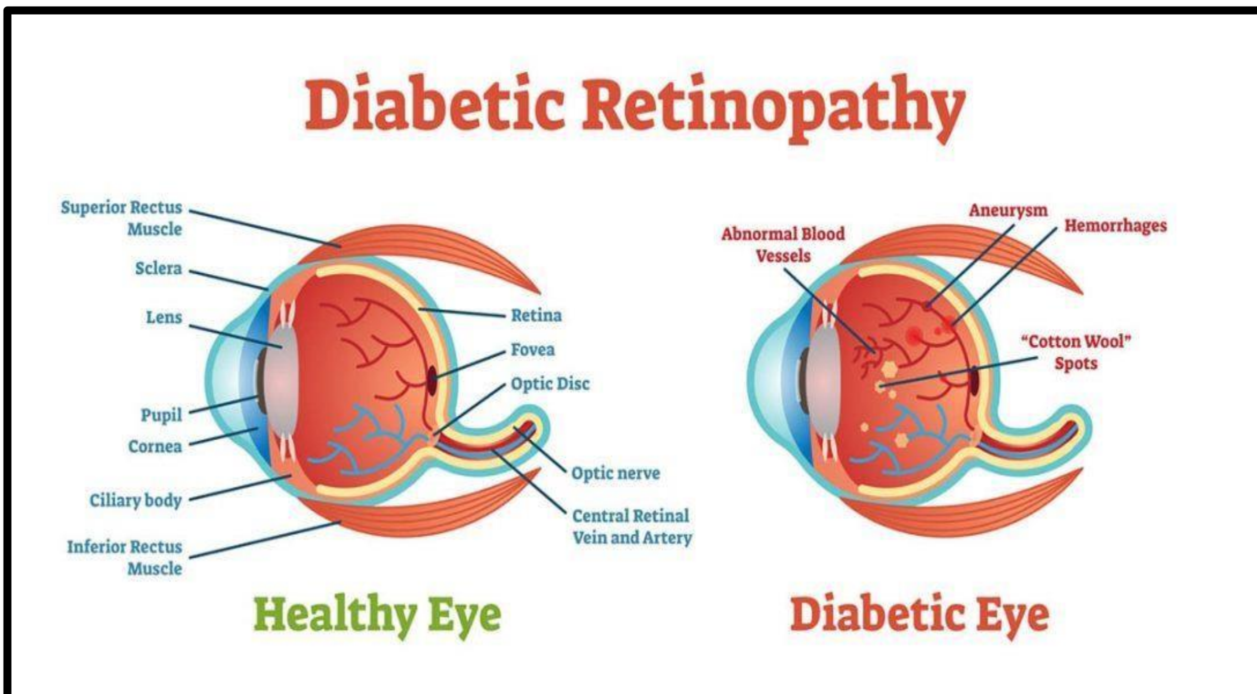
1. Introduction

Diabetes Retinopathy (DR) is a medical condition where the retina is damaged because of fluid leaks from blood vessels into the retina. It is a condition because of Type 1 and Type 2 diabetes and can progress if blood sugar levels are not controlled for a longer duration. These problems adversely affect vision of eye. So, dealing with diseases at prior stage is vital. The presence of DR is quite frequent among diabetic patients and the percentage of diabetic patients worldwide is expected to increase from 425 million in 2018 to 629 million in 2030. Early detection and treatment are crucial to prevent severe vision loss. Traditional methods of diagnosing DR involve manual examination of retinal images by ophthalmologists, a process that is time-consuming and subject to human error. With the advent of deep learning, particularly Convolutional Neural Networks (CNNs), automated and accurate detection of DR has become increasingly feasible.



This report presents the development of a deep learning-based model for diabetic retinopathy detection using a Convolutional Neural Network (CNN) architecture, specifically ResNet50. The implementation utilizes Python libraries such as Numpy and TensorFlow Keras. Key aspects of the model development process include addressing the bias-variance trade-off, hyperparameter tuning, and employing regularization techniques like dropout and data augmentation. The performance of the model is evaluated using various classification metrics, including the confusion matrix, ROC and AUC curve, and a classification report.

Providing a user-friendly interface to detect whether the patient has Diabetic Retinopathy, the user has to upload the fundus image, this image undergoes preprocessing and the trained model predicts the results. Using ResNet50 architecture significantly enhanced the performance of neural networks with more layers. ResNet50 architecture is used to train the model for classification of fundus images into 2(two) categories as: Healthy and DR images. Due to its depth and better transfer learning capabilities, the proposed model with ResNet50 achieved 97.16% accuracy in classification.



2. Literature Review

Many conventional methods, Machine Learning techniques and few Deep Learning approaches have been attempted for Diabetic Retinopathy detection.

- ***Review on Conventional Methods:***

  – Argade et al. proposed Image Processing and Data Mining Techniques for automatic detection of Diabetic Retinopathy [3].

  – Mukherjee et al. proposed another conventional technique. The methodology followed by them included Image Processing which involves background normalization and contrast enhancement using histogram equalization. It is followed by Optical Disk Detection, Blood Vessel Extraction and Exudate Detection [4].

- ***Review on Machine Learning Techniques:***

  – Bhatia et al. proposed a Machine Learning Model for diagnosis of Diabetic Retinopathy using ensemble of classification algorithms, alternating decision tree, AdaBoost, Naive Bayes, Random Forest and SVM and achieved a maximum accuracy of 90 %, sensitivity of 94 % and F1-score of 90 % [5].

  – Labhade et al. applied soft computing techniques for Diabetic Retinopathy Detection in which they used different classifiers like SVM, Random Forests, Gradient boost, AdaBoost, Gaussian Naive Bayes [6].

  – Mohammadian et al. proposed a comparative analysis of 9 common Machine Learning Classification Algorithms for Diabetic Retinopathy Detection [7].

- ***Review on Deep Learning Approaches:***

  – Doshi et al. proposed a Deep Learning Approach involving a Deep Convolutional Neural Network with a specific Network Architecture obtaining a Quadratic Kappa Score of 0.3996 [8].

  – Xu et al. applied Deep Convolutional Neural Networks for early automated detection of Diabetic Retinopathy and achieved a highest accuracy of 94.5% [9].

