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Research Article

Detecting Diabetic Retinopathy in Medical Imaging using Deep Learning

C. Sravani [1], R. Pradeep Kumar Reddy [2*]

[1]Research Scholar, Y.S.R Engineering College of YVU, Proddatur.

[2]Associate Professor, Department of CSE, Y.S.R Engineering College of YVU, Proddatur

Corresponding Author: pradeepmadhavi@gmail.com

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ABSTRACT

Early detection of diabetes-related complications, particularly diabetic retinopathy (DR), is essential to prevent from permanent loss of vision. Diagnosis by ophthalmologists is time-consuming and costly. Recent researches in deep learning has enabled automated analysis of medical images with increased accuracy and efficiency. This research demonstrates deep learning based approach for automated diabetic retinopathy detection using deep convolutional neural network architectures such as Inception-V3 and VGG-16. These architectures are used to extract discriminative features from retinal fundus images. The models are trained and evaluated on a publicly available dataset containing five DR severity classes. The results shows that the Inception-V3 model achieves higher classification accuracy than VGG-16 in identifying different stages of diabetic retinopathy. In addition, a lightweight web-based interface is developed to support practical deployment and user interaction. The findings suggest that deep learning–based methods can assist clinicians by providing consistent performance for diabetic retinopathy detection.

Keywords: Diabetic Retinopathy, Deep Learning, Convolutional Neural Networks, Inception-V3, VGG-16, Medical Image Analysis.

1. INTRODUCTION

Diabetic retinopathy (DR) is one of the most common microvascular complications of diabetes mellitus and a leading cause of preventable blindness worldwide. It is estimated that more than 200 million people will be affected with DR in 2040 [1]. The tiny blood vessels in the retina at the back of the eye are destroyed by Diabetic Retinopathy. There are two types of DR. One type is Non-Proliferative Diabetic Retinopathy (NPDR), in which the tiny blood vessels swell and leak the fluid that causes a macular edema (swelling of the central part of the retina), which is the dominant cause of mild vision loss. The second type of DR is Proliferative Diabetic Retinopathy (PDR), which is the most advanced class, in which blood vessels grow on the retina's surface. These cracks in these blood vessels cause vitreous hemorrhages and severe vision loss. The most common risk factors of DR are diabetes (type 1 and type 2), different medical conditions such as high blood pressure and high cholesterol, pregnancy, and family history. The symptoms include blurred vision, seeing spots and floaters, dark or empty spots in the center of the retina, and decreased vision at night [2].

Detection by ophthalmologists is time-consuming and subject to inter-observer variability, particularly in large-scale screening programs. With the increasing cases of diabetes, there is a growing need for automated and scalable diagnostic tools that can assist clinicians in identifying diabetic retinopathy at

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an early stage.

Convolutional Neural Networks (CNNs) have shown higher performance than traditional machine learning approaches by learning hierarchical feature directly from image data, reducing the need for manual feature extraction.

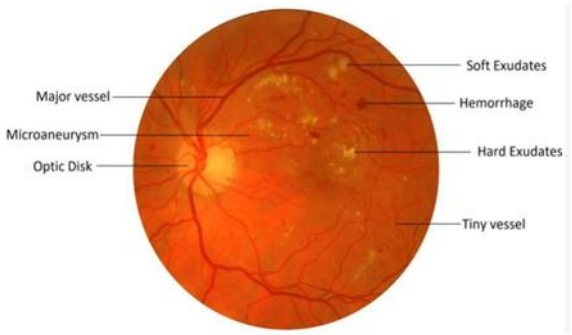


Fig.1 Diabetic Retinopathy

Several deep learning architectures is studied for DR detection, including VGG, ResNet, DenseNet, and Inception-based models. Among all these, Inception architectures are effective due to their ability to capture multi-scale image features with comparatively less computational cost. Further transfer learning enhance performance by leveraging pretrained models on large-scale datasets and adapting them to medical imaging tasks with limited labelled data.

