GAYATRI VIDYA PARISHAD COLLEGE OF ENGINEERING (Autonomous)
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Madhurawada, Visakhapatnam - 530 048.
COLLEGE OF ENGINEERING (AUTONOMOUS)

DEEP LEARNING MODEL FOR DIABETIC RETINOPATHY DETECTION

Batch-7

Department: Computer Science and Engineering

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Abstract

In the Present era, every one is prone to get affected by diseases. The most frequently happening is loss of sight among people who were diabetic. Diagnosing diabetic retinopathy manually with the assistance of an ophthalmologist has been a time-consuming and intensive task. The existing machine learning models are not efficient when it comes to real time usage. The proposed model not only detects diabetic retinopathy but also analyses distinct severe phases, which is done using Deep Learning (DL) and transfer learning methods. This approach enhances the model's ability to accurately classify and diagnose diabetic retinopathy by learning relevant hierarchical features from a diverse set of retinal images. Images are being trained to automatically recognize the progress of DR in a person.

Introduction

- Diabetic retinopathy is a serious eye disease prevalent among individuals with diabetes, characterized by damage to the blood vessels in the retina due to high blood sugar levels.

- A person diagnosed with “Non-proliferate diabetic retinopathy” (NPDR) is said to have tiny blood vessels leak that makes the retina swell, causes the blood vessels in the retina to close off.

- When left untreated, diabetic retinopathy progresses to a more serious stage, called proliferative diabetic retinopathy (PDR).

- In this type, new blood vessels start growing in the retina at an abnormal pace.

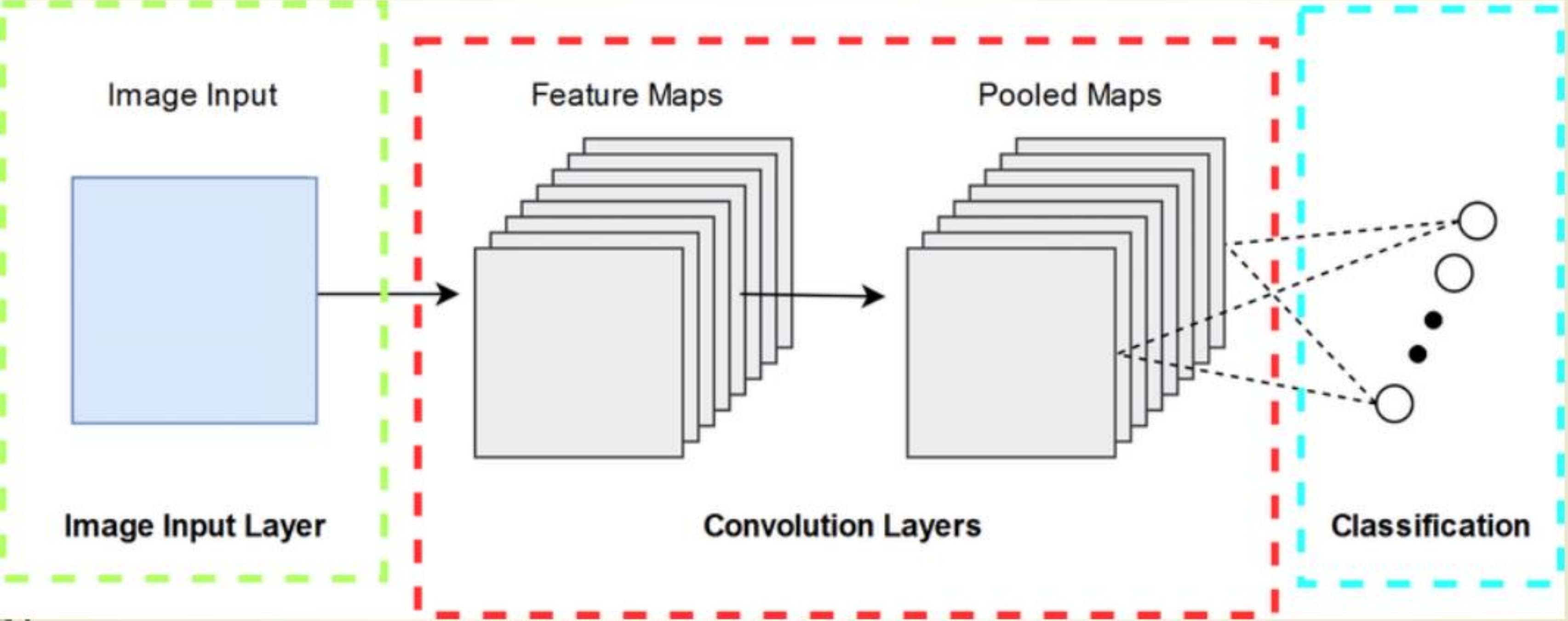
- As a result of the above factors, the optic nerve is damaged and results in vision loss.

