International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 7 July 2022, pp: 1327-1331 www.ijaem.net ISSN: 2395-5252

Prediction of Diabetic Retinopathy Using InceptionV3 Model

Radhika K.P.[1*], Vinay S[2]
[1,2]*Dept.of Computer Science, PES College of Engineering, Mandya, Karnataka, India*

Submitted: 10-07-2022 Revised: 18-07-2022 Accepted: 23-07-2022

ABSTRACT: Diabetic Retinopathy (DR) is a diabetic condition that affects the retina of the eye. It is caused by the damage of the luminous located at the back of the human retina's blood vessels. This was the most common cause of visual impairment among adults in their working years, and it's more likely when diabetes is inadequately managed. Although there are procedures to identify DR, they require an ophthalmologist to examine the retinal image manually. The suggested Diabetic Retinopathy detection approach uses Deep Convolution neural networks using inception v3 model to detect the problem in an automated way. The model was trained on 35126 image data released openly by eyePACS on the Official website of Kaggle using a GPU, and it obtained an accuracy of around 97percent.

Keyword: Deep Leaning, CNN, Retina Images, Inception V3, Diabetic

.

I. INTRODUCTION

Diabetic Retinopathy(DR) is an eye disease affecting the human retina. The capillaries inside the retina enlarge, causing the retina to burst, resulting to blindness. Swelling is the only symptom of Diabetic Retinopathy in the early stages, while blood vessel puncturing is the only symptom in the later final stages. Because the symptoms at the mature phase are hard to recognize, detecting them early can help to prevent impaired vision. The current screening procedure for Diabetic Retinopathy is time-consuming and complicated by a scarcity of qualified ophthalmologists. It entails dilation of the pupils, fluorescence angiography, capture the picture of the retina using a specific camera, and assessment by the physician. DR is estimated to have caused around 5% of global vision disability in 2002, affecting almost 5 million individuals. Furthermore, in rural areas where the rates of diabetes are very high, a lack of trained physicians is a major issue. There are five phases of diabetic retinopathy which are No DR, Mild Non-Proliferative DR (NPDR), Moderate Non-Proliferative DR, Severe Non-Proliferative DR and Proliferative DR. Decreased macular blood flow circulation, increased leukocyte adhesion, and loss of retinal pericytes are all indications of mild non-proliferative Diabetic Retinopathy, which might be difficult to spot. The formation of Microaneurysms is a sign of moderate NPDR. Variations in venous calibre and based on inter retinal micro - vascular anomalies are also visible at this phase. Severe NPDR causes arteries to enlarge to the point that blood circulation is seriously impacted. The injured blood vessels are then replaced with new ones.

These new frail blood vessels rupture quickly in Proliferative Diabetic Retinopathy, resulting in irreversible visible disability.

II. RELATED WORK

A technique for classifying the severity of DR using the MESSIDOR dataset and fractal analysis. The picture segmentation by their approach, the irregular parameters were computed as features. They failed to differentiate between mild and severe DR [1].

An approach for the identification of diabetes mellitus and regular retinal pictures using concurrent neural networks and support vector machines. Exudates, haemorrhage, & microaneurysms are among the characteristics. The proposed framework was divided into two sections by the author: the first section included segmentation method based on neural networks, and the second section carried out grouping by SVM [2].

A methodology for enhanced DR identification by analyzing the region as well as quantity of microaneurysms from fundus pictures from the DIARETDB1 dataset, Green channel segmentation, histogram equalisation, and morphological analysis will be used to pre-process fundus images. For the detection and categorization of microaneurysms, principal component analysis (PCA), contrast limited adaptive histogram equalisation (CLAHE), morphological procedure, and averaging filtering uses SVM[3].

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 7 July 2022, pp: 1327-1331 www.ijaem.net ISSN: 2395-5252

Uses of various textural data and a ml algorithms categorization model to predict DR. Using a local ternary pattern (LTP) and localized energy-based shaped histogram (LESH), the two characteristics haemorrhage and exudates are retrieved. Utilizing relevant features from LTP and LESH, SVM is utilized to learn & categorize the retrieved data[4].