This paper presents a comparative study of two widely used deep learning models VGG-16 and Inception-V3 for multi-class diabetic retinopathy classification using retinal fundus images. The aim of this study is to evaluate their effectiveness in distinguishing between five DR severity levels and to analyse their performance under identical experimental settings.

2. LITERATURE SURVEY

Researchers worldwide have dedicated significant efforts to the development of robust methods for detecting machine learning (ML) and deep learning (DL) methods for diabetic retinopathy (DR). Diabetic retinopathy is major cause of blindness and early detection is important for this, but by manual screening of fundus images it is time consuming and error prone.

Bajwa et al. [1] proposed a deep learning model (CNN), and it uses 57625 fundus images, labeled by clinical experts along with real time dataset of 398 patients (232 males, 166 females) from SIOVS. This study uses intelligent image quality assessment before the classification and attained accuracy of 93.4%. This CNN base system provides efficient, and real time DR detection and supporting ophthalmologists for early diagnosis and treatment.

Kiran et al. [2] designed an automated Deep Learning based classification system that can effectively detects and classifies DR into five severity classes, and this approach used DenseNet-121 model for feature extraction and APTOS 2019 Blindness detection dataset from Kaggle this contain a 5590 high resolution fundus images. The system achieved 96.33% accuracy, and it can significantly reduce the diagnostic time.

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Sampaul et al. [3] introduced an improved CNN-based intelligent prediction framework for diabetic retinopathy to overcome the limitations raised by the traditional machine learning techniques, which was achieved high sensitivity and specificity. But, this study faces high computational complexity and suggested developing more accurate systems.

Shivsharan et al. [4] proposed a deep learning models (CNN, VGG19, DenseNet) with advanced preprocessing and class weight techniques. This study utilized APTOS Blindness Detection dataset, this contains 3662 images and they are divided into five DR levels (0-no, 1-mild, 2-moderate, 3-severe,4-proliferative DR) by clinicians. Among all the DenseNet achieved high accuracy, making it suitable for DR severity prediction.

Kumar et al. [5] introduced a new hybrid model DRISTI that integrates both VGG16 (for feature extraction) and Capsule Networks (for preserving spatial information). This study uses six publicly available retinal image datasets for evaluation and uses augmentation to reduce overfitting, the model achieved high performance. And making it more accurate, robust and clinically reliable.

Revathy et al. [6] proposed a hybrid machine learning model consisting of Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbor (KNN) along with voting classifier for combining results of all three models for final prediction. This study used the Kaggle diabetic retinopathy dataset (2000 images). The proposed model can effectively detect DR by extracting the key features (exudates, hemorrhages, and microaneurysms).

Kokane et al. [7] proposed a deep learning models, which is automatically learns hierarchical features from retinal fundal images, the models are GoogLeNet and AlexNet achieved accuracy of over 70%. The study can improve diabetic retinopathy detection, However, challenges such as generalization, overfitting, and robustness remain in the model across diverse datasets. These highlight that there is a need of more reliable, and clinically applicable automated DR systems.

Chakrabarty [8] introduced an automated deep learning system to detect whether a patient is diabetic or not by using Convolutional Neural Networks (CNN) and achieved high accuracy of over 90%. This study used High Resolution Fundus (HRF) dataset images (30 images) for both training and validation. The research results showed that the proposed system can effectively detect DR with very high accuracy, and it can be helpful to the doctors for early diagnosing and reduce workload.

Johari et al. [9] proposed a AlexNet convolutional neural networks (CNN) architecture for automated DR detection. The study used MESSIDOR (1200 fundus images) and they are classified into normal and exudates, and the model achieved 99.3% training accuracy and 88.3% testing accuracy. The study highlights that automated DR systems can help ophthalmologists for enabling early and accurate treatment.