  – Gargeya et al. proposed a Deep Learning Model for identification of Diabetic Retinopathy and achieved a Sensitivity of 0.93, Specificity of 0.87 and Area Under the Receiver Operating Characteristic Curve of 0.94 [10].

3. Problem Statement

- **Challenges in Manual Testing:**
  Diabetic retinopathy (DR) is a leading cause of vision impairment and blindness among diabetic patients, requiring timely and accurate detection for effective treatment. However, the current diagnosis largely depends on manual examination of retinal images by ophthalmologists. This process is time-consuming, labor-intensive, and subject to human error and variability in interpretation. Additionally, there is a significant shortage of eye care specialists, especially in remote and underserved areas, leading to delays in diagnosis and treatment.

- **Need for an Automated, Accurate Solution:**
  Given the limitations of manual testing, there is an urgent need for an automated, reliable, and efficient solution to detect diabetic retinopathy. A deep learning-based model can offer high accuracy and consistency in identifying DR from retinal images, reducing the burden on healthcare professionals and increasing access to early diagnosis and intervention. Such a solution would improve patient outcomes, prevent vision loss, and enhance the overall efficiency of healthcare systems.

4. Objectives

- ***Develop an Automated Detection Model:*** To create a deep learning-based model capable of analyzing retinal images and accurately detecting signs of diabetic retinopathy.

- ***Improve Early Detection:*** Enhance early detection rates of diabetic retinopathy, enabling timely intervention and treatment.

- ***Scalability and Accessibility:*** Ensure the model is scalable and can be deployed in various healthcare settings, including areas with limited access to ophthalmologists.

- ***Accuracy and Reliability:*** Achieve high levels of accuracy and reliability in detecting diabetic retinopathy, minimizing false positives and negatives.

5. Research Questions

I. Can a deep learning-based model accurately detect diabetic retinopathy from retinal images?

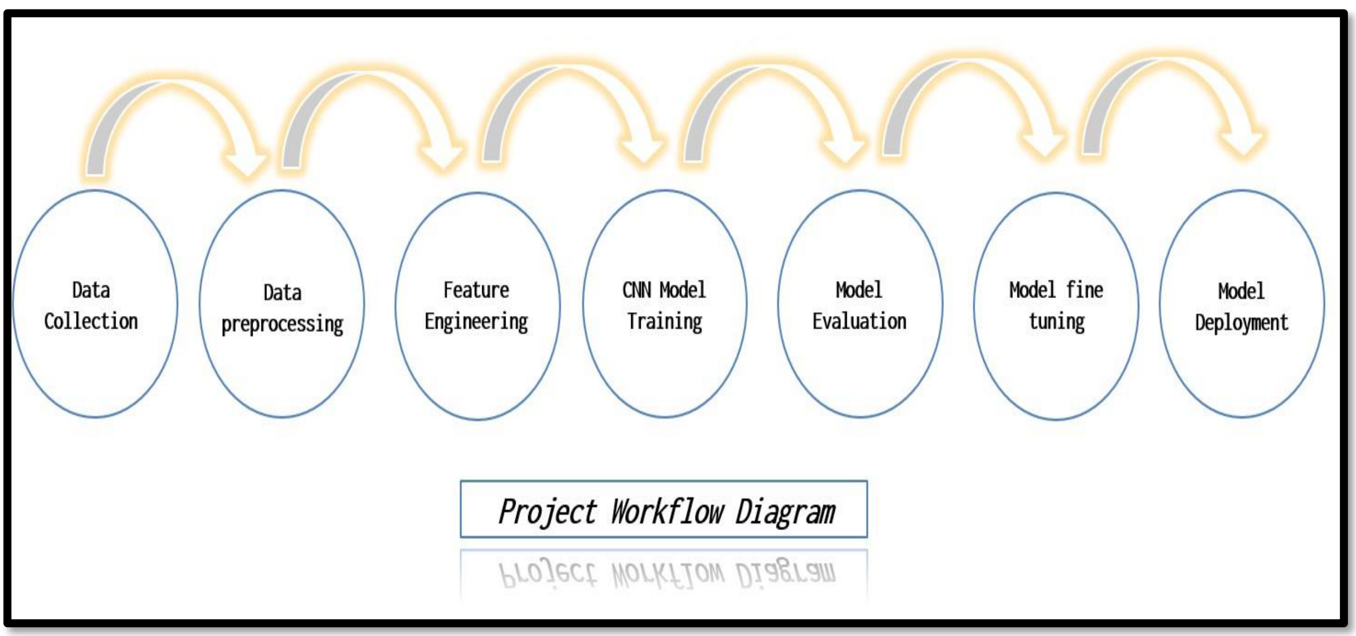
II. How does the performance of the proposed model compare to traditional manual screening methods in terms of accuracy, speed, and scalability?

III. What are the critical features and patterns in retinal images that the model uses to identify diabetic retinopathy?

IV. What are various model used in Diabetic Retinopathy?

V. Which type of datasets has been used for Diabetic Retinopathy?

6. Methodology



I. Data Collection

A large dataset of retinal images was collected from Kaggle. The dataset consists of 2000 retinal images out of which, 1000 images are labelled as 1(Healthy folder) and 1000 images are labelled as 0 (DR_presence folder). Sample Images are shown in Fig 1.

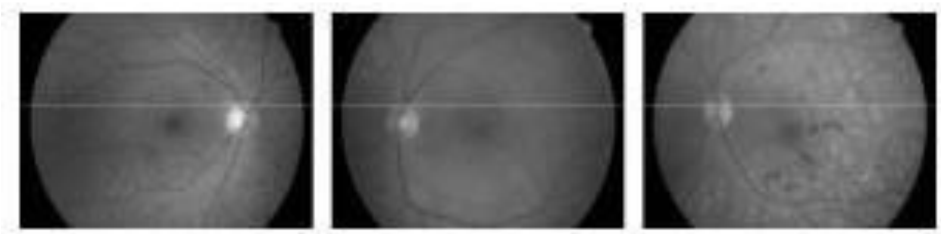


Fig. 1. Dataset Samples

II. Image Pre-Processing

For Deep convolutional neural network worked on spatial data of the fundus images. A primary step involved in the preprocessing is resizing the images. Image Preprocessing requires each of the images to be resized to a standard size and apply filters to amplify feature extraction. But in my dataset images are not in different format, all are in same shape, i.e., (256,256,3) which is RGB image. That's why I don't need resizing. RGB (red, green, blue) images refers to system representing the colors used on an image. Here '256' represents the height and width of the image respectively, and the number 3 represents R, G, B channels.

