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DIABETIC RETINOPATHY DETECTION AND CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORKS(CNN) AND LONG SHORT-TERM MEMORY(LSTM) NETWORK

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ABSTRACT

Diabetic retinopathy is becoming a more prevalent disease in diabetic patients nowadays. The surprising fact about the disease is it leaves no symptoms at the beginning stage and the patient can realize the disease only when his vision starts to fall. If the disease is not found at the earliest it leads to a stage where the probability of curing the disease is less. But if we find the disease at that stage, the patient might be in a situation of losing vision completely.

Hence, this paper aims at finding the disease at the earliest possible stage with the help of Deep Learning (DL) algorithms. Deep neural networks, on the other hand, have brought many breakthroughs in various tasks in recent years. To automate the diagnosis of DR and provide appropriate suggestions to DR patients, we have built a dataset of DR fundus images that have been labeled by the proper treatment method that is required. Using this dataset, we trained deep convolutional neural network models to grade the severities of DR fundus images. This system not only focuses on diabetic retinopathy detection but also on the analysis of different DR stages, which is performed with the help of Deep Learning (DL) and a hybrid Deep Convolutional Neural Network algorithm. CNN and hybrid CNN with LSTM, are used on a huge dataset with around 1500 train images to automatically detect which stage DR has progressed. Five DR stages, which are 0 (No DR), 1 (Mild DR), 2 (Moderate), 3 (Severe), and 4 (Proliferative DR) are processed in the proposed work.

I. INTRODUCTION

Diabetic retinopathy (DR) is the most common cause of blindness among diabetic patients [1]. According to the World Health Organization (WHO), there were 422 million diabetic patients in 2014, 35% of whom developed some type of retinopathy owing to the accumulation of damage to small blood vessels in the retina [2]. The prevalence of DR is much higher among special groups of patients. For example, it is estimated that 40% of type II diabetic patients and 86% of type I diabetic patients in the US have DR, and the rate of DR is estimated to be 43% in rural areas of China [3]. The loss of sight can vary during the gradual development of DR. Generally, DR can be separated into two major stages: non-proliferative DR (NPDR) and proliferative DR (PDR), which is characterized by neovascularization or vitreous/preretinal hemorrhage. Up to 10% of diabetic patients who have no DR will develop NPDR annually, and for patients with severe NPDR, the risk of developing PDR in one year is 75%. The shift from normal status(no apparent abnormality in the retina) to PDR commonly takes many years. Thus, NPDR is often divided into three sub-stages: mild, moderate, and severe NPDR. Together, these five stages make up the widely used 'International Clinical Diabetic Retinopathy Disease Severity Scale' [4]. The best treatment options for patients differ between stages. For patients with no DR or mild NPDR, only regular screening is required; for patients with moderate NPDR or worse, the treatment options vary from scatter laser treatment to vitrectomy. Thus, to provide patients with the appropriate treatment, it is important to rest grade their DR severity. Clinically, the diagnosis of DR is often made with fundus images, which can be acquired by photographing the fundus directly. The common lesions that indicate DR include hard or soft exudates, micro aneurysms and hemorrhages. All of these lesions can be indented from fundus images; sample fundus images containing various types of lesions. To make a more accurate diagnosis, fluorescein angiography can be used because it can reveal ne vessel structures in the retina. However, fluorescein dyes can cause an allergic reaction

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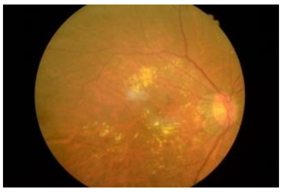
and require functioning kidneys to excrete, and they are usually not available in small hospitals. Currently, fundus images are the most widely used approach for regular screening of DR, since the acquisition of such images is convenient and the visibility of most lesions is sufficient.

(a)



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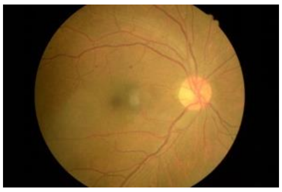

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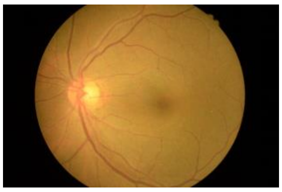


(d)

Figure 1: Sample fundus images with different type of lesions. (a)Fundus with heamorrages. (b) Fundus with exudates. (c)Fundus with microneurysms. (d)A normal fundus.

