



International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)





International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

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Deep Learning for Early Detection of Diabetic Retinopathy

- An Interactive Interface for Real-Time DR Stage Classification

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ABSTRACT: Diabetic Retinopathy (DR) is a severe eye disease in diabetics that can lead to retinal damage and blindness if not properly managed. Traditional DR screening by ophthalmologists is time-consuming, prompting the need for more efficient methods. The MobileNet model classifies DR into five stages—zero through four. To enhance performance, we explore hybrid models: MobileNet + Graph Neural Network (GNN), MobileNet + Recurrent Neural Network (RNN), and ResNet. The MobileNet + GNN hybrid captures complex spatial relationships, while the MobileNet + RNN focuses on sequential dependencies. Additionally, integrating ResNet enhances feature extraction through residual learning, improving classification accuracy. These hybrid approaches aim to optimize DR detection, improving both accuracy and efficiency. A web interface is also developed for users to predict stage of DR.

KEYWORDS: Deep learning, high-resolution fundus images, Django framework

I. INTRODUCTION

Diabetic Retinopathy (DR) is a leading cause of vision loss worldwide, requiring early and accurate detection to prevent blindness. This project leverages MobileNet, a lightweight deep learning model, to classify DR stages from fundus images efficiently. By exploring hybrid architectures with Graph Neural Networks (GNN) and Recurrent Neural Networks (RNN), we enhance spatial and temporal analysis, providing a scalable, automated solution for DR screening and advancing ophthalmic care.

1.1 Importance of Early Detection

Early detection of Diabetic Retinopathy (DR) is crucial to prevent irreversible vision loss and blindness. Timely diagnosis allows for prompt interventions, such as laser treatment or medication, which can slow or halt disease progression. It also reduces the burden on healthcare systems by minimizing advanced-stage complications, improving patient outcomes, and preserving quality of life.

1.2 Current Trends in DR Diagnosis

Current trends in diabetic retinopathy (DR) diagnosis focus on leveraging deep learning models for automated detection and grading of DR stages from retinal fundus images. Hybrid approaches, combining MobileNet with advanced models like Graph Neural Networks (GNNs) or Recurrent Neural Networks (RNNs), are gaining prominence for capturing spatial and temporal patterns. Additionally, telemedicinebased screening systems and advancements in retinal imaging are improving accessibility and diagnostic accuracy, addressing the global burden of DR.

1.3 Medical Imaging Techniques for Diabetic Retinopathy

In the diagnosis and monitoring of diabetic retinopathy (DR), advanced medical imaging techniques are vital for early detection and effective management. This research paper discusses the use of deep learning models to analyze retinal images for the detection and classification of DR. Techniques such as Optical Coherence Tomography (OCT), fundus photography, and fluorescein angiography are widely employed for noninvasive, cost-effective screening. These imaging methods help identify retinal changes, such as microaneurysms, hemorrhages, and fluid accumulation, which are critical



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in diagnosing DR and its complications. The application of AI models enhances the precision and efficiency of these imaging tools, allowing for better monitoring of disease progression and guiding appropriate treatment decisions.

1.4 Challenges in Deep Learning for Diabetic Retinopathy Diagnosis

Despite significant advancements in deep learning (DL) for diabetic retinopathy (DR) diagnosis, several challenges persist. One major obstacle is the need for large, annotated, and diverse datasets that can train DL models effectively. The quality of retinal images can vary based on factors such as the imaging device used, patient positioning, and the presence of comorbid conditions, all of which may influence the accuracy of automated DR detection. Furthermore, the interpretation of DL models remains a challenge due to the complexity of retinal features, requiring models to be interpretable and trusted by clinicians for broader adoption. Overcoming these challenges requires the development of robust, adaptive models that can function across various clinical environments and handle the inherent variability in retinal images to improve diagnostic accuracy and efficiency.

1.5 Research Focus

This study focuses on developing an intelligent analysis system for diabetic retinopathy (DR) detection using transfer learning and deep learning hybrid models. The objective is to enhance diagnostic accuracy by leveraging the deep learning hybrid models. The approach aims to effectively analyze retinal images, identifying key DR features such as microaneurysms, hemorrhages, and exudates. The introduction outlines the foundation for the paper, detailing the methodology, experimental results, and the potential impact of the proposed system in improving early diagnosis and management of diabetic retinopathy.