Carrera et al. [10] proposed a computer-based diagnosis system that uses digital image processing and Support Vector Machine (SVM) to detecting and classifying the Non-Proliferative Diabetic Retinopathy (NPDR)presence in retinal fundal images collected from MESSIDOR dataset. This study uses two classifiers SVM and DT (Decision Tree), SVM outperformed DT by achieving higher accuracy in both detection and classification. And the study highlights that image processing combined with SVM can accurately and efficiently detect diabetic retinopathy.

Thiagarajan et al. [11] proposed a lightweight CNN model for detecting the DR and reduces complexity. This study used small dataset containing nearly 516 images from IRDiR but it still achieved a accuracy of about 80% with less computation and few parameters and the results showed that light models can perform well compared to heavy models.

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3. METHODOLOGY

Inception V3 is used to identify diabetic retinopathy and categorize its severity, the transfer learning model involves deep learning frameworks and architectures to achieve accurate and best results.

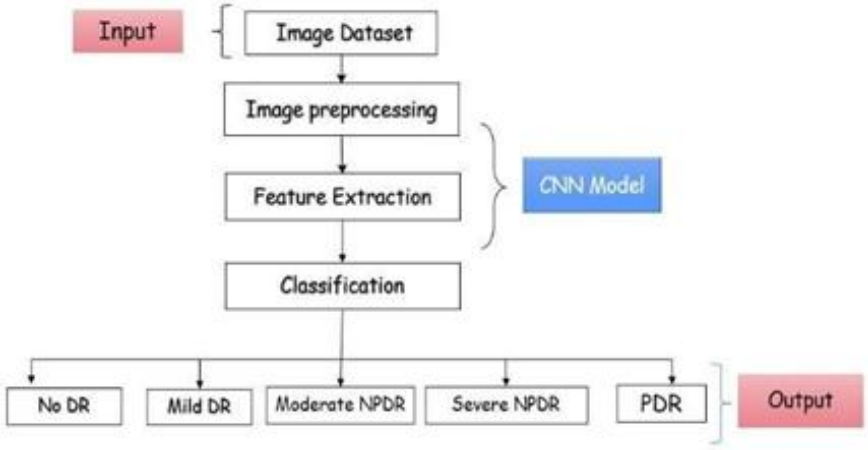


Fig.3.1 Methodology

The Workflow of the methodology gives a better description about the method used as follows, it describes prediction of the diabetic retinopathy.

3.1. Data Collection

The DR Image Classification dataset, available on Kaggle, encompasses around 4000 high-resolution retinal images, each annotated with one of five severity classes representing diabetic retinopathy stages. These stages range from Class 0 indicating no retinopathy to Class 4 signifying proliferative diabetic retinopathy.

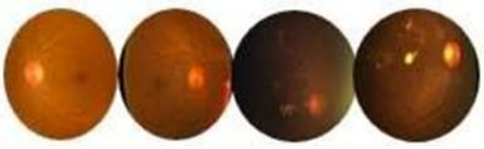


Fig.3.2 The fundus images

A score of 0 indicates no diabetic retinopathy, whereas the other options are moderate, severe, proliferative, mild, and moderate. For the photographs shown in Fig. 3.2, a variety of various camera models and combinations were used. This may cause certain images to appear fuzzy or dark. For quantitative analysis, the dataset comprises an image of diabetic retinopathy. The individual values of all the examined attributes are computed using this dataset.

3.2. Image Processing

The three processes listed below are essentially included in image processing: importing the image using image acquisition tools; analyzing and modifying the image; producing an output that may include an

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altered image or an image-based report.

Data preprocessing for diabetic retinopathy detection includes noise reduction techniques like Gaussian blurring, image registration for alignment, segmentation for isolating retinal structures, data augmentation for diversity, and normalization for standardizing pixel intensities, collectively enhancing model accuracy and robustness.

3.3. The CNN Model

Updates has been made to the Inception v3 deep learning image classification method, which is based on CNN. This method is an enhanced version of the 2014 release of Google Inception-v1 Basic Internet Core Framework. The creation of it was carried out by the Google team, as the name implies.