II. LITERATURE REVIEW

H. Jiang used three deep learning models named Inception V3, ResNet151, Inception-ResNet-V2. They individually performed with an accuracy of 87.91%, 87.20% and 86.18% respectively. When all these models were integrated using the AdaBoost algorithm, it performed with a better accuracy of 88.21%. A filter based retinal vessel extraction method—"fuzzy C means" for exudates detection, "Convex Hull" used for detection and removal of optical disk was proposed by A. Roy and D. Dutta. Support Vector Machines (SVM) algorithm was used for the classification of images into NDPR and PDR. An efficacy rate of 91.23% was achieved in the system proposed. "AD2Net" which was built by Z. Qian, where the main advantage of this system is that it speeds up the diagnosis process and also improved the efficiency of treatment. The "AD2Net" model combines the advantages of ResNet and DenseNet. Further, it uses the attention mechanism method that encourages the model to pay more attention to the useful features so as to improve classification to a considerable extent. This model achieved an accuracy of 83.2%. The paper, described a hybrid, deep learning technique called the E-DenseNet model for diagnosing different DR stages. E-DenseNet model is a combination of EyeNet and DenseNet and makes use of transfer learning. By combining the two models and customizing the embedded dense blocks of the EyeNet architecture, the researchers have obtained a lot of benefits. The main advantage of the model was that it could accurately classify images with less time(training) and memory. This model achieved an accuracy of 91.6% and a Kappa score of 0.883.

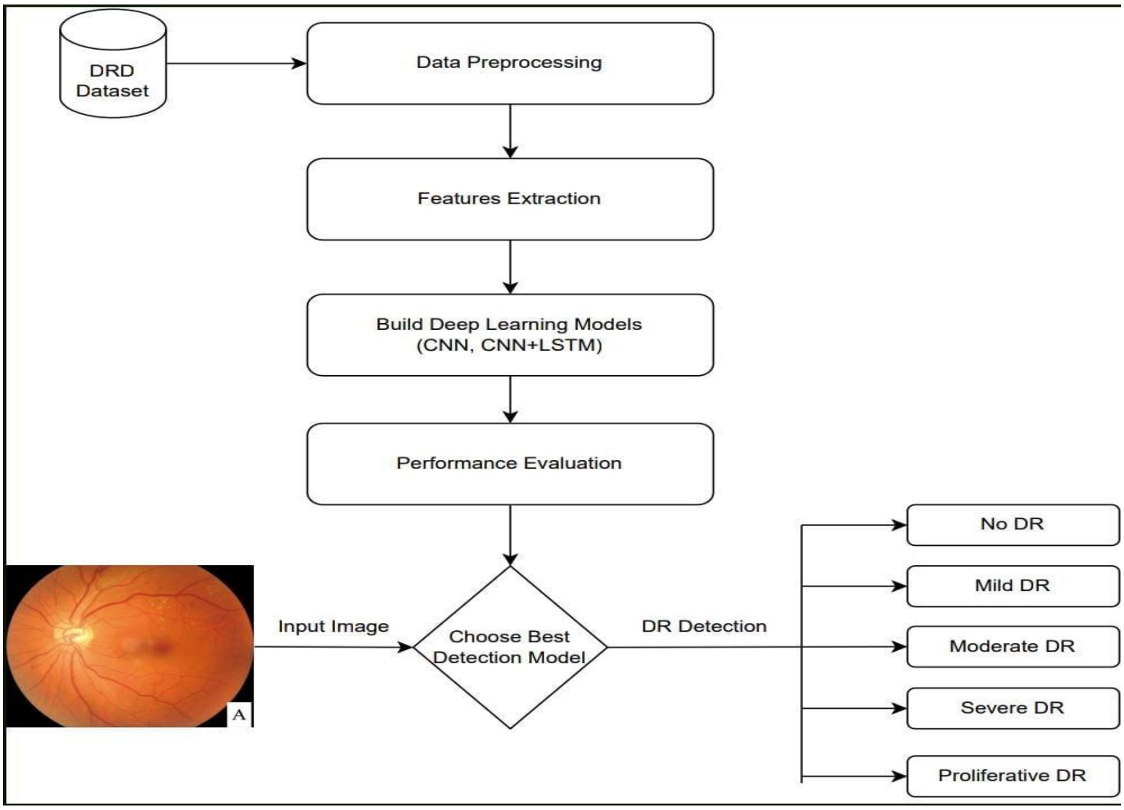
The approach proposed in achieved an area under the curve of 93.4% using "SOFT-MAX BoVW" method. S. Dua focused on a blood vessel detection technique called quadtrees and post-filtration of edges. Anomalies were detected by comparing the information on retinal blood vessel morphology to the diameters of blood vessels in a normal eye. Various fusion techniques have been discussed in to integrate different classifiers to accurately classify images with diabetic retinopathy. This method proved to be advantageous.

