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DEEP INSIGHT: UNVEILING DIABETIC RETINOPATHY THROUGH ADVANCED NEURAL NETWORKS

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Abstract : Diabetic retinopathy (DR) is a severe eye condition caused by diabetes, potentially leading to blindness if untreated. This project develops a machine learning model to classify DR stages using color fundus images. Data was sourced from the Aptos 2019 Blindness Detection dataset, the IDRiD dataset, and a custom dataset from Paraguay. Preprocessing included enhancing images with CLAHE. DenseNet169 was chosen after evaluating several pre-trained models and was on the Dataset. This model provides an effective solution for early detection and classification of DR.

***IndexTerms* – Diabetic Retinopathy, DenseNet169, Deep Learning , Retinopathy Classification, DenseNet121, InceptionV3**

I. INTRODUCTION

Diabetic retinopathy (DR) is the leading cause of visual loss globally, and its timely detection is crucial for preventing severe vision impairment. Manual diagnosis of DR is resource-intensive and time-consuming, often leading to treatment delays and poorer patient outcomes. This project aims to develop a neural network system that can accurately detect and categorize DR from retinal images using advanced deep learning techniques, such as convolutional neural networks (CNNs). By analyzing images of patients' left and right eyes, the system will classify the severity of DR into five categories: no DR, mild, moderate, severe, and proliferative DR, scored from 0 to 4. The primary objective is to create an automated analysis system that can quickly generate a score based on this scale, thus facilitating early diagnosis and intervention. The initiative seeks to minimize the risk of vision loss and enhance patient care by streamlining the screening process.

II. LITERATURE SURVEY

To categorize the DR stages, Qummar et al. [1] trained an ensemble architecture of five deep CNN models in 2019. These models were ResNet50, Inception V3, Xception, Dense121, and Dense169. Rich feature encoding is possible with this ensemble architecture, which enhances classification performance. According to the experimental findings, the suggested model performs better than other popular models that were trained on the same Kaggle dataset and is capable of correctly identifying five stages of DR. Through the integration of many architectures, including ResNet-20 and Inception modules, the methodology allows for a comprehensive analysis of retinal images, capturing their richness and depth.

A innovative hybrid Strawberry-based Convolution Neural Framework (SbCNF) was developed in 2023 by K Mithili et al. to identify and classify retinopathy from retinal images [2]. The principal aim is to enable prompt identification and management of conditions linked to increased blood pressure and glucose levels. The SbCNF algorithm is designed specifically to extract retinal veins from fundus retinal pictures, providing essential information for disease diagnosis. Its great accuracy is primarily due to its reduced processing cost. This makes it effective in the identification of retinopathy. Nevertheless, the work does not address any potential drawbacks or difficulties with the suggested SbCNF algorithm and does not provide a thorough analysis of the classification methods used.

A hybrid Convolutional Neural Network (CNN) model that combines ResNet50 and Inceptionv3 for reliable feature extraction in DR identification from fundus pictures was proposed by Ghulam Ali et al. [3] in 2023. An analysis is out using a fundus picture dataset that is accessible to the public highlights how successful the suggested strategy is. The model shows encouraging results in DR identification, indicating its potential significance in clinical practice. This is in line with the recognition of the importance of early detection and intervention in preventing diabetic vision loss.

Mohaimenul et al. developed a robust and lightweight deep learning model for the categorization of a wide variety of diabetic retinopathy (DR) images [4]. The goal of the project is to develop an automatic DR identification system that is faster and more accurate than manual approaches. To this end, three different DR datasets—APTOS, Messidor2, and IDRiD—are combined to create a collection of 5,819 raw photos. While using three augmentation strategies results in a balanced dataset, using several image preparation techniques improves image quality. The paper also compares the performance of six pre-trained models: VGG16, VGG19, MobileNetV2, ResNet50, InceptionV3, and Xception. The suggested model outperforms the others in terms of accuracy and is robust.

III. PROPOSED WORK

The proposed system leverages advanced deep learning techniques to automate the detection and classification of diabetic retinopathy stages from retinal images. The process begins with image acquisition, where retinal images are captured using standard fundus cameras and uploaded to the system. These images then undergo preprocessing, including the application of Contrast Limited Adaptive Histogram Equalization (CLAHE), to enhance their quality. A pre-trained deep learning model, DenseNet169, is fine-tuned on the Aptos Blindness Detection 2019 and IDRiD datasets to accurately classify the images into different stages of diabetic retinopathy. The system processes the images and predicts the stage of diabetic retinopathy, providing a confidence score for each prediction. A user-friendly web interface built using Flask allows users to upload images and view the prediction results, ensuring an accessible and efficient diagnostic tool for medical professionals.