On the ImageNet dataset, the picture recognition model Inception v3 has demonstrated an accuracy of more than 78.1. The model is the result of numerous concepts that have been developed over time by various researchers. There are 48 layers in an Inception V3 model,

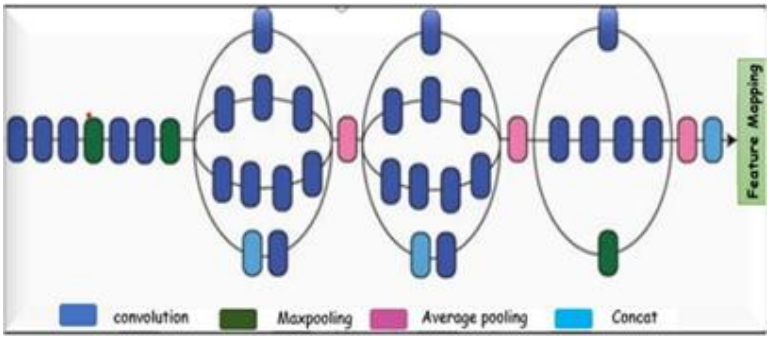


Fig.3.4 Inception v3 Architecture

which is a minor increase over the Inception V1 and V2 forms. The efficiency of this model is remarkable. As per the Inception v3 trained model below are Training and validation Accuracy values Training Accuracy: 0.90, validation Accuracy: 0.93.

3.4. Classification

Diabetic retinopathy classification typically involves distinguishing between multiple severity levels, ranging from mild to severe stages of the disease. Inception-v3 can handle multi-class classification tasks effectively, providing a nuanced assessment of retinal images based on the detected features.

3.5. Output

The final step where the model outputs its predictions, which could be the classification of the fundus images into different categories based on observed pathologies.

4. IMPLEMENTATION

Implementing a solution for diabetic retinopathy typically involves leveraging medical imaging techniques, such as fundus photography and applying machine learning algorithms for image analysis and diagnosis.

Here's a high-level overview of the implementation process:

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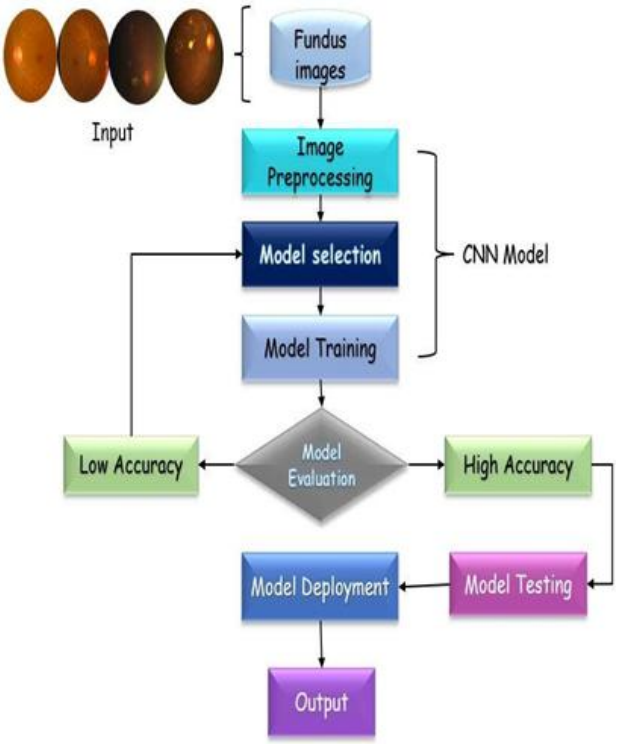


Fig 4.1 Implementation

4.1 Data Preparation

Downloaded the dataset from the Kaggle datasets and which contains approximately 4000 images and 5 classes. Three sets of the dataset were created: training, validation, and test sets using a 70-15-15 ratio. The training set, comprising 70% of data, was used for model training. A 15% validation set aided in hyperparameter tuning and preventing overfitting. The remaining 15% served as an independent test set to assess model generalization. This approach ensured a robust evaluation while maintaining data integrity. The split was performed using scikit-learn's train_test_split function. This methodology ensures a balanced and unbiased assessment of the machine learning model's performance.

