DIABETIC RETINOPATHY USING CNN

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ABSTRACT: Diabetic Retinopathy (DR) is a common complication of diabetes that can lead to visual impairment and blindness if not managed effectively. In the present scenario, diabetic retinopathy remains a significant concern globally, with millions of individuals at risk of developing this condition. Early diagnosis is crucial to prevent vision loss. Traditional methods of identifying DR require manual examination by ophthalmologists, which can be time-consuming and prone to human error.

This paper proposes the use of automated detection of DR model from retinal images. And also explains how the model shows difference in prediction with various sets of training and testing datasets. The model got an overall accuracy of 97% when four cases are considered where training images are 8%, 12%, 40%, and 50% and testing images are 92%, 88%, 60%, and 50% respectively. Once the model is trained and saved, it can predict whether the input fundus image is having the Diabetic Retinopathy or not. If the fundus image contains the DR it classifies the severeness of Diabetic Retinopathy.

INDEX TERMS: Diabetic Retinopathy, Fundus image, CNN, Deep Learning, Image classification

I. INTRODUCTION

Diabetic retinopathy is a retinal vascular disorder appears in the diabetic patients. The count of DR patients is expected to be doubled among Americans from 7.7 million to 14.6 million between 2010 and 2050. The Hispanic Americans are expected to be affected severely and rapidly from 1.2 million to 5.3 million. The duration of diabetes is a key factor in the arrival of retinopathy, with the increase in diabetes duration will increase the risk of the DR development. It is also noticed that patients with diabetes usually unaware of the possibility of DR, which leads towards the delayed diagnosis and treatment [1]. Manual detection of DR is time-consuming and requires trained clinical experts to analyze digital color fundus images. However, the delayed outcomes can result in a lack of follow-up and misinformation for patients [2].

Diabetic retinopathy has been manually tested by ophthalmologists until now. Manual diagnosis of DR is timeconsuming, and therefore, computer-aided diagnosis is gaining attention. Non-proliferative diabetic retinopathy fundus images. The extracted features are then concatenated and fed to the IR-CNN for classification of DR. Additionally, we conduct experiments with image enhancement and data augmentation methods to improve the performance of (NPDR) causes retinal swelling and leakage of tiny blood vessels, leading to macular edema and vision loss. Other types of NPDR include blood vessel closure and macular ischemia, as well as the formation of exudates that can affect human vision [3]. Proliferative diabetic retinopathy (PDR) is the most severe stage of the disease, in which new blood vessels start developing in the retina through neovascularization. These new vessels can bleed in the vitreous, causing dark floaters, and if bleeding is extensive, it can result in blurred vision. Scar tissue formation is common in PDR and can cause macular problems or contribute to independent retinal tissue. PDR is a severe condition that can affect both central and peripheral vision.

The existing models are unable to detect the disease at early stages and complicated due to high computational cost with low performance. To address these issues, various techniques have been proposed for automatic detection of DR from fundus images, including DL-based approaches. In this study, we propose a novel DL model for DR detection, utilizing InceptionV3 and Resnet50 for feature extraction of proposed model. The proposed Deep learning model efficiently diagnoses the diabetic retinopathy at early stage and perform significantly better than existing techniques.

II. LITERATURE SURVEY

S.No	Work	Dataset	Technique	Purpose	Performance analysis
1.	(Wang et al., 2019)	Lab Dataset	Cosine Similarity, Logistic Regression	Prediction of severity and grading of DR	91.2% for DR related features 95.6% for DR severity prediction
2.	(Esmaeili et al., 2014)	Private Data	Curvelet Transformation, Equalisation algorithm	Prediction Of DR	sen/spec of 94/87
3.	(Dorizzi et al., 2019)	DiaretDB1 and Messidor	CNN, Probability map	Reduce the complexity of the model	ROC of 0.912 and sen of 0.940
4.	(Dhara et al., 2015)	Messidor	Morphological features, CLAHE, SVM	Detection of DR	AUC mild:0.9106 Moderate:0.8372 Severe:0.9750
5.	(Sakshi Gunde and Gupta, 2020)	DIARETDB0	Green Channel, Otsu Algorithm, Circular Hough transform	Detection of DR using blobs and blood vessel	sen/spec of 73/70 in blob detection and 77/80 in blood vessel detection
6.	(Hajeb Mohammad Alipour et al., 2012)	Local dataset	Curvelet based enhancement, SVM	Detection and Grading of DR	Sen/spec of 100% in grading
7.	(Rahim et al., 2015)	Eye Clinic, Department of Ophthalmology, Hospital Melaka, Malaysia (Local Dataset)	Grayscale, fuzzy filtering, fuzzy edge detection, Decision tree, Knearest neighbour	Detection of DR and Maculopathy	Category II misclassification error/acc/sen/spec of 0.4395/0.5605/0.4500/0.5956 for binary decision tree and 0.2975/0.7025/0.6500/0.7297 for k-nearest neighbor
8.	(Gao et al., 2019)	Sichuan Provincial People's Hospital (Lab Dataset)	Inception V-3	Proposed an approach for grading the 4-stage severity of DR	Accuracy:88.72%
9.	(Qummar, 2019)	Kaggle	CNN Models Resnet50, Inceptionv3, Xception, Dense121, Dense169	Classify five stages of DR	–
10.	(Carson Lam and MD1, 2017)	Private Dataset	CNN, transfer learning, googlenet, alexnet	Detection and Grading of DR	74.5% on 2- ary classification, 68.8% on 3-ary classification and 57.2% on 4-ary
11.	(Zeng et al., 2019)	Kaggle diabetic retinopathy competition	Inception V-3, Siamese like network structure	A model is proposed with transfer learning and a Siamese-like structure.	Kappa:0.829 AUC:0.951

III. METHODOLOGY

The process of DR detection starts by importing necessary libraries and setting the image size to 512x512 pixels. The training and validation images are loaded from the specified directories, and the number of images in each folder is calculated to ensure that there is a balanced distribution of images across different classes.