An SVM-based kernel combined with a finite mixture of SDD (Scaled Dirichlet Distributions) was developed by Bourouis, Sami. The model offered flexibility in classification. Support Vector Machine (SVM) and KNN classifier were used in for the classification of images into the two classes NPDR and PDR by detecting the presence of micro-aneurysms and lesions. It was observed that the SVM algorithm performed better than the KNN algorithm. A. P. Bhatkar and G. U. Kharat focused on building a Multi-Layer Perception Neural Network to detect diabetic retinopathy in retinal images. The classifier classified retinal images into two categories (DR and No DR) using a feature vector formed with the help of Discrete Cosine Transform (DCT) but couldn't predict the severity of diabetic retinopathy. A comparative study between two CNN architectures-DenseNet and VGG16 was made in. It was observed that the DenseNet model performed with an accuracy of 96.11%. In, back ground subtraction methodology was used to detect lesions and de-correlation stretch based method was used to remove falsely detected lesion. When tested on the DiaretDB database, the algorithm performed with a sensitivity of 0.87 and F-Score of 0.78. To detect the stage of diabetic retinopathy, one must detect exudates and microaneurysms.

Prasad et al. used various morphological and segmentation techniques to detect blood vessels, exudates and microaneurysms. The image was divided into four sub images. Haar wavelet transformations are applied on the features extracted. Techniques like principal component analysis and linear discriminant analysis were applied to select important features. Back propagation neural network was used to classify the images as diabetic or non-diabetic. Deep learning models like Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) were used in. CNN was used to detect lesions and the LSTM was used to generate descriptive sentences based on those lesions. The output from the CNN was fed as input to LSTM. This algorithm achieved an accuracy of 90%. A. T. Nagi proposed a novel technique, the two stage classifier. It is an ensemble technique that combines various machine learning algorithms for classification. It was observed that it performed better in terms of parallelism and accuracy.

III. METHODOLOGY

System Architecture:



CNN

A CNN architecture combination of an input layer, a few convolutional layers, a few fully-connected layers, and an output layer. Briefly, explained all layers in the following.

Input Layer:

In the CNN model, the input layer is the first layer where it has been pre-determined so the input image should be pre-processed before it applies to the layer. The gray color images of size 48 X 48 pixels are deriving datasets from Kaggle web resources where it can use for training and validation.

ConvPool Layers:

In the CNN architecture, the convolution and pooling layers are working together based on the batch process. Here each batch contains a number of images and the filter weights affected on those batches. As well as every convolution layer fed-batch images as input of 3-dimension width x height x color-channel. For reduction of dimensionality, every convolution layer makes it as subsampling which is called pooling. This pooling can be categorized into max pooling and average pooling methods. In this system after performed by convolution layer, the max pooling is performed to pool the image size of 2x2 pixels up to takes a maximum of four pixels. When the pooling method is done then only image height and width are affected.

Fully Connected Layer:

The fully connected layer was inspired by the brain neurons and how they transmit the signals. This layer consumes the number of inputs features and transforms features through layers communicated with trainable weights. The fully-connected layer uses 2 hidden layers of sizes 500 and 300 units. These layers weights are prepared by forward propagation of training data and then backward propagation preparation of its errors.

Output Layer:

The layer output layer is connected with a second hidden layer with seven distinct classes if we classify the face expression recognition or having two classes if working with gender classification. In the output layer by using of Softmax activation method, the estimated output is figured out using the probabilities for two classes. Finally, which class has the highest probability then that is the predicted class (output).

LSTM Model:

The CNN model above is only capable of handling a single image, transforming it from input pixels into an internal matrix or vector representation.

We need to repeat this operation across multiple images and allow the LSTM to build up an internal state and update weights using BPTT across a sequence of the internal vector representations of input images.

The CNN could be fixed in the case of using an existing pre-trained model like VGG for feature extraction from images. The CNN may not be trained, and we may wish to train it by backpropagating errors from the LSTM across multiple input images to the CNN model.

In both of these cases, conceptually there is a single CNN model and a sequence of LSTM models, one for each time step. We want to apply the CNN model to each input image and pass on the output of each input image to the LSTM as a single time step.

About Dataset

https://www.kaggle.com/c/diabetic-retinopathy-detection/data?select=train.zip.005

You are provided with a large set of high-resolution retina images taken under a variety of imaging conditions. A left and right field is provided for every subject. Images are labeled with a subject id as well as either left or right (e.g. 1_left.jpeg is the left eye of patient id 1).

A clinician has rated the presence of diabetic retinopathy in each image on a scale of 0 to 4, according to the following scale:

0 - No DR

1 - Mild

2 - Moderate

3 - Severe

4 - Proliferative DR

Your task is to create an automated analysis system capable of assigning a score based on this scale.