4.2. Image Preprocessing

Image preprocessing using the OpenCV library typically involves several common steps, including resizing and Gaussian blur[12].

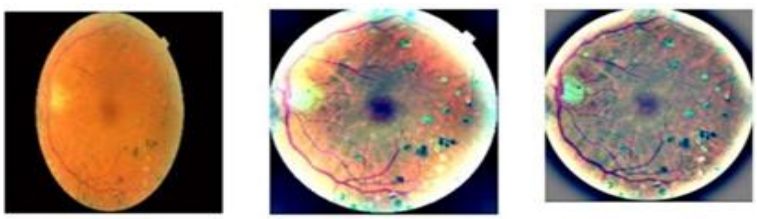


Fig 4.2 Image Preprocessing

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4.2.1. Resizing

Standardizes image dimensions for consistent processing, facilitating seamless integration into computer vision tasks. OpenCV's cv2.resize() function simplifies this process by allowing users to specify target dimensions.

4.2.2. Gaussian Blur

Smooths pixel values using a Gaussian kernel, reducing noise and enhancing features for improved image quality. OpenCV's cv2.GaussianBlur() function offers a straightforward implementation for noise reduction. Integral in enhancing the reliability of image processing algorithms by ensuring accurate feature extraction. Widely applicable across domains like medical imaging and pattern recognition.

4.3. Model Architecture Selection

Model Architecture selection plays a prominent role, The kind of problem that needs to be solved determines which model architecture should be used, the size and complexity of the dataset and the available computing resources. Model Selection is process of deciding which algorithm and model architecture is best suited for a particular problem and dataset.

These are the chosen Convolutional Neural Network model. CNNs are particularly effective for image recognition tasks because they can automatically and adaptively learn spatial hierarchies of features from input images. The fig 4.3 and fig 4.4 are the selected CNN models.

4.3.1. VGG-16

4.3.2.

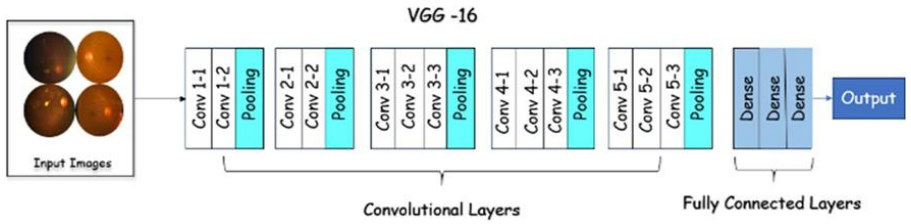


Fig 4.3 VGG-16 Model

The Fig 4.3 outlines the VGG-16 neural network's structure; a prominent model used for image processing tasks. VGG-16 is composed of a sequential stack of convolutional layers, numbered from 'Conv1_1' to 'Conv5_3', which progressively extract and refine features from the input images. Interspersed among these are pooling layers that reduce dimensionality and computational requirements. This series of layers constitutes the model's feature extraction component. Following the convolutional base, VGG-16 has three dense (fully connected) layers that culminate in an output layer, presumably equipped with a softmax function to classify the images into different categories.

4.3.2 Inception v3

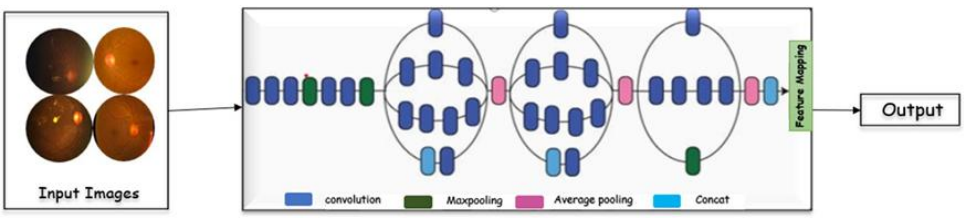


Fig 4.4 Inception v3

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The Fig 4.4 depicts an Inception module, which is a building block for Inception networks such as Google Net or InceptionV3. These networks are designed to perform image recognition and classification tasks. The Inception module is characterized by convolutional layer towers that are parallel and have varying kernel sizes, enabling the model to capture data at different scales and pooling layers. The outputs of these towers are then concatenated along the channel dimension, which provides a rich representation of the input data at multiple levels of abstraction. This architecture allows the network to be deeper and wider while keeping the computational cost in check.