Next, the InceptionV3 model is loaded with pre-trained weights from ImageNet, and the top layers are removed. The input shape is set to the specified image size, and the model is set to be non-trainable. The output of the InceptionV3 model is flattened, and a new dense layer with 5 output nodes and softmax activation is added to the model. The model is then compiled with categorical cross-entropy loss and Adam optimizer.

The training and validation data generators are defined to apply data augmentation techniques such as shearing, zooming, and horizontal flipping to the training data. The training and validation generators are then used to load the data from the specified directories and feed it to the model during training. The model is trained for 50 epochs with a batch size of 32, and the loss and accuracy are plotted for both training and validation data.

Finally, the model is saved. A function is defined to load an image, resize it to the specified dimension, and predict the class of the image using the trained model. The function takes an image file path as input and returns the predicted class of the image.

The model is trained using a balanced dataset of training and validation images, and data augmentation techniques are applied to the training data to increase the model's robustness. The trained model is then saved to a file for future use, and a function is defined to load an image and predict its class using the trained model as DR severity.

A. Inception V3 for Feature Extraction

In the domain of medical imaging, the InceptionV3 model, which is the most prevalent adaptation of the GoogleLeNet architecture [31]. It is extensively used for classification purposes. The architecture of Inceptionv3 model is illustrated in Figure 2.

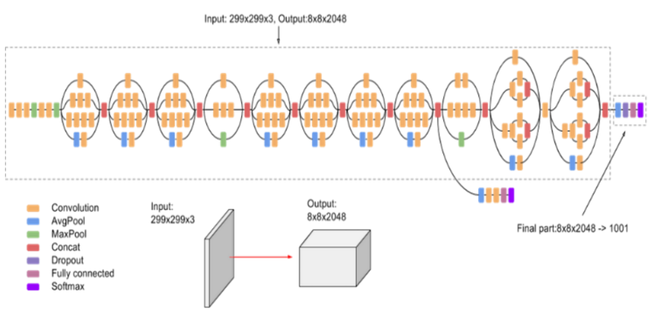


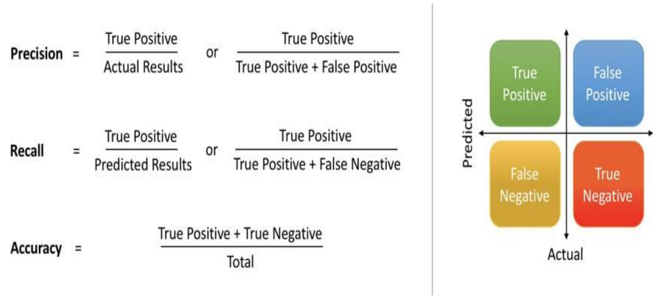
FIGURE 1. Inception v3 model

B. EVALUATION METRICS

The objective of evaluation metrics is to assess the efficiency of ML models. Following is the brief description of performance evaluation metrics used in this research.

C. IMAGE ENHANCEMENT METHODS

The pre-processing step plays a pivotal role in enhancing the



quality of retinal images by eliminating noise. The proposed approach employs a set of pre-processing techniques aimed at optimizing image quality, which are briefly outlined below.

1. Rescales pixel values,
2. Adjusts Shear range,
3. Adjusts Zoom range,
4. Applies Horizontal flip.

IV. EXPERIMENTS AND RESULTS

The analysis table of four cases is being depicted below:

CASE	Training Images	Test Images	Accuracy(%)
I	163	1754	90.99
II	217	1700	94.82
III	770	1147	95.55
IV	958	959	98.54

Table 1: Result Analysis table

In result analysis, the terms Rate of Acceptance and Rate of Rejection plays vital role. They are discussed as follows:

Rate of Acceptance and Rate of Rejection includes four terms

True Acceptance: True acceptance occurs when a positive instance is correctly classified as positive by the system.

True Rejection: True rejection occurs when a negative instance is correctly classified as negative by the system.

False Acceptance: False acceptance occurs when a negative instance is incorrectly classified as positive by the system.

False Rejection: False rejection occurs when a positive instance is incorrectly classified as negative by the system.

CASE 1	True	False
Acceptance	838	74
Rejection	758	84

Table 2: ROA & ROR – Case 1

CASE II	True	False
Acceptance	820	34
Rejection	792	54

Table 3: ROA & ROR – Case 2

CASE III	True	False
Acceptance	574	12
Rejection	522	39

Table 4: ROA & ROR – Case 3

CASE IV	True	False
Acceptance	458	25
Rejection	433	43

Table 5: ROA & ROR – Case 4

V.CONCLUSION

Automated detection of DR using deep learning algorithms has shown promising results in detecting referable DR with high sensitivity and specificity. These models have the potential to improve the efficiency of DR screening, prevent visual loss and blindness, and reduce the workload of ophthalmologists. Further research is necessary to determine the feasibility of applying these algorithms in clinical settings and to assess their impact on public health. Here, we have attained 97% Accuracy by considering four different cases. Early detection is now possible which interms offers potentiality in Healthcare settings.

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