- For the purpose of speeding up the process and precise predictions, we had developed a model based on deep-learning.

Existing System

- Existing systems for diabetic retinopathy detection use conventional CNN as a single base model for classification of data [1].
- These systems involve preprocessing steps like image resizing and normalization, followed by model training and evaluation.
- The deployment of these models in healthcare settings allow for automated detection and early intervention of diabetic retinopathy.

Existing System



Detection using single CNN Model

Drawbacks of Existing Research

- **Low Accuracy:**

--> Existing system lacks accuracy.

--> This is due to usage of poor preprocessing techniques and cnn model architecture.

- **Lack of handling Unbalanced Data:**

--> The dataset available on various platform may contain unbalanced data i.e the frequency of one class is majority over the others.

--> This also leads to high chances of increase in error rates while generalizing to new data.

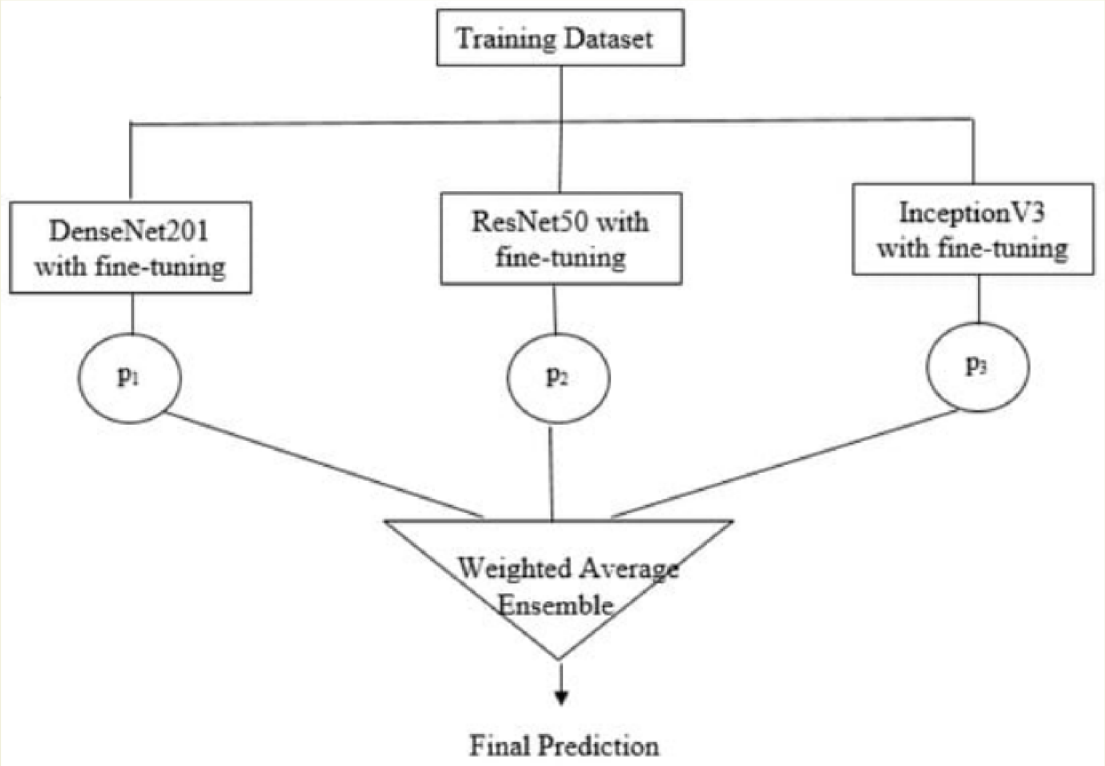
- **Challenge of data distribution**:

--> If the data distribution changes significantly after the model is trained, the model might become less effective because it has been optimized for the characteristics of the initial distribution.

Proposed System With Advantages

- The proposed diabetic retinopathy detection offers acceptable level of accuracy as compared to previous models.
- The idea is to use MODEL ENSEMBLING of pretrained models [2].
- We will first try out by identifying two or three best models as a base and further fine tune them for final output generation.
- We will decide on a strategy to combine the predictions from multiple models using some common methods like average voting, where each model is given some importance.