VGG-16 typically has more parameters due to its fully connected layers, whereas Inception modules are more parameter-efficient due to their use of concatenation instead of dense layers. The Inception network often requires less computational resources than VGG-16 because of its dimensionality reduction techniques before expensive operations like 3x3 convolutions.

4.4. Model Training

To effectively train a model for diabetic retinopathy classification, we employ transfer learning techniques using pretrained Inception- v3 and VGG-16 models, which have been trained on the extensive ImageNet dataset. Key steps involve freezing the early layers of these models to retain their ability to recognize basic image features, while customizing the models with additional dense and dropout layers tailored to the specifics of diabetic retinopathy.Because the task involves multiple classes, the model is constructed using the Adam optimizer and a categorical cross-entropy loss function.

4.5. Model Evaluation

The process focuses on fine-tuning the models to achieve high accuracy in detecting and classifying the severity of diabetic retinopathy, making extensive use of the learned features from ImageNet and adjusting them to the specific requirements of medical image analysis.

Evaluation Metrics:

Accuracy: Measures the percentage of correct predictions across all classes.

$$\textbf{Accuracy} = \frac{\text{Number of correctly predicted}}{\text{Total number of predictions}} \times 100\%$$

Loss: SoftMax loss, sometimes referred to as categorical cross-entropy loss, is a loss function problems that is widely used in multi-class classification problems

$$f(\bar{x}\rightarrow\iota) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}}$$

$$\text{CCE} = -\sum_{i=1}^{n} y_i \log\left(f(x_i)\right)$$

$f(\bar{x}\rightarrow\iota)$ = Softmax Function

CCE: Categorial Cross Entropy

We have trained the dataset per Epoch=20 to know which model suite best.

An epoch in the context of deep learning is a single full pass of the neural network's training dataset, during which it updates its weights in an effort to minimize the loss function and improve its ability to make accurate predictions or classifications.

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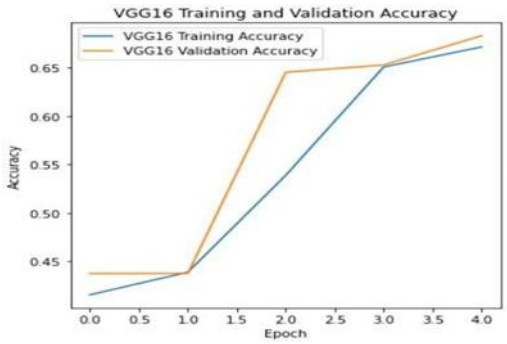


Fig 4.5 VGG 16 Accuracy plot

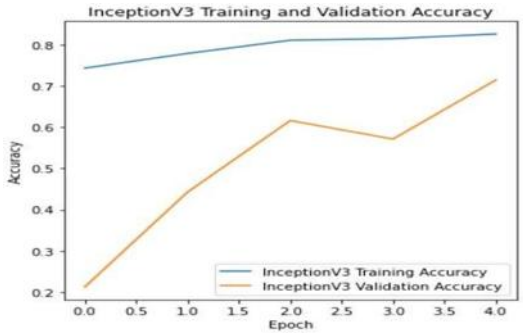


Fig 4.6 Inception v3 Accuracy plot

Fig 4.5 and 4.6 shows that the training accuracy for InceptionV3 starts higher than that of VGG16, at about 0.6 (or 60%), and increases sharply to close to 0.8 (or 80%) by epoch 4. InceptionV3 seems to learn faster than VGG16, as indicated by the higher training accuracy after the same number of epochs.