II. LITERATURE SURVEY

Varun Gulshan et al. (2016) developed and validated a deep learning algorithm for detecting referable diabetic retinopathy (RDR) in retinal fundus photographs. The algorithm learns from large datasets, removing the need for explicitly defined rules. Sensitivity and specificity for detecting RDR, including moderate or worse DR and diabetic macular edema, were assessed against ophthalmologist panel decisions. The evaluation included operating points optimized for high specificity and high sensitivity, demonstrating the algorithm's clinical potential in medical imaging.

Kele Xu et al. (2017) proposed using deep convolutional neural networks (CNNs) for the early automated detection of diabetic retinopathy (DR) in color fundus images. The study highlights the significance of early DR detection in preventing irreversible vision loss and demonstrates the superior performance of CNNs compared to traditional feature-based methods. The approach achieved high accuracy, outperforming classical techniques in classifying retinal images. Sheikh Muhammad Saiful Islam et al. (2018) developed a deep convolutional neural network for early detection and grading of diabetic retinopathy (DR) using retinal fundus images. The model detects microaneurysms, the earliest signs of DR, and grades images into five severity levels with low accuracy.

Lam C. et al. (2018) utilized convolutional neural networks (CNNs) for automated staging of diabetic retinopathy (DR) using color fundus images. Their approach achieved 95% validation sensitivity and demonstrated improved accuracy with preprocessing and expert-verified datasets. Transfer learning on pretrained models like GoogLeNet and AlexNet further enhanced test accuracies for binary and multinomial classifications.

III. METHODOLOGY

To improve the detection of diabetic retinopathy, the approach incorporates hybrid deep learning models. Combining MobileNet with a Graph Neural Network (GNN) enhances the model's capacity to identify intricate patterns by capturing both spatial and relational features from retinal images. Furthermore, to improve the detection of progressive changes in the stages of diabetic retinopathy, MobileNet is combined with a Recurrent Neural Network (RNN) to take advantage of temporal dependencies in sequential image data. ResNet is used because of its deep residual learning capabilities, which enable it to more accurately extract robust features from images. Retinal image data is used to train these models, which are then optimized for recall and precision. Users can upload images for real-time analysis after the models are integrated into a web interface created with the Django framework.



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3.1 Working flow:

3.1.1 Data Collection: Gathered retinal images from multiple sources including Kaggle.

Based on dataset of Diabetic retinopathy it divided into various types

Normal: No signs of diabetic retinopathy.

Mild: Early signs of diabetic retinopathy, often characterized by microaneurysms or slight changes in the blood vessels.

Moderate: More noticeable changes in the retina, such as increased microaneurysms, hemorrhages, and hard exudates.

Severe: Advanced stages with more widespread damage, including larger hemorrhages, cotton wool spots, and extensive exudates.

Proliferative: The most severe stage where abnormal new blood vessels (neovascularization) grow in the retina, which may lead to vision loss.

3.1.2 Pre-processing Techniques:

To improve the model's performance, pre-processing techniques are applied to retinal images before training.

Image Resizing: Standardized all images to 224x224 pixels.

Normalization: Scaled pixel values to the range [0, 1].

Label Encoding: Transformed textual labels ('No DR', 'DR') into numerical values (0, 1)

3.1.3 Transfer Learning (TL):

Utilization of pre-trained deep learning models to extract features from DR images:

MobileNetV2: MobileNet is a lightweight and efficient convolutional neural network (CNN) architecture designed for mobile and embedded vision applications, developed by Google. It's particularly well-suited for devices with limited computational resources, such as smartphones, while still providing excellent performance on image classification and object detection tasks.

Resnet Extracted features are stored for further analysis.

3.1.4 Model Training and Evaluation:

Dataset Split: Partitioned the data into training (70%), validation (15%), and test (15%) sets.

Performance Metrics: Used Accuracy, Sensitivity, and Specificity as primary evaluation metrics.

Model Validation: Leveraged the validation set for hyperparameter tuning and model optimization.

3.2 Limitations in Existing System:

Imbalanced Data: In many diabetic retinopathy datasets, there is an imbalance in the distribution of different stages of DR. For example, there may be many more images of healthy retinas compared to those showing severe DR, leading to the model becoming biased toward the majority class, resulting in poor performance in detecting rare or severe cases.

Quality of Input Images: Diabetic retinopathy detection relies heavily on the quality of the retinal images. Low-resolution or poorly captured images, which can occur due to patient movement or suboptimal imaging conditions, may hinder the model's ability to detect and classify DR correctly. Deep learning models may struggle when dealing with noisy or low-quality input images.