A technique for fuzzy C means-based image retrieval and SVM-based diagnosis of eye disease. Top hat filter and texture analysis are used to remove blood flow. The exudates & retinal vascular density are consider as the symptoms. Fuzzy C means segmentation is used to collect exudate. The input vector Gaussian Radial Basis function are mapped into the SVM kernel mode[5].

The categorises distinct phases of DR according to blood vessels, haemorrhage, and exudates. Utilizing picture pre-processing, the attributes are retrieved & put into neural network. The photos are classified to 3 categories as light, medium non-proliferative DR, & proliferative DR, using SVM-based training applied to the data. However, if the discharge regions in the iris image are larger than the size of a disk drive, the technique may not produce the desired results[6]

Technique for morphological characteristics exudates recognition via colour fundus images. The model applies thresholding, erosion, dilation, boolean AND operation, histogram equalisation, grayscale conversion, & watersheds modification. The technology generates an output that includes exudate ranges that are influenced by diabetes mellitus[7].

For categorizing non-proliferative diabetes mellitus using soft margin SVM. Non-proliferative DR is categorized according to the intensity of hard exudates found in retinal fundus pictures. Using mathematical morphology, hard exudates are divided up. However, the approach has not had micoaneurysms or bleeds as attributes[8].

GMM classifier-based automated approach for the detection of red lesion diabetic retinopathy. The features are obtained using supervised learning, filter-based methods, and mathematical morphology. Patient microaneurysm strength is divided into 4 categories[9]

An automated process for strong exudate recognition using colored accents plus sharp edges were used as two aspects. Sharp edge detection, color-based categorization, and the extraction of the optic disc were the methods used in exudate recognition procedure. The DRIVE and DIARETDB0 datasets were used for training and testing purposes. The device's frontend (GUI) was created using MATLAB 7.8 [10]

III. EXISTING SYSTEM

In their study, Enrique Carrera et.al suggested a methodology based on SVM to aid in the early detection of DR. A preliminary data pre-processing level divides as hard excess fluid, microaneurysms & blood vessels in this method, allowing features to be extracted for use with SVM. The responsiveness of the model tested on the STARE dataset was 94.6 percent.

IV. PROPOSED SYSTEM

We present an autonomous deep-learning-based method for DR phase identification that makes use of single photo of the human retina in this suggested technique. The method given here will being utilised as an accurate screening procedure to early diagnosis of DR. The model was created with Keras and a TensorFlow backend for Python. The Inception V3 architecture is used to implement the suggested system.

The suggested dataset can be downloaded for free from the web. All of the photos are of different persons, taken with multiple cameras, and are of various sizes. Because the data is so noisy, various preprocessing processes were used to convert all of the photos into a format that could be used for training.

V. METHODOLOGIES

In this study, a method for diabetic retinopathy treatment is suggested that utilizes a mixture of several approaches. Recognizing diabetic retinopathy is the key advancement of this suggested technique.

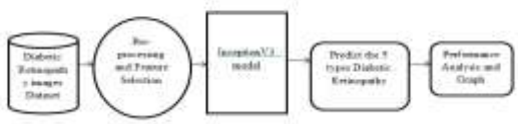

Fig-2: System Architecture

Framework studied and implemented key critical image preprocessing algorithms for future DR framework advances.

A. Data Collection

We established a form during first phase which obtain all source datasets for training and testing purpose also we give the data set in model folder. The dataset consists of 2222 Diabetic Retinopathy images, which we have collected from eyePACS from the Kaggle website.

B. Data Pre-Processing

Pre-processing of data is used to enhance specific visual features or decrease unwanted

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 7 July 2022, pp: 1327-1331 www.ijaem.net ISSN: 2395-5252

distortions for better image information that are relevant for later processing. The term "pre-processing" refers to activities involving if both input and the output were have several images, the minimum abstraction is achieved. Here we use KerasImageDataGenerator.

Keras ImageDataGenerator is just an excellent tool! Though our system is now in training, it enables us to edit our photos in real-time! We can make whatever arbitrary changes we wsant when each areas of practice images is sent to the model.