IV. METHODOLOGY

4.1 Data Collection

The Aptos 2019 Blindness Detection , The Indian Diabetic Retinopathy Image Dataset (IDRiD) and UNA, Paraguay Fundus Image dataset are the main datasets used in this study. These datasets were selected because they include extensive and annotated retinal scan images, which are essential for creating a reliable diabetic retinopathy detection algorithm. The Aptos 2019 Blindness Detection: This Dataset is made up of retinal photos that were collected in a range of imaging circumstances. On a scale of 0 to 4, each image has a label indicating the severity degree of diabetic retinopathy; 0 denotes no diabetic retinopathy and 4 denotes the most severe level. The rationale behind selecting this dataset in particular is because APTOS, which was created using a variety of camera models and types, includes 5590 retinal images. The Indian Diabetic Retinopathy Image Dataset (IDRiD): To add more granularity and support the model's generalization, the IDRiD dataset comprises images classified by different degrees of diabetic retinopathy and diabetic macular edema. The dataset annotates diabetic retinopathy lesions and normal structures and contains 516 retina images, enabling researchers to train and evaluate machine learning models effectively. UNA, Paraguay Fundus Images: This dataset consists of 757 color fundus photos taken using ZEISS's VISUCAM 500 camera. Expert ophthalmologists have divided these images into other groups, such as Proliferative Diabetic Retinopathy (PDR) and Non-Proliferative Diabetic Retinopathy (NPDR).

4.2 Data Preprocessing

To improve image quality and guarantee that the input fed into the neural network is standardized and normalized, effective preprocessing is essential. Among the preprocessing actions are: Image Resizing To maintain uniformity and conformity with the input requirements of the pre-trained models employed, all photos are shrunk to 224 x 224 pixels. Contrast Limited Adaptive Histogram Equalization (CLAHE) Contrast Limited Adaptive Histogram Equalization, or CLAHE, is a sophisticated image processing method used to enhance contrast. In contrast to conventional histogram equalization, which enhances the contrast of the entire image, CLAHE operates by separating the image into discrete, contextual areas known as tiles. Localized contrast enhancement is made possible by independently applying histogram equalization to each tile. This method works especially well for photos that have various lighting or detail levels in different areas. This method is used to improve the retinal pictures' contrast. By modifying the image histogram, CLAHE assists in emphasizing the characteristics of the retina, which is especially helpful for medical photographs. CLAHE has a contrast limiting step to prevent over-amplification of noise and to prevent areas that are too bright or dark. To do this, a clip limit must be specified, limiting the amplification of pixel values above a predetermined level. The extra pixels are then re-distributed throughout the histogram to maintain the enhancement's equilibrium and aesthetic appeal. In order to create a smooth and improved image, the processed tiles are then blended using bilinear interpolation to eliminate false borders. In medical imaging, CLAHE is frequently utilized to improve the appearance of characteristics like blood vessels and lesions. One example of this is the examination of diabetic retinopathy. CLAHE provides a more accurate and thorough representation of image data, assisting in improved diagnosis and analysis. This is achieved by enhancing local contrast while avoiding the drawbacks of conventional approaches. Normalization By dividing by 255, pixel values are normalized to fall between 0 and 1. This stage facilitates faster convergence during model training by guaranteeing a consistent data distribution Data Augmentation Data augmentation strategies are used to increase the model's generalization and prevent overfitting. Among these methods, Rotation: Shaping pictures within a range at random. Zooming: Making arbitrary adjustments to the zoom. Horizontal and Vertical Shifts: Translating images horizontally and vertically. Shearing: Giving the pictures shear adjustments. Flipping: To improve the training data's diversity, perform arbitrary horizontal flips. TensorFlow's ImageDataGenerator is used for data augmentation; during training, it dynamically performs these modifications.

4.3 Model selection

To determine which convolutional neural network (CNN) architecture is best suited for this task, a number of pre-trained CNN models are assessed. Among the chosen models are DenseNet169, This network is well-known for its dense layer connection, which enhances gradient flow and promotes feature reuse. MobileNet, provides an excellent balance between efficiency and performance, tailored for embedded and mobile vision applications. DenseNet121, allows gradient flows over skip connections, which makes use of residual learning to facilitate the training of deeper networks. InceptionV3, enables the network to record a variety of spatial hierarchies by combining multiple convolutional filters of varying sizes. Using the retinal images, each model is adjusted, making use of the pre-trained weights on ImageNet to gain an advantage over transfer learning.