The table below shows the clear information about performances of two models

S.no	CNN Model	Accuracy	Loss
1	VGG-16	0.67	0.68
2	Inception v3	0.82	0.71

The model's accuracy is assessed. If the model performs well, it moves forward in the process. If the model performs poorly (low accuracy), there may be a feedback loop.

5. RESULTS

Following the Vgg-16 and Inception v3 model comparison.Table 1 shows that the Inception v3 is performing better than the VGG-16. So that the inception v3 is suggested for the purpose of developing Diabetic Retinopathy prediction system.

The below Fig 5.1 and Fig 5.2 give the information about the inception v3 model Performance and per epochs=20.

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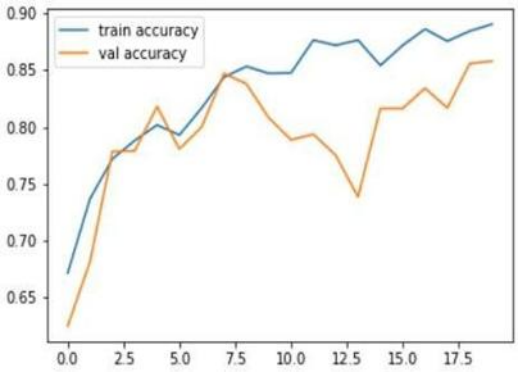


Fig 5.1 Inception v3 per epoch Accuracy

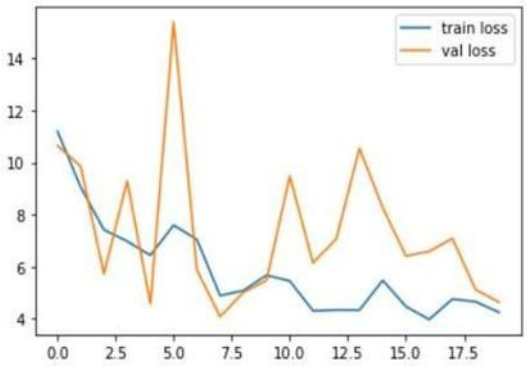


Fig 5.2 Inception v3 per epoch Loss

To make sure the algorithm used in the system is reliable, we tested it using images of no_dr, mild, Moderate, Severe, and Proliferative DR. The algorithm identified No DR, Mild, Moderate, Severe, and Proliferative DR pictures as the outcome, as expected.



Fig 5.3 Accuracy at best epoch

The plots of accuracy and loss on the training and validation datasets over training epochs are displayed in Figures 5.3 and 5.4, where the optimal epoch is indicated by a high accuracy and a low loss.

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Fig 5.4 Loss at best epoch

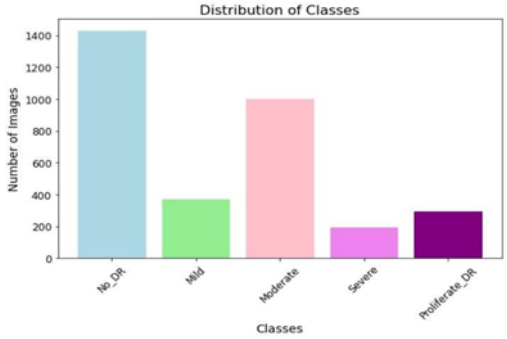


Fig 5.5 Distribution of Classes

Fig 5.5 displays the distribution of five classes: mild, moderate, no_dr, proliferative_dr, and severe. Each class is represented along the x- axis, while the corresponding count of images is depicted on the y-axis, providing insight into the dataset's class distribution.



Fig 5.6 Training Images plot

Fig 5.6 displays the distribution of training images across five classes: mild, moderate, no_dr, proliferative_dr, and severe. Each class is represented along the x-axis, while the corresponding count of images is depicted on the y-axis, providing insight into the dataset's class distribution.