For example,

- Firstly, take each image and convert them into 1-D array (channel wise).
- Then concatenate 3 channel's 1-D array into single 1D array.
- After that label as per the folder (labelled as 1(Healthy folder) or labelled as 0 (DR_presence folder) from which the image actually taken.
- So, for 1000 images from each folder are processed with label then combine them and after that shuffle the dataset.
- I have 256x256x3 image so 1-D array have (256x256x3) =196608 values.

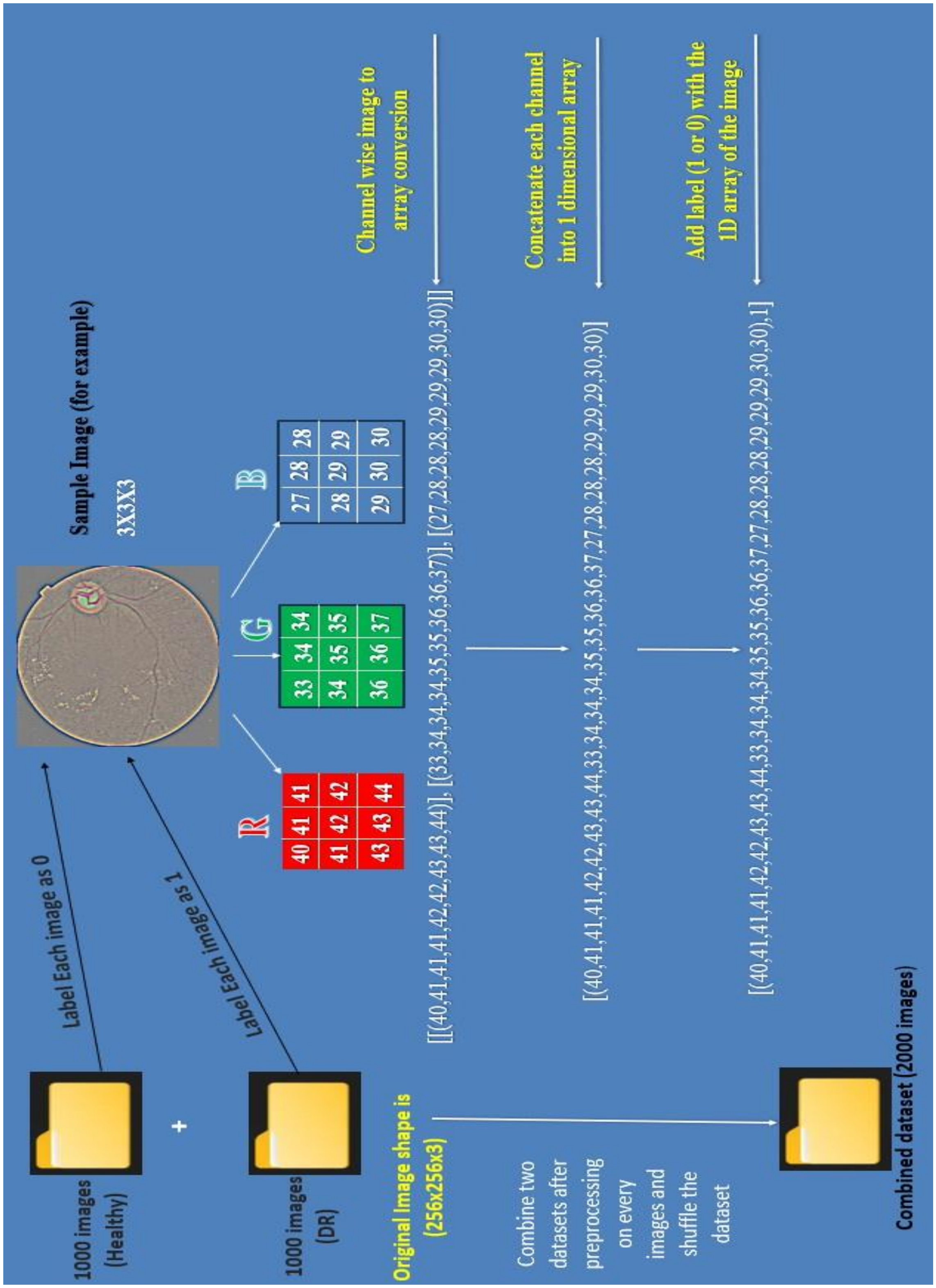


Fig. 2. Image preprocessing (step by step approach)

III. Feature Engineering

This step is actually included feature selection, train-test splitting, reshaping independent feature for model training.

- ***Feature selection:***
  As I see in the image preprocessing step I convert every images into single 1-D array with label. So, the single 1-D array will be consider as independent features(X) and the label is consider as dependent feature(y).

```
Shape of independent features (images) array: (2000, 196608)
Shape of dependent features (labels) array: (2000,)
```