Proposed System With Advantages



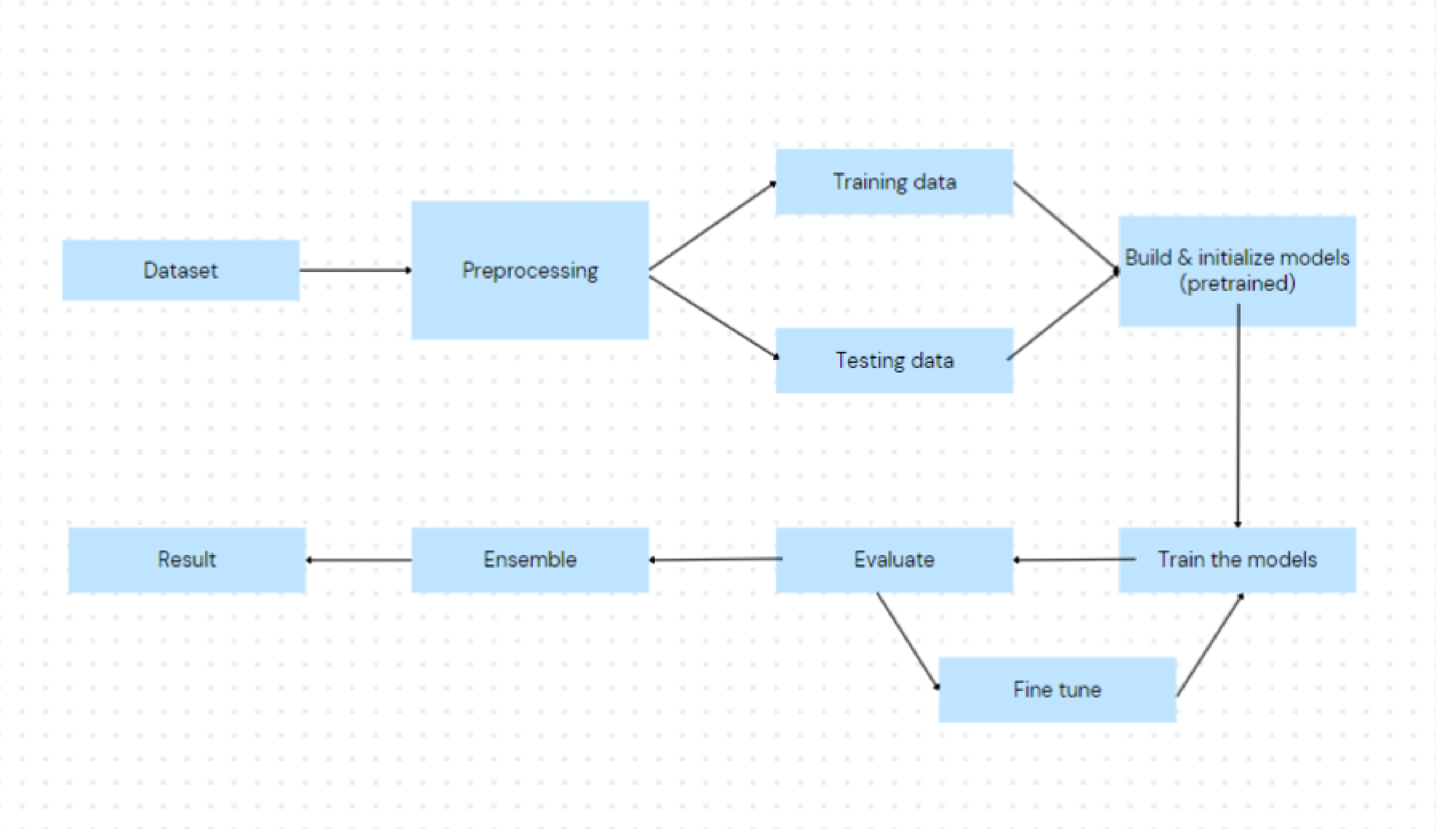
Ensemble architecture

Proposed System With Advantages

Advantages:

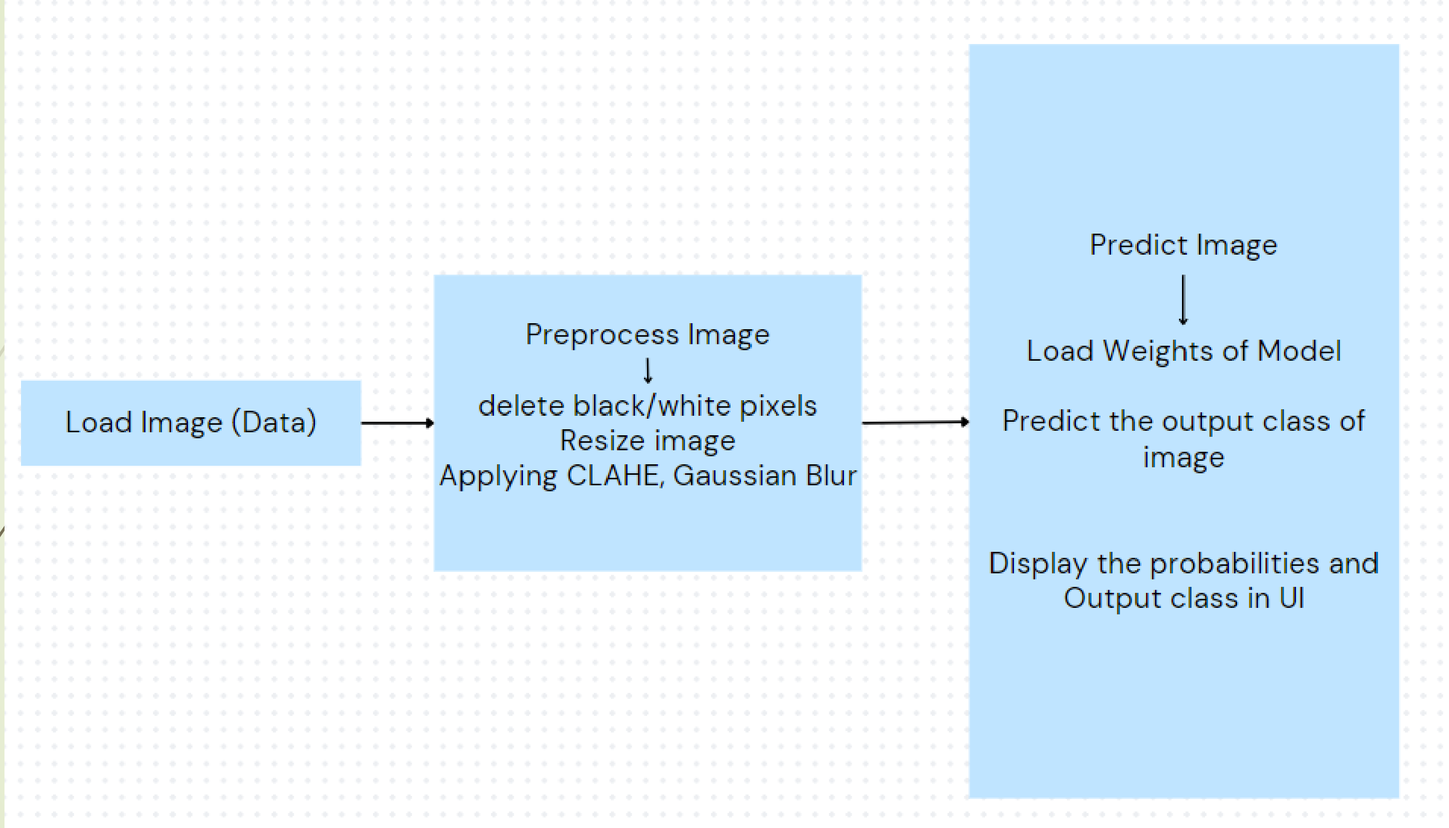
1. Improves overall performance by reducing overfitting, capturing deeper aspects of the data, and providing a more robust solution.
2. It is more robust to noisy data or outliers. If a particular model is affected by noise, the impact can be reduced when combined with other models.
3. When the distribution shifts, the combined knowledge from diverse models allows the ensemble to adapt to new patterns more effectively.