4.4 DenseNet169 Model

Known for its dense connectivity pattern in which each layer receives input from all previous layers and passes its own feature maps to all subsequent layers. DenseNets are a family of sophisticated convolutional neural network architectures that includes DenseNet169. This particular design has several advantages that make DenseNet169 particularly effective for medical image analysis, including the detection of diabetic retinopathy. In DenseNet169, every layer is feed-forwardly directly connected to every other layer. This indicates that all feature maps from previous layers make up the input for each layer. In addition to encouraging feature reuse, improving feature propagation, reducing the number of parameters significantly, and mitigating the vanishing gradient problem, these dense connections also aid. DenseNet169's growth rate, or the number of filters added to each layer, is 32. Rich feature representation is maintained while the model's complexity is managed thanks to this balanced growth rate. Before performing 3x3 convolutions, DenseNet169 employs bottleneck layers, which use 1x1 convolutions to decrease the number of input feature maps. This bottleneck design lowers the number of parameters and increases computing efficiency. DenseNet169 use batch normalization, 1x1 convolution, and 2x2 average pooling as transition layers to regulate the network's complexity and size. By lowering the number and spatial dimensions of feature maps, these layers improve efficiency and generalization. The ImageNet dataset, which has over a million photos and 1000 classes, is frequently used to begin DenseNet169 with weights that have already been trained for transfer learning. Mechanisms for hyperparameter adjustment and validation are also included in the training environment to guard against overfitting and guarantee ideal model performance.

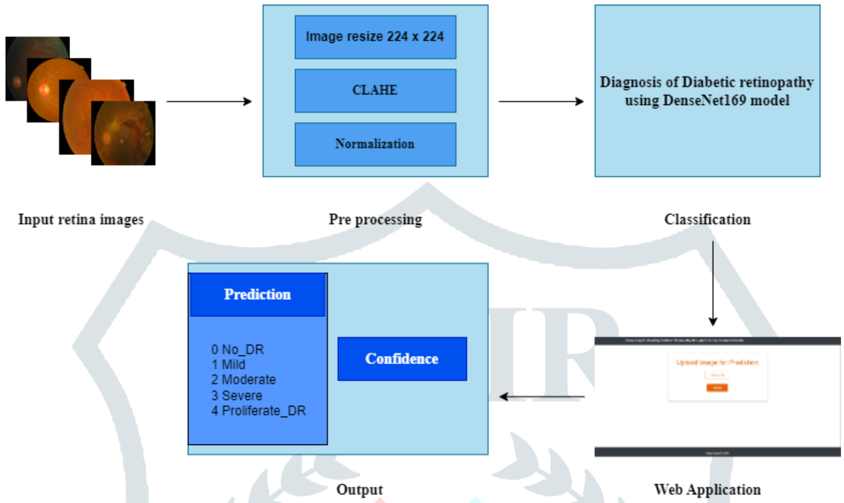

Fig.1 Overview of the Proposed System

The formula for a dense layer with ReLU activation is

$$z = W*x+b \tag{4.1}$$

$$a = ReLU(z) = \max(0,z) \tag{4.2}$$

where W is the weight matrix, x is the input, b is the bias vector, and a is the output after the activation function

V. RESULT ANALYSIS

Table 5.1: Summary of Model Performance

Model	Training Accuracy	Validation Accuracy	Training Time (sec)
DenseNet121	80	70	385
InceptionV3	75	72	252
DenseNet169	83	76	353

Figure 2 illustrates the precision comparison among DenseNet121, DenseNet169, and InceptionV3 models across different diabetic retinopathy classes. DenseNet121 shows high precision for the 'No_DR' class (0.94) but struggles with the 'Severe' class (0.00). DenseNet169 maintains high precision for 'No_DR' (0.94) and 'Mild' (0.76). InceptionV3 has the lowest precision for 'Mild' (0.53) but performs well for 'No_DR' (0.93), similar to the other models. These results highlight each model's strengths and areas for improvement in accurately identifying diabetic retinopathy stages.
The table 5.1 compares three deep learning models: DenseNet121, InceptionV3, and DenseNet169. DenseNet169 achieved the highest validation accuracy at 76% and a training accuracy of 83% with a training time of 353 seconds. InceptionV3, with a validation accuracy of 72%, trained the fastest at 252 seconds, making it a good balance between performance and efficiency.