Latency in Real-Time Applications: In some clinical environments, real-time decision-making is crucial. Deep learning models, especially those with large architectures, can introduce delays in processing time, which may be problematic in a fast-paced clinical setting where time-sensitive decisions are critical.

3.3 Proposed System:

Our proposed system for Diabetic Retinopathy (DR) screening integrates MobileNet with advanced neural network architectures to enhance detection accuracy and efficiency. The core model, MobileNet, is trained on 217 high-resolution fundus images from the Kaggle dataset to classify DR into five stages. To further improve performance, we introduce two hybrid models: MobileNet + Graph Neural Network (GNN) to capture complex spatial relationships in retinal images, and MobileNet + Recurrent Neural Network (RNN) to address sequential dependencies and temporal patterns. These hybrids aim to optimize DR classification by leveraging both structural and sequential data insights.



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3.4 Problem Description:

Diabetic Retinopathy (DR) is a progressive eye disease caused by high blood sugar levels, leading to retinal damage and potentially resulting in vision loss or blindness if not detected early. Current DR screening methods are labor-intensive, prone to variability, and often require specialized expertise, making them unsuitable for large-scale implementation. To address these challenges, our proposed system leverages MobileNet, a lightweight deep learning model, trained on high-resolution fundus images to classify DR into five stages. To enhance accuracy and efficiency, we incorporate hybrid architectures—MobileNet + Graph Neural Network (GNN) for capturing spatial relationships within retinal images and MobileNet + Recurrent Neural Network (RNN) for analyzing sequential and temporal patterns. This system aims to provide an automated, scalable, and precise solution for early DR detection, improving patient outcomes and reducing the burden on healthcare systems.

3.5 Web Interface Implementation:

A Django-based web application is developed to allow users to upload ultrasound images and receive a classification result. The interface includes:

- User Registration/Login: Implemented using MySQL Connector to store user credentials.
- Image Upload System: Users can upload retinal fundus images via an HTML form.
- Backend Processing:
 - The uploaded image is preprocessed. Features are extracted using pretrained models.
 - The Hybrid models, Resnet predicts the DR stage (*Normal, Mild, Moderate, Severe, Proliferative*).
- Result Display: The final classification result is shown on the web interface.

IV. IMPLEMENTATION

This project addresses the need for automated, efficient, and accurate detection of Diabetic Retinopathy (DR) using advanced deep learning techniques. The study leverages MobileNet, a lightweight model, along with hybrid architectures combining MobileNet with Graph Neural Networks (GNN) and Recurrent Neural Networks (RNN), trained on high-resolution retinal fundus images. The system facilitates the classification of DR into five stages for early diagnosis and improved ophthalmic care.

Importing Libraries: The project starts by importing necessary libraries and frameworks:

- Libraries like NumPy, Pandas, OpenCV, Keras, Torch, Matplotlib, and scikit-learn are imported for deep learning model building, image preprocessing, data manipulation, and performance evaluation.
 - Transfer learning models such as MobileNet, and ResNet are used as base architectures for feature extraction.
- ```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import cv2
import os
import tensorflow as tf
```

**Pre-processing images:** For diabetic retinopathy, fundus images. The data loading, image preprocessing, and feature extraction steps should be adapted to handle fundus images.

```
Data augmentation for training, resizing for validation and testing from torchvision import transforms
```

```
transform_train = transforms.Compose([
 transforms.RandomResizedCrop(224), # Randomly crop and resize
 transforms.RandomHorizontalFlip(), # Randomly flip the image horizontally
 transforms.RandomRotation(20), # Randomly rotate the image
 transforms.ToTensor(),
 transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
])
```

```
transform_val = transforms.Compose([
 transforms.Resize(256), transforms.CenterCrop(224),
 transforms.ToTensor(), transforms.Normalize(mean=[0.485, 0.456, 0.406],
 std=[0.229, 0.224, 0.225]),])
```