Image augmentation using Keras

It was straightforward to add to our photographs thanks to Keras which uses ImageDataGenerator class. It comprises several data augmentation techniques including standardization, spin, shifts, twists, plus intensity adjustments among others.

At each epoch, The ImageDataGenerator class makes sure that the model gets fresh iterations of the photographs at every epoch. Furthermore, it's doesn't add the edited images towards the original corpus; instead, it only returns them. If that was the situation, our system would become overfit because of repeated exposure to the original photographs.

In this paper we will retrieve the images and their labels. Then applied ImageDataGenerator with rescale image (224,224) as all images should have same size for recognition. Then convert the images into numpy array.

C. Algorithm

In this paper we have used Inception v3 to solve this problem.

The Inception V3 is now a CNN-based deep-learning image classification algorithm. The method is an improved form of foundational framework Inception V1, which was made available in GoogLeNet in 2014. Like the title suggests, a Google team developed it.

The following things are applied in Inception v3 Model are as follows:

a. Factoring into lesser convolutions
b. Irregular Convolutions through Spatial Factorization
c. Auxiliary Approaches Usefulness
d. Effective Grid Area Reduce

After performing all the optimizations, the final Inception V3 model looks like this

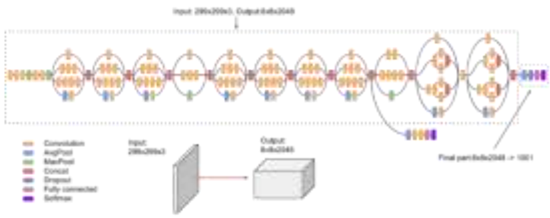

Fig-1: Inception V3 Model

An Inception V3 model does have a total of 42 layers, which is a small increase over the inception V1 as well as V2 forms. The efficiency of this model is absolutely remarkable.

As per the trained model below are Accuracy, Precision, Recall and F-Measure values

Accuracy: 0.977
Precision: 0.972
Recall: 0.977
F-Measure: 0.977

VI. WORKING OF THE SYSTEM

Step 1: Login to the system.
Step 2: select the image from the testing dataset.
Step 3: System will predict the DR level for the uploaded images and gives the output with the level of the DR

VII. EXPECTED RESULT

We tested the system with No DR, Mild Non-Proliferative DR (NPDR), Moderate Non-Proliferative DR, Severe Non-Proliferative DR and Proliferative DR images to ensure that the algorithm utilized in the system is robust. As predicted, the algorithm spotted the result as No DR, Mild-NPDR, Moderate-NPDR, Severe-NPDR and Proliferative DR images.

Snapshots

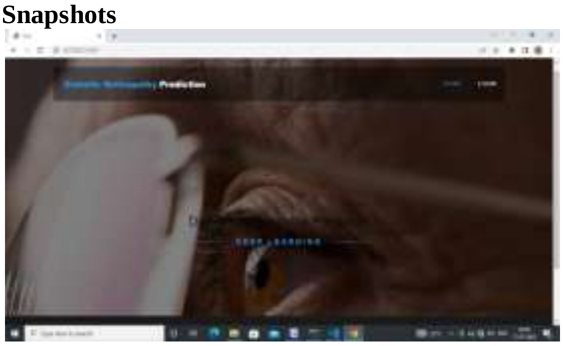

Fig.1: Home page

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 7 July 2022, pp: 1327-1331 www.ijaem.net ISSN: 2395-5252