- ***Train-test splitting:***

```
# Split the data into training and test sets (70% training, 30% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

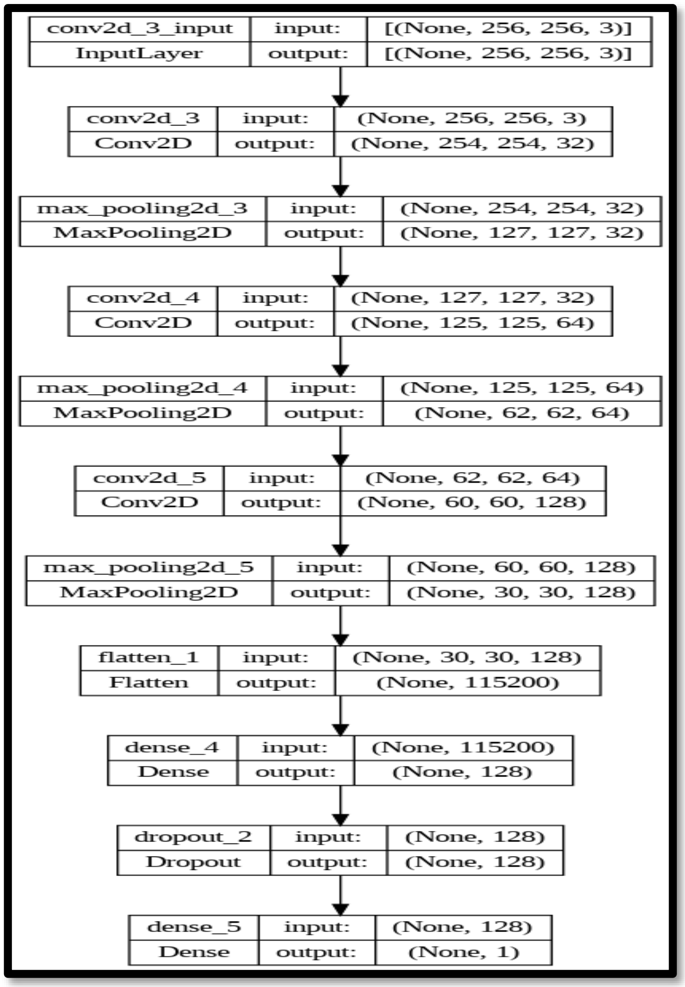
Number of samples in X_train set: (1400, 196608)
Number of samples in X_test set: (600, 196608)
Number of samples in y_train set: (1400,)
Number of samples in y_test set: (600,)

- ***Independent features reshaping for model training:***