Flowchart



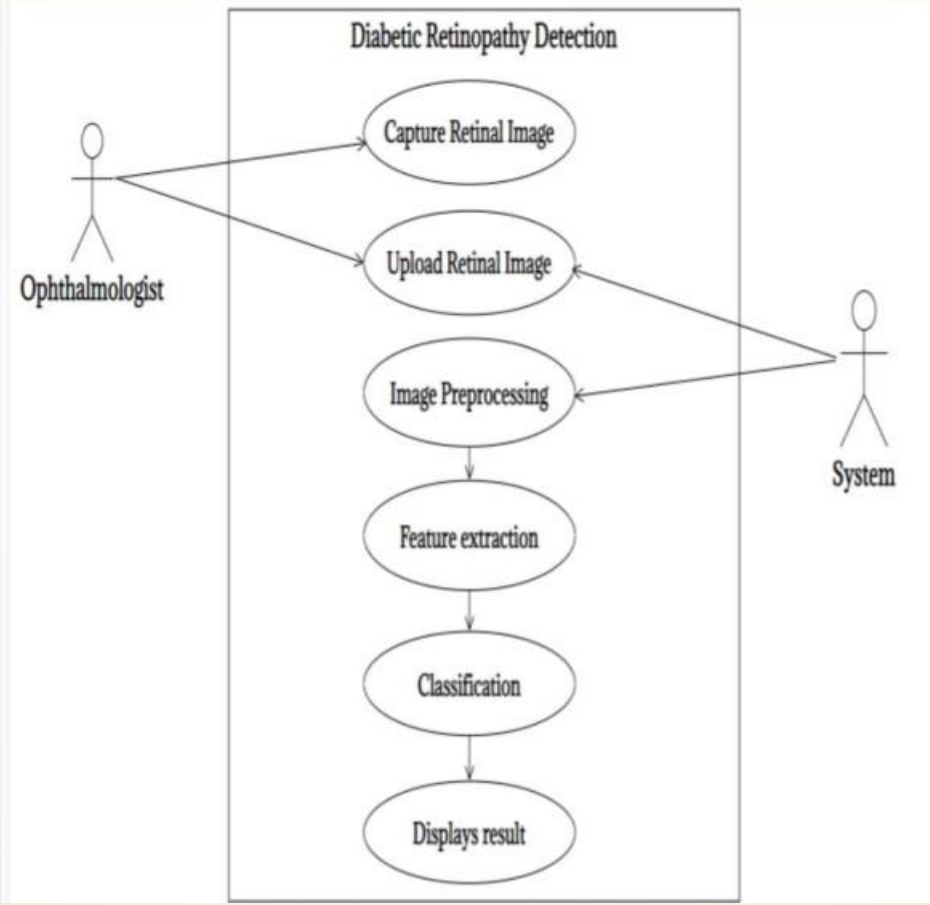
Flow chart of proposed system (Backend model)

Flowchart



Workflow of End Application

Use case diagram



Algorithm

Data Preprocessing	Data Splitting	Load Pretrained Models	Ensemble & Test
Perform data augmentation and then pre-process the image by turning it into grayscale and applying gaussian filter	**Divide the preprocessed dataset into training and testing sets to facilitate model training and evaluation.**	**Load Convolutional pre-trained models like Dense Net , ResNet50, and Inception model with weights trained on ImageNet**	**Add a Global Average Pooling layer and a Dense layer for each pre-trained model to extract features and use the "concatenate" layer to merge the features**

Hardware Requirements

- **Processor** - Intel Core
- **i5Hard Disk** - 512GB
- **RAM** - 8GB

Software Requirements

- **Programming Languages** - Python
- **Libraries** – Pandas, Matplotlib, Tensorflow, Numpy , PyQt5 [3]
- **Technologies** – Streamlit cloud
- **Platforms** – Visual Studio Code , Google Colab

Implementation

1.Data Collection and Preprocessing:

1. Gather a dataset of retinal images labeled with diabetic retinopathy severity levels.
2. Preprocess the images, including resizing, normalization, and augmentation to enhance the model's robustness.

2.Model Initialization:

1. Import the required libraries for deep learning and image processing (e.g., TensorFlow, Keras, OpenCV) and load the pre-trained DenseNet201, InceptionV3, and MobileNetV2 models.

3.Feature Extraction:

1. Utilize the pre-trained models to extract features from the retinal images. This involves removing the fully connected layers and using the output from the last convolutional layer as features.

4.Ensemble Learning Setup:

1. Define the ensemble learning approach (e.g., averaging predictions, weighted averaging, majority voting).
2. Determine the weighting scheme for combining predictions if using weighted averaging.

Implementation

5.Training and Fine-tuning:

1. Split the dataset into training, validation, and testing sets.
2. Fine-tune the pre-trained models on the training set, adjusting the last layers to adapt to the diabetic retinopathy detection task.
3. Validate the models on the validation set and adjust hyperparameters as needed

6.Ensemble Model Integration:

1. Combine the predictions from DenseNet201, InceptionV3, and MobileNetV2 using the chosen ensemble learning approach

7.Evaluation:

1. Evaluate the ensemble model's performance on the testing set using appropriate metrics such as accuracy, precision, recall, and F1-score.
2. Analyze any misclassifications or areas for improvement.

Result Discussion

- We have classified our input data set into 4 classes i.e No_DR, Mild, Moderate, Severe respectively.
- We have developed an interface using "PyQt5" (Python library for developing GUI Applications) with detailed info and a simplified "Streamlit" webapp.