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**Model Training:** As the focus is on DR, the model training will be done with DR data, with the loss function, optimizer, and training procedure remaining the same. The classification report and confusion matrix should provide insights into the performance of the model across different stages of DR. Finally, the function converts the lists of images and masks into numpy arrays and returns. It is mainly used to prepare data for any machine learning tasks such as semantic segmentation, in which aligned images and masks are needed. shown in aligned Images are needed.

```
for epoch in range(15):
 model.train()
 running_loss = 0.0 for data,
 targets in train_loader:
 optimizer.zero_grad() edge_index = torch.tensor([[0, 1], [1, 0]], dtype=torch.long,
 device=data.device) data, targets = data.to(next(model.parameters()).device),
 targets.to(next(model.parameters()).device) outputs = model(data, edge_index) loss = criterion(outputs,
 targets) loss.backward() optimizer.step() running_loss += loss.item() * data.size(0) train_loss =
 running_loss / len(train_loader.dataset) train_acc = compute_accuracy(train_loader)
```

Finally a web application built with Django enables users to upload ultrasound images for classification. It features a user authentication system using MySQL for registration and login. Uploaded images are processed in the backend, where they undergo preprocessing and feature extraction using pretrained models. An hybrid models then analyzes the extracted features to determine whether the DR is Normal, Mild, Moderate, Severe and Proliferative. The classification result is displayed on the web interface, ensuring a seamless and userfriendly experience for medical image analysis. In that interface it includes

**Register:** Users register an account in the system with their credentials, gaining access to the DR stage classification. Registration ensures secure and personalized access.

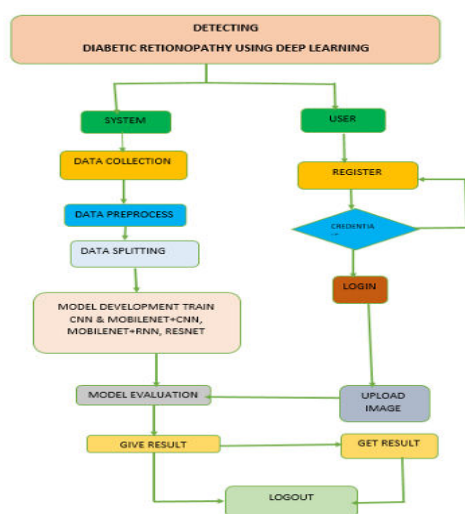
**Login:** Users log in with their registered credentials to access the system's functionalities, including uploading fundus images for DR stage classification.

**Upload Data:** Users can upload fundus images to the system. These images are processed and analyzed by the trained models for classification into (0-4) stages.

**View Results:** After analysis, users receive and view the results from the models. The system outputs a clear diagnosis, indicating whether the uploaded image shows different stages.

**Logout:** Users can securely log out of the system once their session is complete, ensuring their personal information and session data remain protected.

### V. WORKFLOW OF PROPOSED SYSTEM





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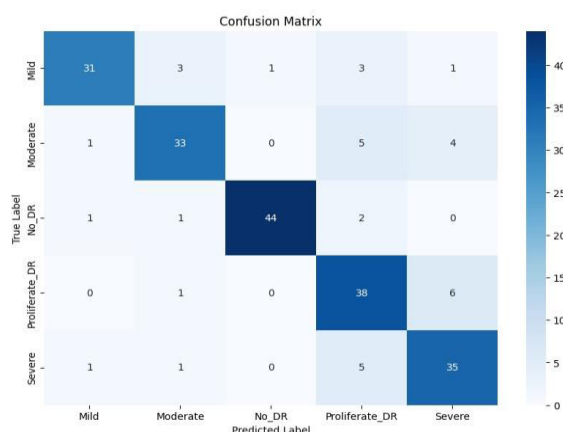
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### VI. RESULT AND ANALYSIS

#### 6.1 Result analysis for MobileNet and GNN Algorithm

Classification Report:

|                | precision | recall | f1-score | support |
|----------------|-----------|--------|----------|---------|
| Mild           | 0.91      | 0.79   | 0.85     | 39      |
| Moderate       | 0.85      | 0.77   | 0.80     | 43      |
| No-DR          | 0.98      | 0.92   | 0.95     | 48      |
| Proliferate-DR | 0.72      | 0.84   | 0.78     | 45      |
| Severe         | 0.76      | 0.83   | 0.80     | 42      |
| accuracy       |           |        | 0.83     | 217     |
| macro avg      | 0.84      | 0.83   | 0.83     | 217     |
| weighted avg   | 0.84      | 0.83   | 0.84     | 217     |



The model performs well overall with an accuracy of 83%. It excels at identifying No-DR, but struggles with Proliferate-DR due to lower precision. Mild and Moderate classes show moderate performance, especially in recall. Further improvement in reducing false positives, particularly for Proliferate-DR, is needed.