```
Number of samples in training set: (1400, 256, 256, 3)
Number of samples in test set: (600, 256, 256, 3)
```

IV. Model Training

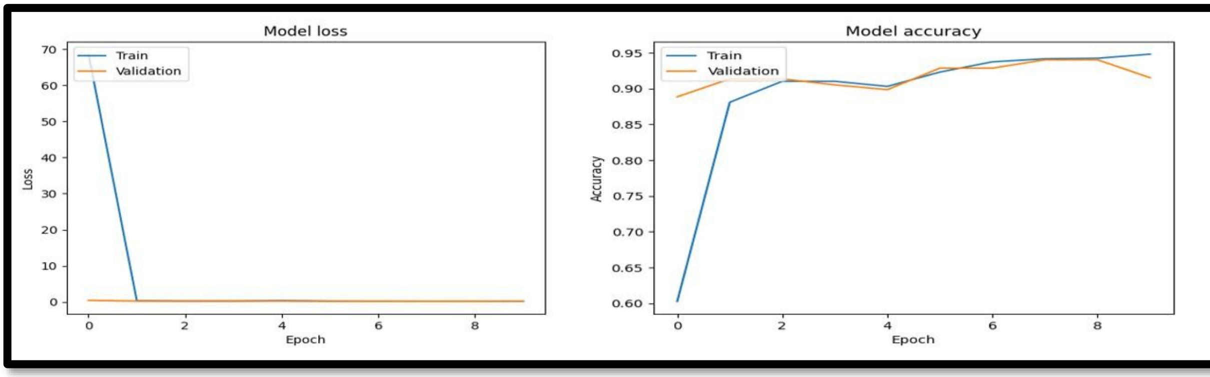
- ***Build Custom CNN Model***



V. Model Evaluation:

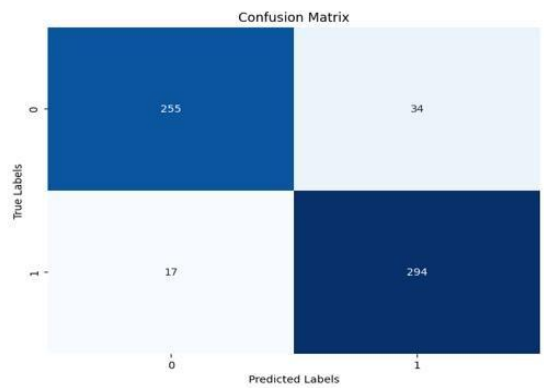
```
Epoch 1/10
44/44 [==============================] - 5s 76ms/step - loss: 68.6369 - accuracy: 0.6029 - val_loss: 0.4068 - val_accuracy: 0.8883
Epoch 2/10
44/44 [==============================] - 3s 75ms/step - loss: 0.3305 - accuracy: 0.8807 - val_loss: 0.2185 - val_accuracy: 0.9133
Epoch 3/10
44/44 [==============================] - 3s 67ms/step - loss: 0.2361 - accuracy: 0.9100 - val_loss: 0.2049 - val_accuracy: 0.9133
Epoch 4/10
44/44 [==============================] - 3s 66ms/step - loss: 0.2351 - accuracy: 0.9100 - val_loss: 0.2276 - val_accuracy: 0.9050
Epoch 5/10
44/44 [==============================] - 3s 66ms/step - loss: 0.3696 - accuracy: 0.9029 - val_loss: 0.2147 - val_accuracy: 0.8983
Epoch 6/10
44/44 [==============================] - 3s 67ms/step - loss: 0.1987 - accuracy: 0.9229 - val_loss: 0.1803 - val_accuracy: 0.9283
Epoch 7/10
44/44 [==============================] - 3s 68ms/step - loss: 0.1723 - accuracy: 0.9371 - val_loss: 0.1655 - val_accuracy: 0.9283
Epoch 8/10
44/44 [==============================] - 3s 67ms/step - loss: 0.1611 - accuracy: 0.9414 - val_loss: 0.1501 - val_accuracy: 0.9400
Epoch 9/10
44/44 [==============================] - 3s 66ms/step - loss: 0.1651 - accuracy: 0.9421 - val_loss: 0.1542 - val_accuracy: 0.9400
Epoch 10/10
44/44 [==============================] - 3s 66ms/step - loss: 0.1561 - accuracy: 0.9479 - val_loss: 0.2014 - val_accuracy: 0.9150
19/19 [==============================] - 0s 20ms/step - loss: 0.2014 - accuracy: 0.9150
Cusstom model Test Loss: 0.2013990581035614
Custom model Test Accuracy: 0.9150000214576721
```

<u>Custom model loss and model accuracy</u>

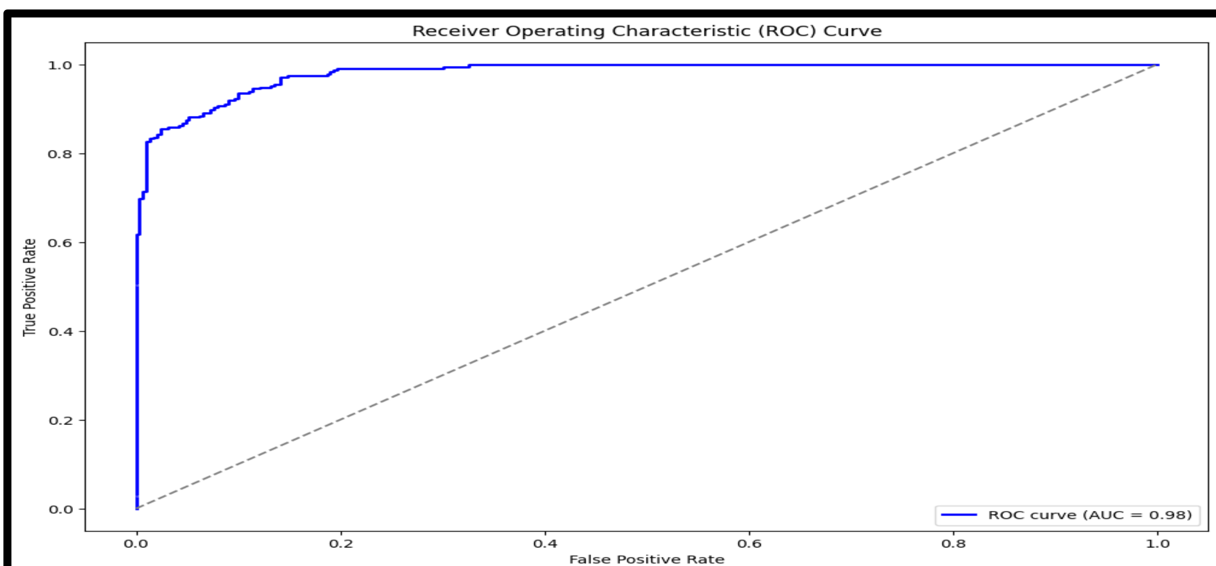


<u>***Custom model loss and model accuracy curve for training and validation data***</u>

	precision	recall	f1-score	support
0	0.94	0.88	0.91	289
1	0.90	0.95	0.92	311
accuracy			0.92	600
macro avg	0.92	0.91	0.91	600
weighted avg	0.92	0.92	0.91	600



<u>***Custom model classification report and confusion matrix***</u>

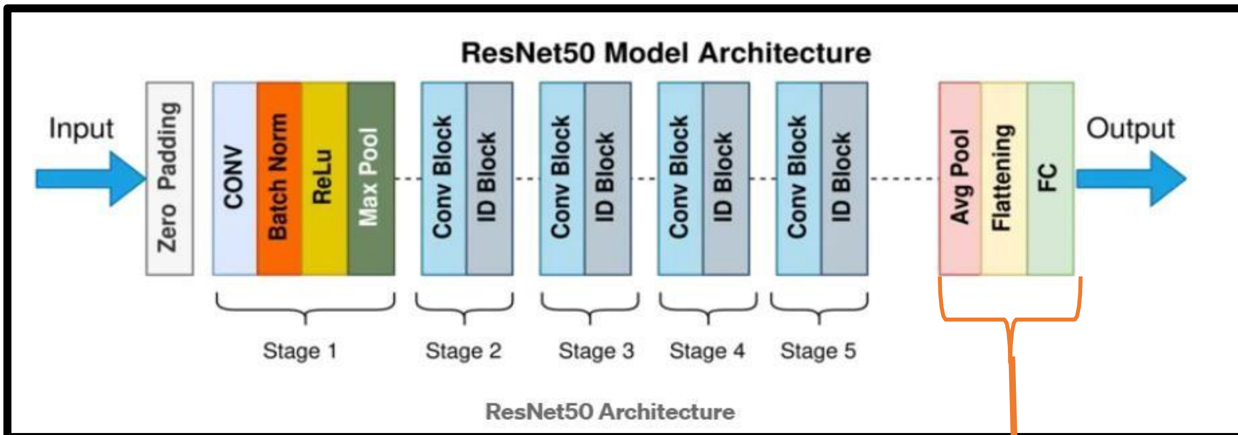


<u>***Custom model ROC curve and AUC score***</u>

VI. Model fine tuning:

As I see model accuracy is 91.5% and the precision, recall score also very low. So, for that reason I implemented the concept called ‘Transfer learning’. I implement various pretrained models such as VGG-16, VGG-19, inceptionV3, ResNet50 etc. But out of them ResNet50 model perform well among all.

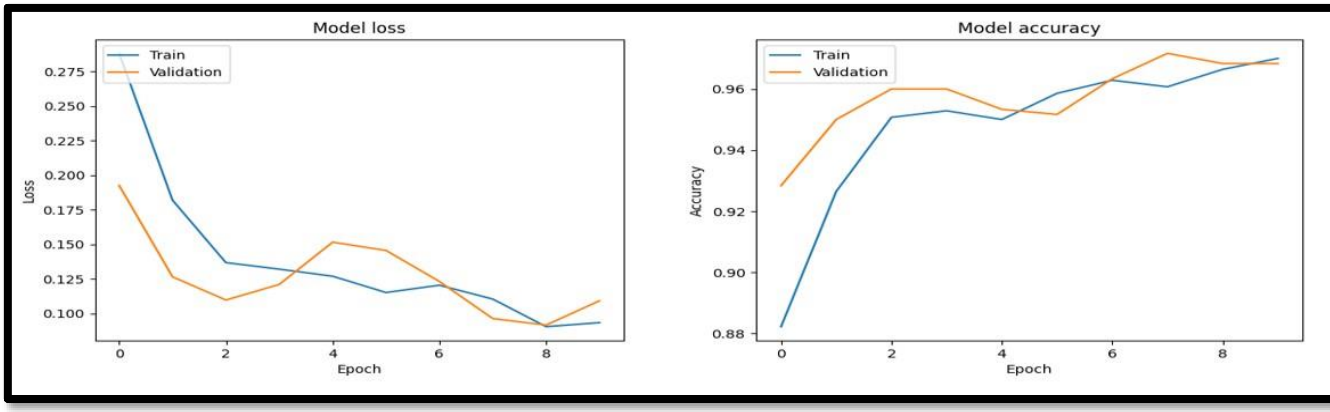
	Model	Accuracy
0	VGG16	0.9345
1	VGG19	0.9399
2	InceptionV3	0.9422
3	ResNet50	0.9716
4	MobileNetV1	0.9546