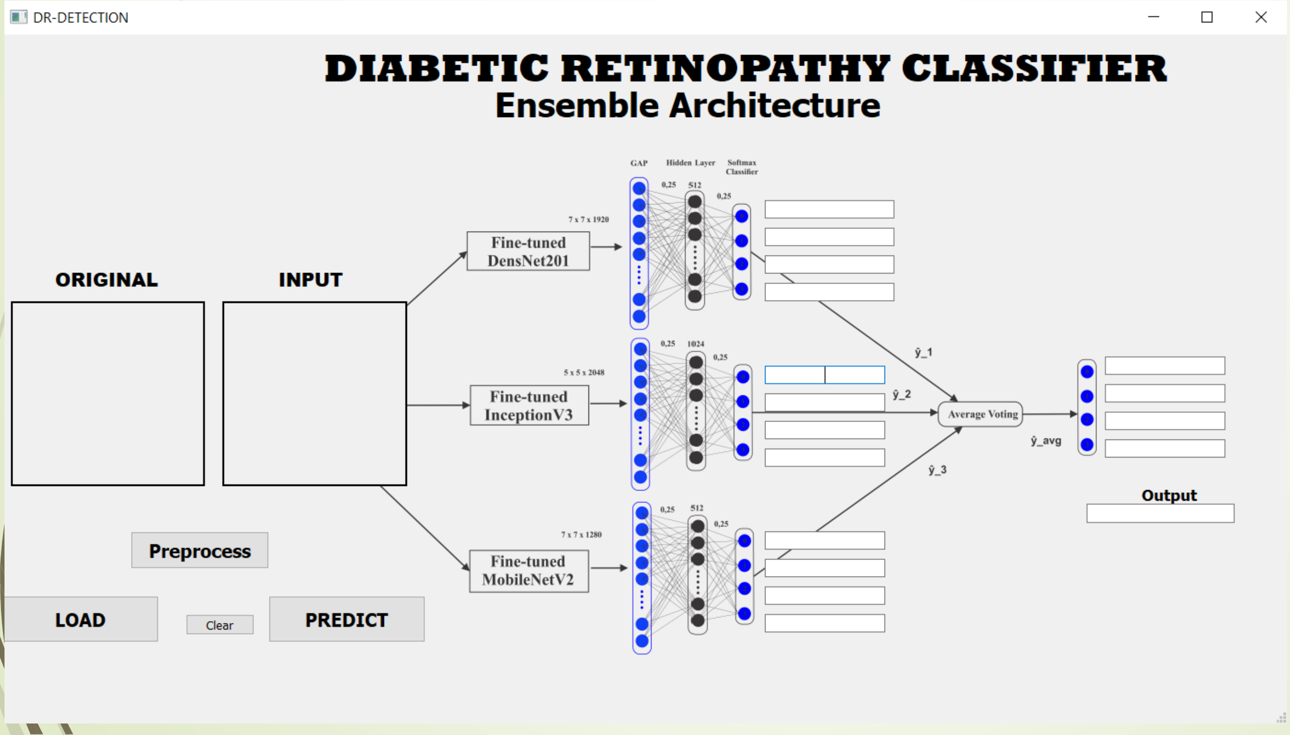
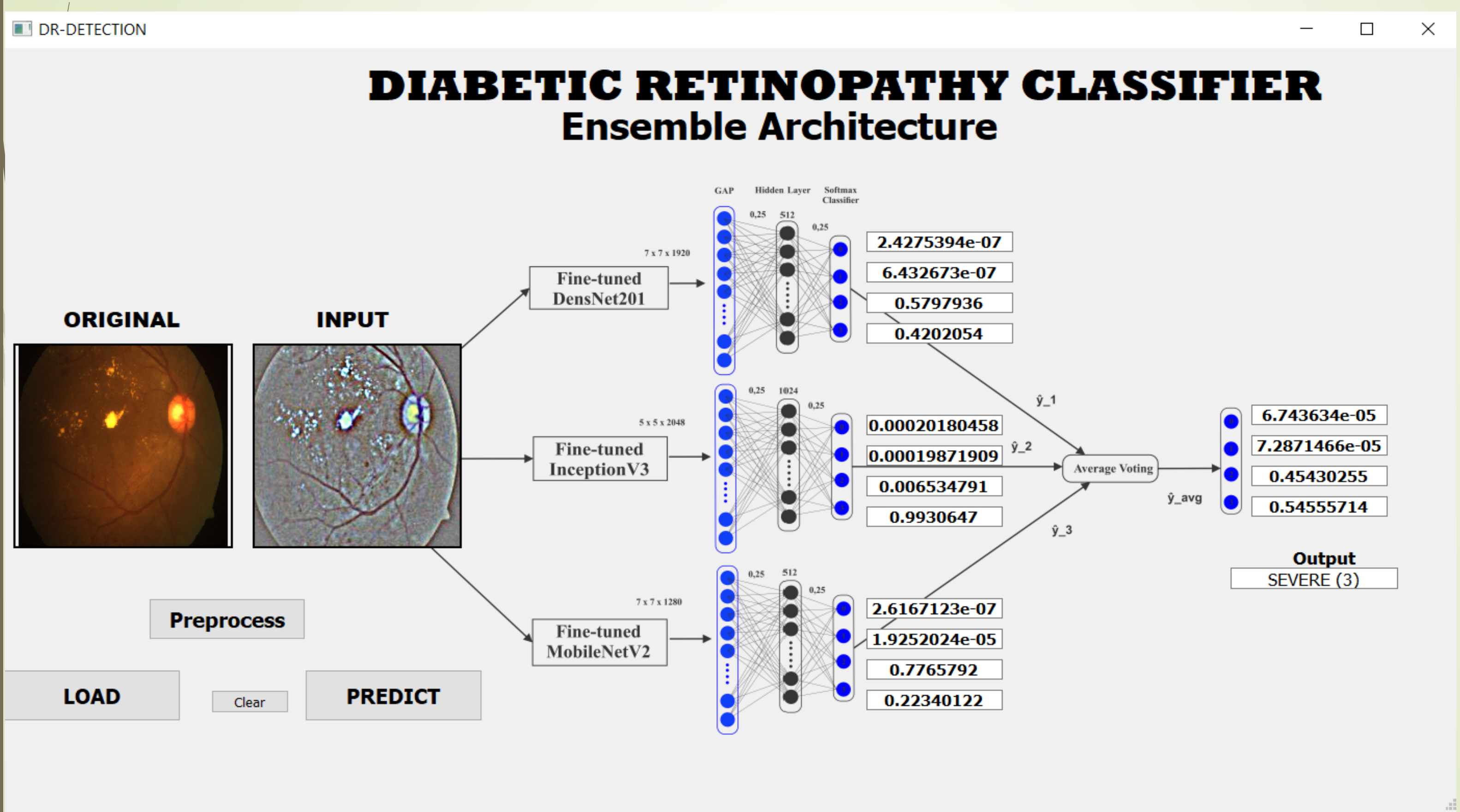