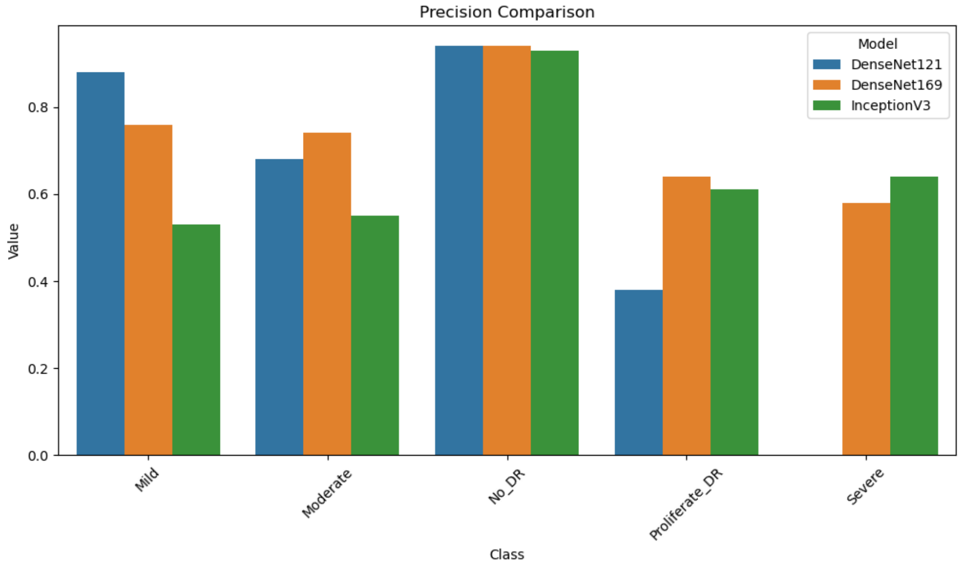

Fig.2 – Precision Comparison Graph

Figure 3 shows the Image Upload page for the prediction of Diabetic Retinopathy Stage. Figure 4, 5, 6, 7 and 8 shows the results of no DR, mild, moderate, severe, and proliferative DR Classes.

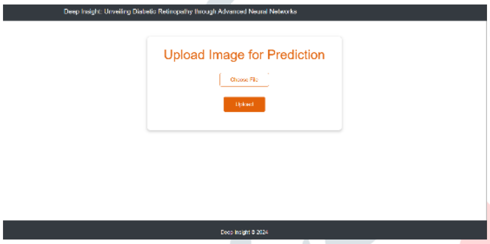

Fig. 3 – Image Upload Page

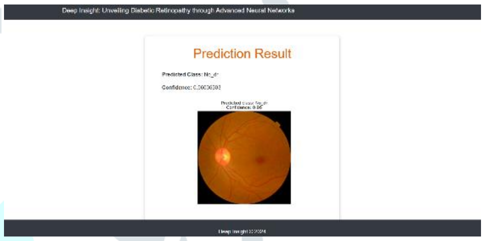

Fig. 4 – No_DR Class Prediction

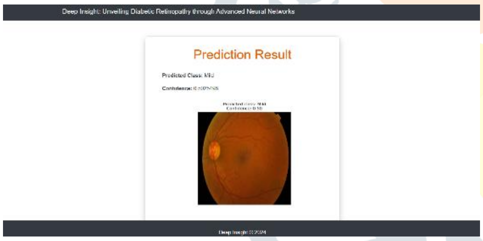

Fig. 5 – Mild Class Prediction

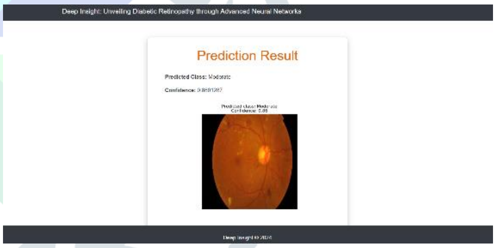

Fig. 6 – Moderate Class Prediction

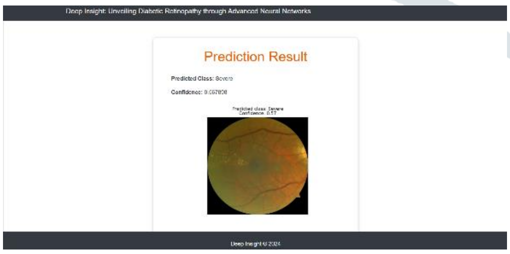

Fig. 7 – Severe Class Predction

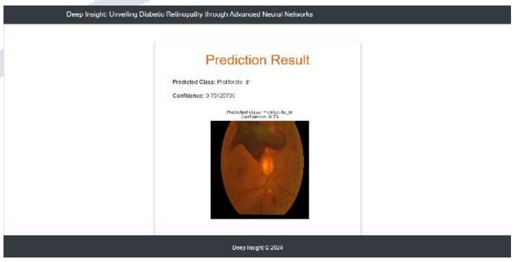

Fig. 8 – Prolierate_DR Class Prediction

VI. CONCLUSION

In this project, we developed and evaluated deep learning models DenseNet121, DenseNet169, and InceptionV3—for classifying diabetic retinopathy stages using retinal images. DenseNet169 emerged as the most robust model, achieving high precision, recall, F1-scores, accuracy, and low loss, making it particularly effective for reliable classification. DenseNet121 also performed well, while InceptionV3 showed potential with further tuning. This project underscores the significance of model selection in medical image classification and sets the stage for future enhancements and real-world clinical applications, with DenseNet169 with 82% training accuracy standing out as a promising model for future research and development.

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