```
x = base_model.output
x = layers.GlobalAveragePooling2D()(x)
x = layers.Dense(128, activation='relu')(x)
x = layers.Dropout(0.3)(x)
predictions = layers.Dense(1, activation='sigmoid')(x)
```

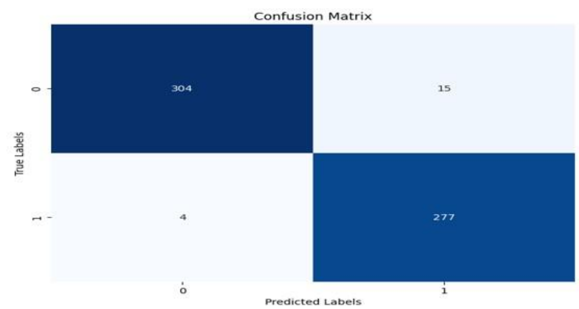
```
Epoch 1/10
44/44 [==============================] - 13s 204ms/step - loss: 0.2969 - accuracy: 0.8907 - val_loss: 0.1530 - val_accuracy: 0.9400
Epoch 2/10
44/44 [==============================] - 7s 169ms/step - loss: 0.1750 - accuracy: 0.9357 - val_loss: 0.1246 - val_accuracy: 0.9550
Epoch 3/10
44/44 [==============================] - 7s 167ms/step - loss: 0.1395 - accuracy: 0.9571 - val_loss: 0.1048 - val_accuracy: 0.9633
Epoch 4/10
44/44 [==============================] - 8s 180ms/step - loss: 0.1414 - accuracy: 0.9486 - val_loss: 0.1185 - val_accuracy: 0.9550
Epoch 5/10
44/44 [==============================] - 8s 179ms/step - loss: 0.1303 - accuracy: 0.9507 - val_loss: 0.0944 - val_accuracy: 0.9700
Epoch 6/10
44/44 [==============================] - 7s 170ms/step - loss: 0.1140 - accuracy: 0.9600 - val_loss: 0.1781 - val_accuracy: 0.9267
Epoch 7/10
44/44 [==============================] - 7s 169ms/step - loss: 0.1136 - accuracy: 0.9600 - val_loss: 0.0949 - val_accuracy: 0.9733
Epoch 8/10
44/44 [==============================] - 8s 177ms/step - loss: 0.0999 - accuracy: 0.9650 - val_loss: 0.1140 - val_accuracy: 0.9550
Epoch 9/10
44/44 [==============================] - 8s 178ms/step - loss: 0.0944 - accuracy: 0.9679 - val_loss: 0.0846 - val_accuracy: 0.9717
Epoch 10/10
44/44 [==============================] - 8s 175ms/step - loss: 0.0873 - accuracy: 0.9714 - val_loss: 0.0913 - val_accuracy: 0.9717
19/19 [==============================] - 2s 113ms/step - loss: 0.0913 - accuracy: 0.9717
Resnet50 model Test Loss: 0.09134776145219803
Resnet50 model Test Accuracy: 0.971666693687439
```

ResNet50 model loss and model accuracy

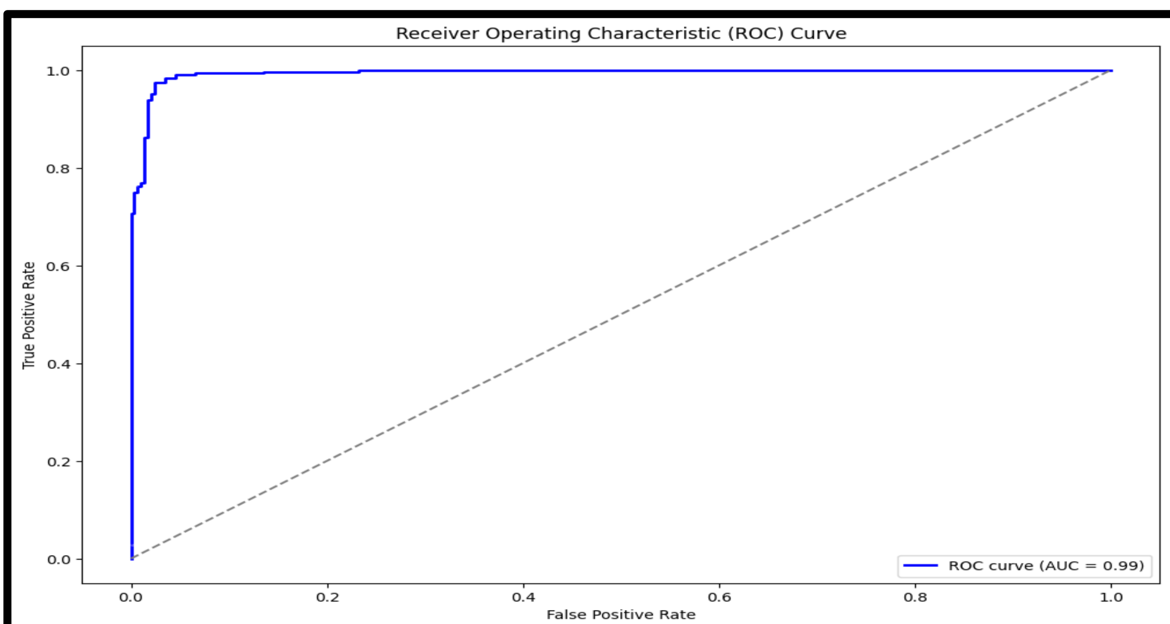


ResNet50 model loss and model accuracy curve for training and validation data

	precision	recall	f1-score	support
0	0.99	0.95	0.97	319
1	0.95	0.99	0.97	281
accuracy			0.97	600
macro avg	0.97	0.97	0.97	600
weighted avg	0.97	0.97	0.97	600



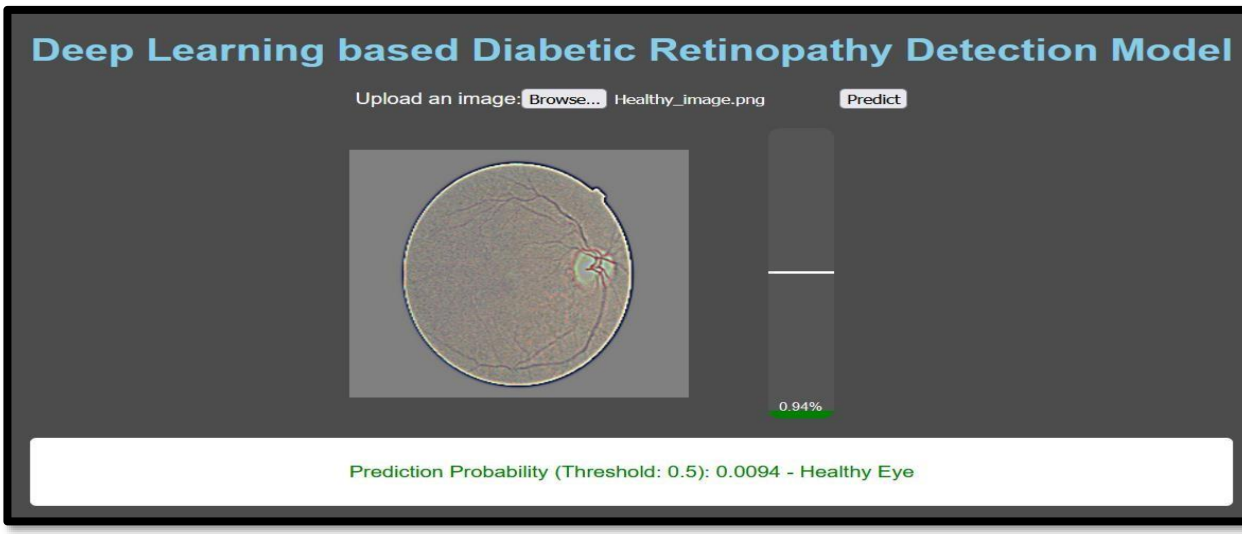
ResNet50 model classification report and confusion matrix



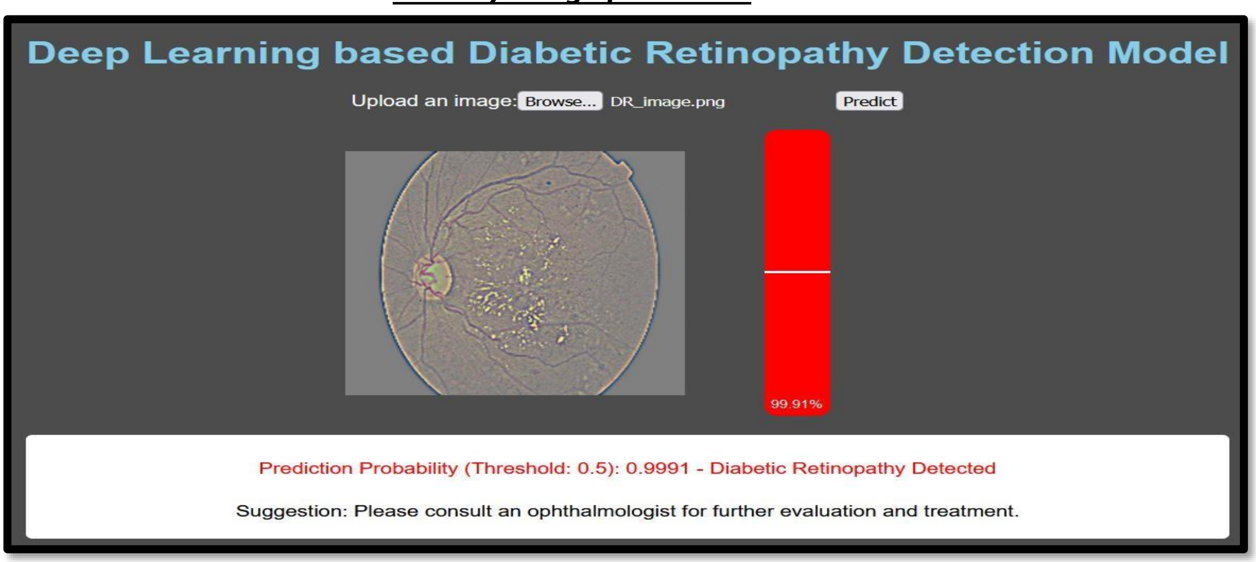
ResNet50 model ROC curve and AUC score

VII. Model Deployment

After implementing the diabetic retinopathy model, I used the Flask framework to deploy it. The Flask framework provided an efficient and straightforward way to deploy the model, allowing for seamless integration with a web-based interface and enabling easy access for users. Deployment through Flask ensured that the model could be hosted on a server and accessed via a web browser. The flexibility of Flask made it ideal for handling the model's input and output, ensuring a smooth user experience. By leveraging Flask, the deployment process of the diabetic retinopathy model was streamlined and effective.



Healthy image prediction



Diabetic Retinopathy image prediction

CONCLUSION

The project aimed to develop a deep learning model for the automated detection and classification of diabetic retinopathy. The model was trained on a large dataset of retinal images and achieved high accuracy in identifying the presence and absence of the disease.

The key accomplishments of this work include:

1. **Model Performance**: My model demonstrated high accuracy (97.16%) in classification of diabetic retinopathy. By employing a CNN architecture, I achieved robust feature extraction and classification capabilities, which are crucial for distinguishing between healthy and affected retinal images.