Fig. GUI INTERFACE

Result Discussion

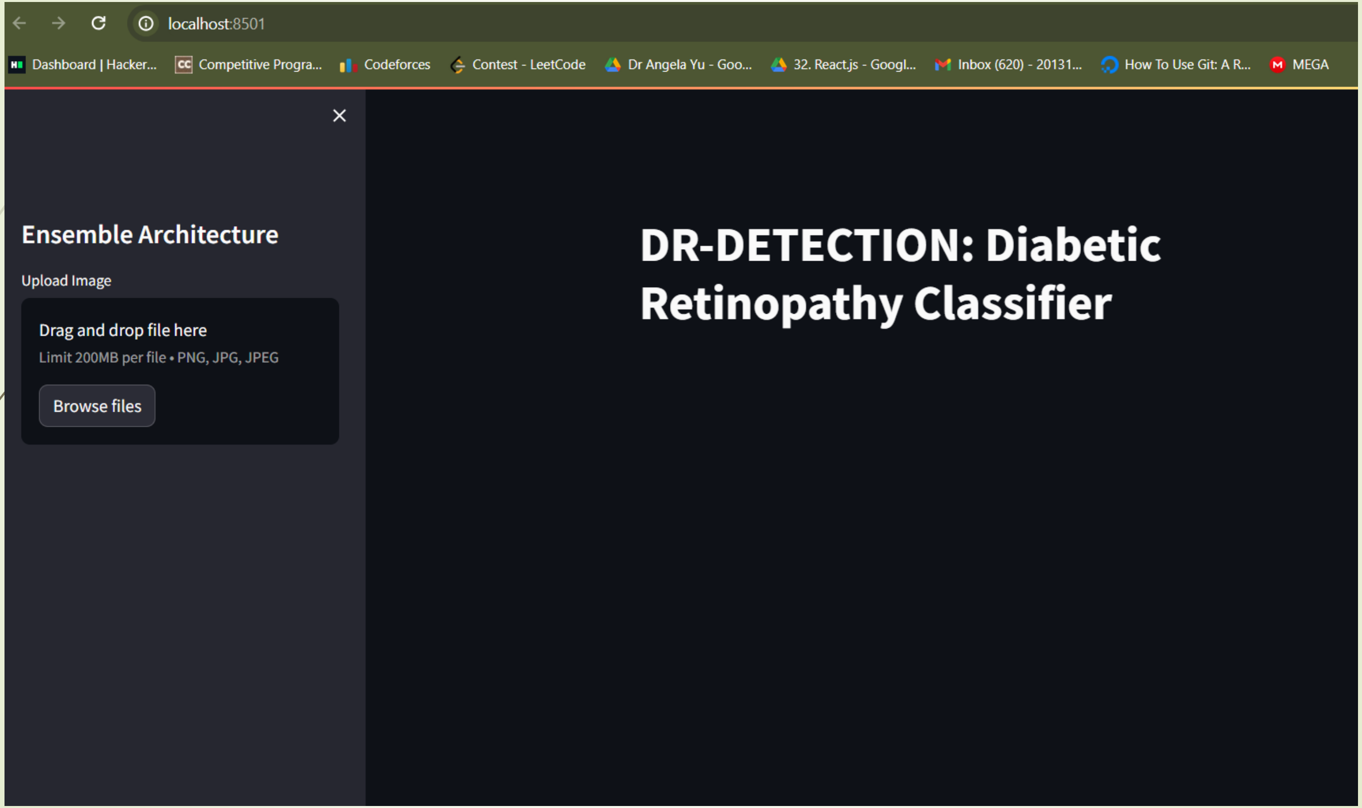
- After loading the input image and predicting the result using GUI Application.