#### 6.2 Result analysis for MobileNet and RNN Algorithm

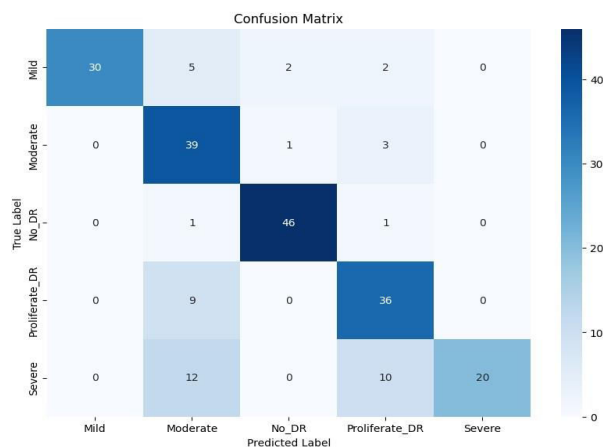
Classification Report:

|                | precision | recall | f1-score | support |
|----------------|-----------|--------|----------|---------|
| Mild           | 1.00      | 0.77   | 0.87     | 39      |
| Moderate       | 0.59      | 0.91   | 0.72     | 43      |
| No_DR          | 0.94      | 0.96   | 0.95     | 48      |
| Proliferate_DR | 0.69      | 0.80   | 0.74     | 45      |
| Severe         | 1.00      | 0.48   | 0.65     | 42      |
| accuracy       |           |        | 0.79     | 217     |
| macro avg      | 0.84      | 0.78   | 0.78     | 217     |
| weighted avg   | 0.84      | 0.79   | 0.79     | 217     |



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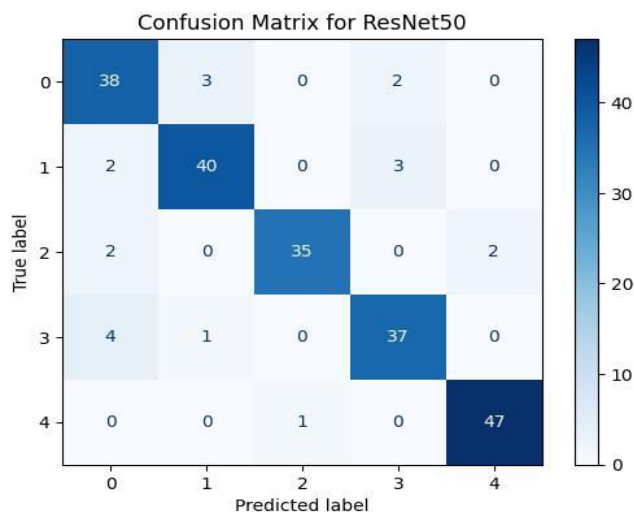
The model has an overall accuracy of 79%, with strong performance in identifying Mild and No\_DR classes. However, Severe has a low recall (0.48), indicating poor identification of severe cases. Moderate and Proliferate\_DR show decent performance but need improvement in precision. Enhancing the recall for Severe and Proliferate\_DR would improve overall results.

### 6.3 Result analysis for ResNet Algorithm

#### Classification Report:

|   | precision | recall | f1-score | support |
|---|-----------|--------|----------|---------|
| 0 | 0.83      | 0.88   | 0.85     | 43      |
| 1 | 0.91      | 0.89   | 0.90     | 45      |
| 2 | 0.97      | 0.90   | 0.93     | 39      |
| 3 | 0.88      | 0.88   | 0.88     | 42      |
| 4 | 0.96      | 0.98   | 0.97     | 48      |

|              |      |      |      |     |
|--------------|------|------|------|-----|
| accuracy     |      |      | 0.91 | 217 |
| macro avg    | 0.91 | 0.91 | 0.91 | 217 |
| weighted avg | 0.91 | 0.91 | 0.91 | 217 |