2. **Data Preprocessing and Augmentation**: Effective preprocessing techniques, including image resizing and augmentation, were essential in enhancing the model's generalization ability. These steps helped in mitigating overfitting and improved the model's performance on unseen data.
3. **Validation and Testing**: Rigorous validation and testing protocols ensured the reliability of my model.
4. **Clinical Relevance**: The integration of my model into clinical workflows has the potential to expedite the screening process for diabetic retinopathy. Early detection is crucial for preventing severe vision impairment, and my model can serve as a valuable tool for ophthalmologists and other healthcare providers.
5. **Future Work**: While my model has shown promising results, there is room for further improvement. Future work may focus on expanding the dataset to include a wider variety of retinal images, incorporating additional features such as patient demographics, and exploring the use of other deep learning architectures. Additionally, real-world clinical trials would be beneficial to validate the model's effectiveness in diverse healthcare settings.

In conclusion, the development of a deep learning-based diabetic retinopathy detection model represents a significant advancement in the field of medical imaging. By providing a reliable and efficient tool for early diagnosis, this model holds the potential to significantly reduce the burden of diabetic retinopathy and improve the quality of life for millions of patients worldwide.

Limitation

Here are several key limitations to consider:

1. Data Limitations

A. Quality and Quantity of Data

- **Insufficient Training Data**: Deep learning models require large amounts of labelled data to perform effectively. Insufficient data can lead to poor model performance and overfitting.
- **Quality of Annotations**: The accuracy of the model heavily depends on the quality of the annotations. Inconsistent or incorrect labelling by human experts can introduce noise and affect the model's performance.
- **Imbalanced Datasets**: If the dataset is imbalanced (e.g., significantly more healthy images than diseased ones), the model may become biased towards the majority class, reducing its ability to detect diabetic retinopathy accurately.

B. Data Diversity

- **Lack of Diversity**: A dataset that lacks diversity in terms of patient demographics, imaging conditions, and disease stages may not generalize well to real-world scenarios.
- **Source Variability**: Images from different devices or clinical settings can have varying qualities, which can affect the model's performance if not properly addressed.

2. Model Limitations

A. Generalization

- **Overfitting**: The model may perform well on the training data but fail to generalize to new, unseen data due to overfitting.
- **Limited Generalization**: Even with diverse training data, the model may not generalize well to different imaging devices not represented in the training set.

B. Model Complexity and Interpretability

- **Black-box Nature**: Deep learning models, particularly convolutional neural networks (CNNs), are often criticized for their lack of interpretability. Understanding the decision-making process of these models is challenging, which can be problematic in clinical settings.

- **Computational Complexity**: Deep learning models can be computationally intensive, requiring significant resources for training and inference, which may limit their practical deployment in resource-constrained environments.