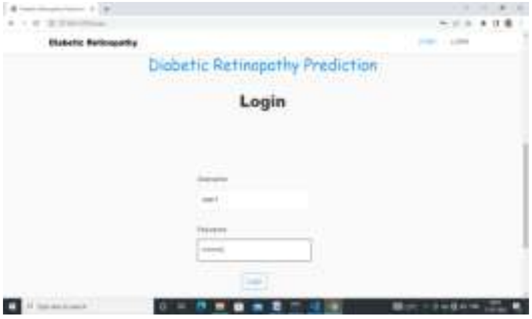

Fig.2: Login page


Fig.3: Classified image as Healthy DR


Fig.4: Classified image as Mild DR


Fig.4: Classified image as Moderate DR

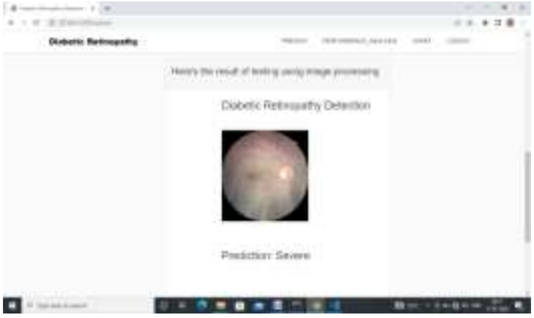
Fig.5: Classified image as Severe DR


Fig.6: Classified image as Proliferate_DR

VIII. CONCLUSION

Given the lack of doctors available for manual DR recognition an automated technique can significantly minimize the amount of manual work needed for diagnosis. The current model uses Deep Neural network to classify retinal pictures, thus relies less on human extraction of features and offers a more complete method of DR detection. Having regard to the difficulty of such collection, this model is applicable according to a number of measures. On expanding the dataset much more and retraining a learning algorithm with fresh retinal pictures, efficiency can be raised even higher. It is really a common practice that enhances a system. Even while the approach might not yet have all trust of afflicted patients, future development could be advantageous for both the surgeons & patients. Patients may trust the system to provide an actual diagnosis, while surgeons could trust it to lighten their burdensome workload.

IX. FUTURE WORK

We utilized a jupyter notebook to construct the software, and it was a success. In Python, using web application our project has been successfully tested. We also looked into the project's uses and future scope. Our solution can be linked to mobile application to make more easy access.

REFERENCES

[1]. Farrikh Alzami.et.al, "Diabetic retinopathy Grade Classification based on Fractal analysis and Random Forest", International Seminar on Application for Technology of Information-2019
[2]. Qomariah et.al, "Classification of Diabetic Retinopathy Using CNN & SVM" -2019
[3]. S. Kumar and B. Kumar," Diabetic Retinopathy Detection by Extracting Area and Number of Microaneurysm from Colour Fundus Image," 2018 5th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, 2018, pp. 359-364.
[4]. M. Chetoui, M. A. Akhloufi and M. Kardouchi," Diabetic Retinopathy Detection Using Machine Learning and Texture Features," 2018 IEEE Canadian Conference on Electrical & Computer Engineering (CCECE), Quebec City, QC, 2018, pp. 1-4.
[5]. S Choudary, C Giri," Classification of DR using SVM", April-2016
[6]. Sangwan, "Identification of Stages of DR", International Conference on Computer sciences(ICCS)-2015
[7]. A. Chandran, K. K. Nisha and S. Vineetha," Computer aided approach for proliferative diabetic retinopathy detection in color retinal images," 2016 International Conference on Next Generation Intelligent Systems (ICNGIS), Kottayam, 2016, pp. 1-6.
[8]. S. Kanth, A. Jaiswal and M. Kakkar," Identification of different stages of Diabetic Retinopathy using artificial neural network," 2013 Sixth International Conference on Contemporary Computing (IC3), Noida, 2013, pp. 479-484.
[9]. V Saravanan et.al,"Automatic Red Lesion detection in DR" 2013 International Conference on Communication Technologies (ICCT)-2013
[10]. B Venkatalakshmi, Niveditha,"GUI for Enhanced Retinal Image Analysis for DR",2013
[11]. A. Herliana, T. Arifin, S. Susanti and A. B. Hikmah," Feature Selection of Diabetic Retinopathy Disease Using Particle Swarm Optimization and Neural Network," 2018 6th International Conference on Cyber and IT Service Management (ICITSM), Parapat, Indonesia, 2018, pp. 1-4.
[12]. Z. A. Omar, M. Hanafi, S. Mashohor, N. F. M. Mahfudz and M. Muna'im," Automatic diabetic retinopathy detection and classification system," 2017 7th IEEE International Conference on System Engineering and Technology (ICSET), Shah Alam, 2017, pp. 162-166.
[13]. https://www.kaggle.com/c/diabetic-retinopathy-detection/data