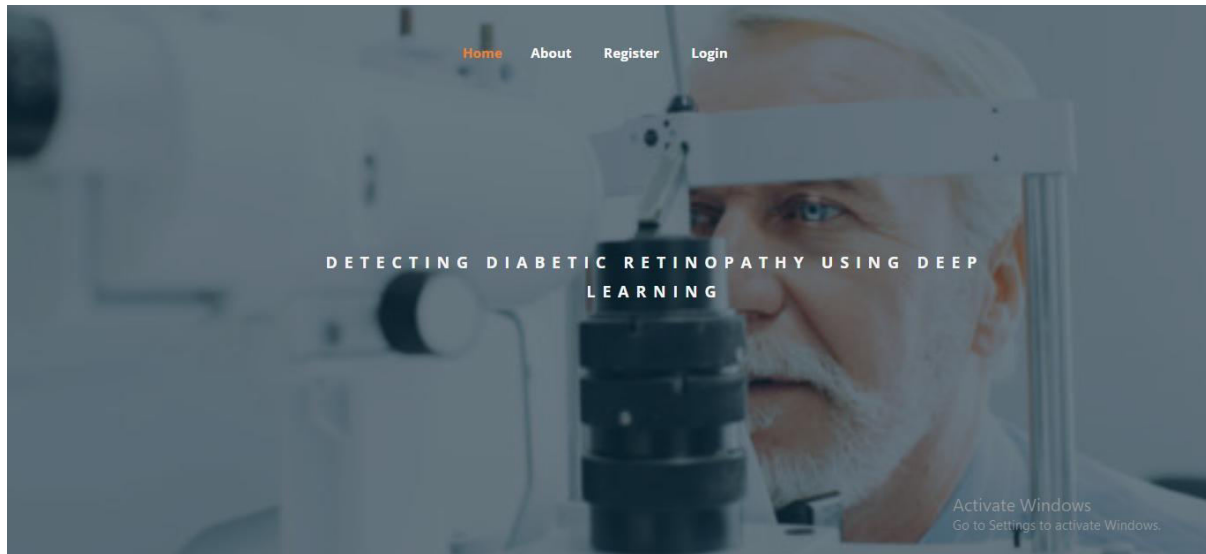


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The model achieves an excellent overall accuracy of 91%. It performs consistently well across all classes, with the highest precision and recall for class 4. The macro avg and weighted avg f1-scores of 0.91 indicate a wellbalanced performance. Overall, the model demonstrates strong generalization and accuracy across all categories.

**Index Page:** Welcomes users and provides navigation to registration and login



**About Page:** This page Give All about the Information of diabetic retinopathy



**Registration Page:** Captures user credentials



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Home About **Register** Login

Create an Account

Email

Enter Email

Password

Enter Password

Confirm Password

confirm Password

Register

Already have an account? Sign in

**Login Page:** Validates users and grants access to diagnostic features.

Home About Register **Login**

Login

Email

Enter Email

Password

Enter Password

Login

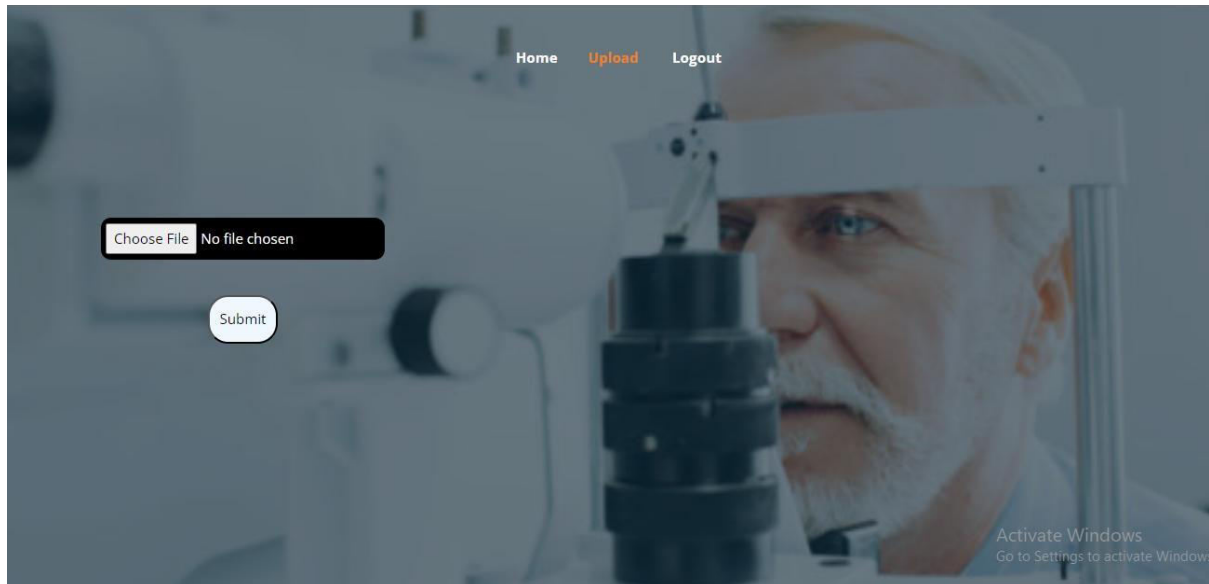
Dont have an account ? Sign Up.