Predicting using GUI App

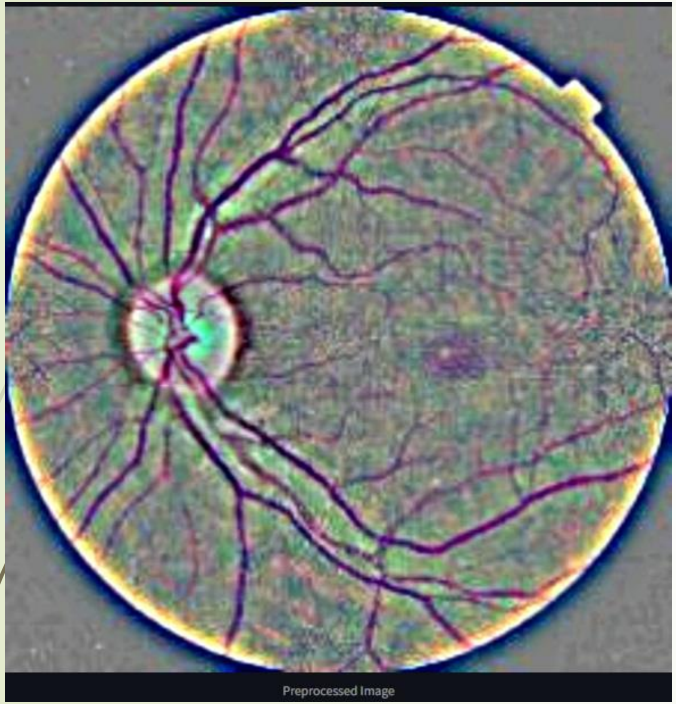
Result Discussion

- Now, we can try and implement the same logic using Streamlit webapp.

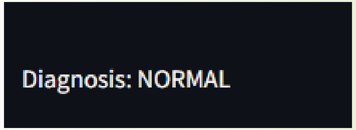


Streamlit webapp

Result Discussion



Preprocessed image



Output diagnosis

Conclusions

In conclusion, our diabetic retinopathy detection project, employing ensemble learning with a commendable accuracy of ~0.9, showcases the effective fusion of machine learning and medical diagnostics. The ensemble approach demonstrates robustness in identifying diabetic retinopathy signs, laying a foundation for further refinement and integration of advanced techniques. Future endeavors aim to optimize the response time of the model and scalability thus simplifying real-time implementation, ultimately contributing to more accurate and accessible early intervention in diabetic retinopathy cases.

Reference Links

[1] https://www.sciencedirect.com/science/article/pii/S1877050916311929

[2] https://www.mdpi.com/1832596

[3] https://www.geeksforgeeks.org/python-introduction-to-pyqt5/

[4] https://www.kaggle.com/c/diabetic-retinopathy-detection/data

[5] https://www.sciencedirect.com/science/article/pii/S1319157823000228


Thank
You