3. Clinical Integration

A. Real-world Application

- **Clinical Validation**: The model needs thorough validation in real-world clinical settings to ensure it performs well outside of controlled experimental conditions.
- **Acceptance by Clinicians**: The adoption of deep learning models in clinical practice requires acceptance and trust from healthcare providers, which can be hindered by the model's complexity and lack of transparency.

4. Performance Metrics

A. Evaluation Metrics

- **Inadequate Metrics**: Commonly used metrics like accuracy, precision, and recall may not fully capture the model’s performance, especially in detecting rare but critical cases.
- **Threshold Selection**: The choice of threshold for classification can significantly impact the model’s performance metrics, making it important to choose thresholds that balance sensitivity and specificity appropriately.

5. Maintenance and Updates

A. Model Drift

- **Model Degradation**: Over time, the model’s performance may degrade due to changes in disease prevalence, new imaging technologies, or variations in clinical practices, necessitating regular updates and retraining.
- **Continuous Learning**: Implementing a system for continuous learning and updating the model with new data is challenging but necessary to maintain high performance.

REFERENCES

[1].Google colab link:
https://colab.research.google.com/drive/1c9TosAP3w8MNhqrXq0_luVGTd8XTUmnK?authuser=4#scrollTo=Nxqn5PRTcBDM

[2]. Dataset link: https://www.kaggle.com/datasets/sovitrath/diabetic-retinopathy-224x224-2019-data

[3]. Ketki S. Argade, Kshitija A. Deshmukh, Madhura M. Narkhede, Nayan N. Sonawane and Sandeep Jore: "Automatic Detection of Diabetic Retinopa-thy using Image Processing and Data Mining Techniques", International Conference on Green Computing and Internet of Things (ICGCIoT), 2015.

[4]. Anupriyaa Mukherjee, Diksha Rathore, Supriya Shree and Asst Prof. Shaik Jameel:"Diagnosis of Diabetic Retinopathy", Int. Journal of Engineering Research and Applications, ISSN : 2248-9622,Vol. 5, Issue 2, (Part -4) February 2015.

[5]. Karan Bhatia, Shikhar Arora and Ravi Tomar:"Diagnosis of Diabetic Retinopathy Using Machine Learning Classification Algorithm", 2nd International Conference on Next Generation Computing Technologies (NGCT), 2016.

[6]. Jyoti Dnyaneshwar Labhade, L. K. Chouthmol and Suraj Deshmukh:"Diabetic retinopathy detection using soft computing techniques", Conference on Automatic Control and Dynamic Optimization Techniques (ICACDOT), 2016.

[7]. Saboora Mohammadian, Ali Karsaz and Yaser M. Roshan:"A Comparative Analysis of Classification Algorithms in Diabetic Retinopathy Screening", 29th International Conference on Software Engineering and Knowledge Engineering (SEKE), 2017.

[8]. Darshit Doshi, Aniket Shenoy, Deep Sidhpura and Prachi Gharpure:"Diabetic retinopathy detection using deep convolutional neural networks", International Conference on Computing, Analytics and Security Trends (CAST), 2016.

[9]. Kele Xu, Dawei Feng and Haibo Mi:"Deep Convolutional Neural Network-Based Early Automated Detection of Diabetic Retinopathy Using Fundus Image", Molecules, 2017 (Open Access Journal), 22,2054; doi:10.3390/molecules22122054.

[10]. Rishab Gargeya and Theodore Leng:"Automated Identification of Diabetic Retinopathy Using Deep Learning", American Academy of Ophthalmology, 2017.

[11]. Github Link: https://github.com/SumedhaBanerjee/Master-Thesis-2024.git