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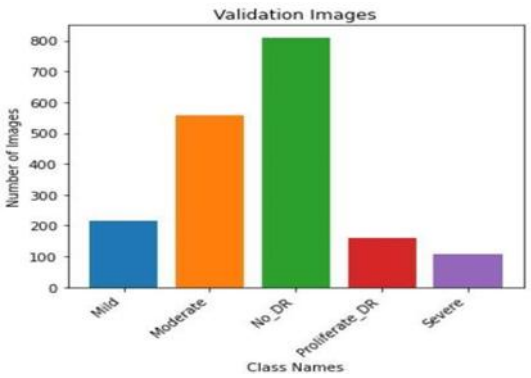


Fig 5.7 Validation Images plot

Fig 5.7 displays the distribution of validation images across five classes: mild, moderate, no_dr, proliferative_dr, and severe. Each class is represented along the x-axis, while the corresponding count of images is depicted on the y-axis, providing insight into the dataset's class distribution.



Fig 5.8 Home Page

Fig 5.8 shows after successful login, users are redirected to the homepage, where they encounter an image representing diabetic retinopathy.

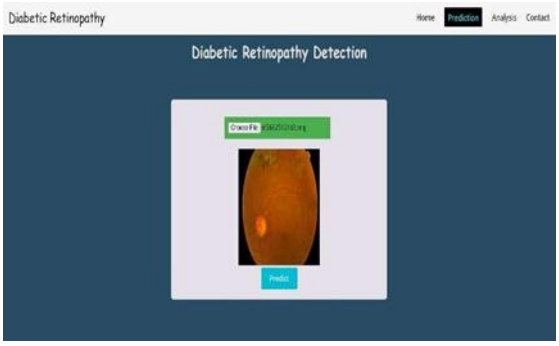


Fig 5.9 Upload the image

Fig 5.9 shows that after clicking on the prediction button, users are prompted to upload fundus images to get the results.

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Fig 5.10 Predictions

Fig 5.10 shows After uploading the fundus image, Predicting the result indicating the severity level of retinopathy, such as proliferative.

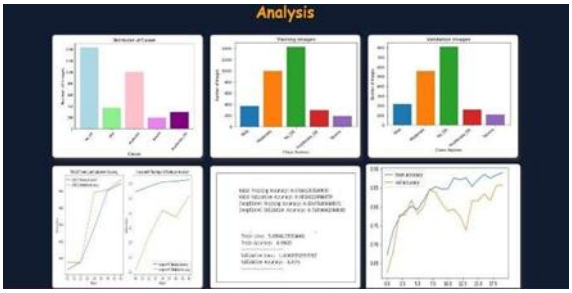


Fig 5.11 Analysis page

Fig 5.11 displays that after clicking on the analysis button, users are directed to the analysis page, where they can view detailed insights.

6. CONCLUSION

In this study, we have successfully applied deep transfer learning techniques, specifically leveraging the Inception-v3 architecture, to effectively identify diabetic retinopathy (DR) within retinal fundus images. The suggested method for categorizing DR images was very accurate, provided consistency in the interpretation of each individual DR image, and could help ophthalmologists decide which DR images to refer. Importantly, our approach streamlines the DR detection process by eliminating the need for manual feature engineering from the retinal fundus image dataset. Moreover, efforts should be directed towards developing user-friendly software that can serve as an effective DR screening tool in clinical settings, providing invaluable decision-making assistance to healthcare professionals.

7. FUTURE WORK

In our forthcoming research endeavors, we aim to expand upon our current progress by extending the integration of our software with mobile devices, thereby enhancing accessibility and usability for a wider audience. Building upon our successful implementation utilizing Jupyter Notebook and Flask for web

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integration, we plan to optimize our solution for seamless operation across various mobile platforms. We will focus on refining the user experience and interface design to ensure smooth navigation and interaction on mobile devices. By addressing these aspects, we envision our project evolving into a versatile and indispensable tool for diabetic retinopathy screening, catering to the diverse needs of healthcare practitioners and patients alike.

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