**Upload Page:** Allows users to upload diabetic retinopathy images

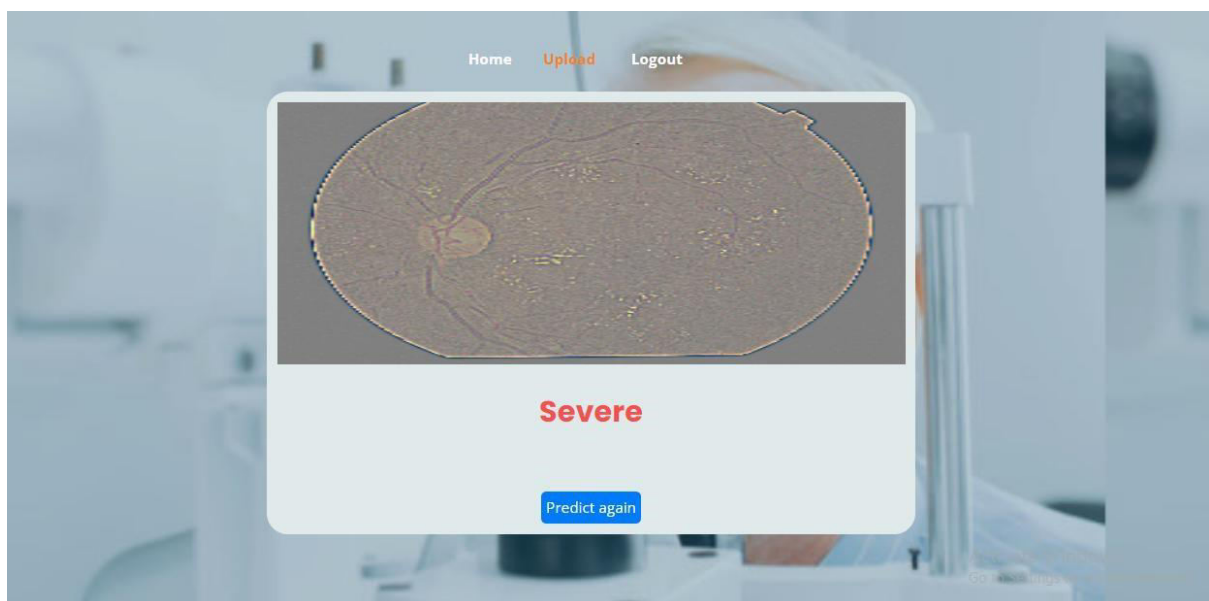


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**Results Page:** Displays classification results



### VII. CONCLUSION

In conclusion, the application of deep learning in detecting diabetic retinopathy represents a significant advancement in the field of medical diagnostics. This innovative approach has shown promising results in automating the early detection of diabetic retinopathy, thereby enabling timely interventions and reducing the risk of vision loss in diabetic patients. With further refinement and integration into healthcare systems, deep learning models can contribute to more efficient and accessible screening, ultimately improving the quality of life for individuals with diabetes.



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### VIII. FUTURE SCOPE

In the future, the project for detecting diabetic retinopathy using deep learning could be significantly enhanced by integrating several improvements. These could include the use of more advanced deep learning architectures, such as ensemble methods and transfer learning, to bolster diagnostic accuracy. The data augmentation techniques could be extended by employing Generative Adversarial Networks (GANs) for more nuanced data generation. Adding features like patient medical history and localized disease prediction could lead to more personalized diagnostics. Real-time analysis capabilities could be integrated into a streamlined GUI or even a mobile application, making immediate diagnoses more feasible. To scale the solution, a cloud-based architecture and an API for integration with existing healthcare systems could be developed. Multi-modal inputs, including other types of retinal scans and patient lifestyle factors, could be incorporated for a richer diagnostic framework. Lastly, ongoing efforts should be made to assess and mitigate any biases in the model and to maintain transparency in its diagnostic criteria and results.

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