The images in the dataset come from different models and types of cameras, which can affect the visual appearance of left vs. right. Some images are shown as one would see the retina anatomically (macula on the left, optic nerve on the right for the right eye). Others are shown as one would see through a microscope condensing lens (i.e. inverted, as one sees in a typical live eye exam). There are generally two ways to tell if an image is inverted:

- It is inverted if the macula (the small dark central area) is slightly higher than the midline through the optic nerve. If the macula is lower than the midline of the optic nerve, it's not inverted.

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- If there is a notch on the side of the image (square, triangle, or circle) then it's not inverted. If there is no notch, it's inverted.

Like any real-world data set, you will encounter noise in both the images and labels. Images may contain artifacts, be out of focus, underexposed, or overexposed. A major aim of this competition is to develop robust algorithms that can function in the presence of noise and variation.

File descriptions

Due to the extremely large size of this dataset, we have separated the files into multi-part archives. We recommend using 7zip or keka to extract. Note that the rules do not allow sharing of the data outside of Kaggle.

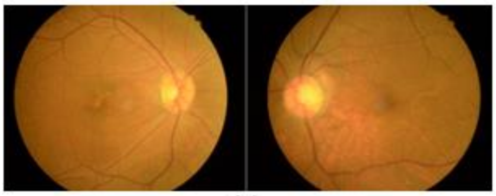
- **train.zip.* -** the training set (5 files total)
- **test.zip.* -** the test set (7 files total)
- **sample.zip -** a small set of images to preview the full dataset
- **sampleSubmission.csv -** a sample submission file in the correct format
- **trainLabels.csv -** contains the scores for the training set

IV. EARLIER WORK

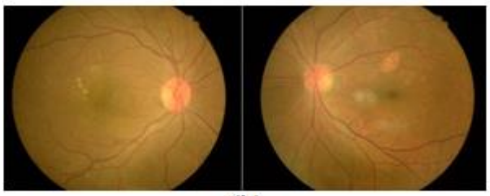
Much work has been done in using computers to make automatic DR diagnoses. Traditional methods often deploy various feature extraction modules to first extract useful information from fundus images. Then, the extracted features are fed into certain machine learning classifiers, such as random forests, support vector machines, and the AdaBoost classifier. Such handcrafted feature-based methods are laborious and often fail to yield good results. In the recent decade, deep neural networks (DNNs) have achieved revolutionary results in many areas. They bring about breakthroughs in computer vision, speech recognition, natural language processing, etc. Many applications of deep neural networks have demonstrated performance that can surpass human beings. The use of DNNs in the diagnosis of DR has also attracted much interest, and much progress has been made. However, despite the many advances that have been made, clinical application of automatic DR diagnosis systems remains unavailable and many works still need to be done.

V. PROPOSED METHOD

Blindness or Diabetic Retinopathy is a problem with diabetes that causes the retina's blood vessels to swell and leak fluids and blood. It is a condition because of Type 1 and Type 2 diabetes and can progress if blood sugar levels are not controlled for a longer duration. These problems affect the vision of the eye. So, dealing with diseases at the prior stage is vital. Diabetic Retinopathy is perceived by the presence of different types of lesions on a retina image. Providing a user-friendly interface to detect whether the patient has Diabetic Retinopathy. The user has to upload the fundus image, this image undergoes preprocessing and the trained model predicts the results. Using CNN+LSTM hybrid model architecture significantly enhanced the performance of neural networks with more layers. This architecture is used to train the model for the classification of fundus images into 5 categories such as No_DR, Mild, Moderate, Proliferate, and Severe.



(a)



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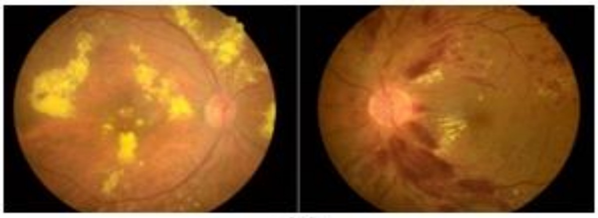
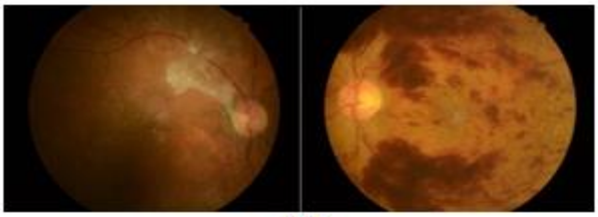


(c)



(d)

Figure 2: Sample fundus images and corresponding labels. (a) Normal. (b) Moderate. (c) Heavy. (d) Severe

VI. RESULT AND ANALYSIS

Index Page:

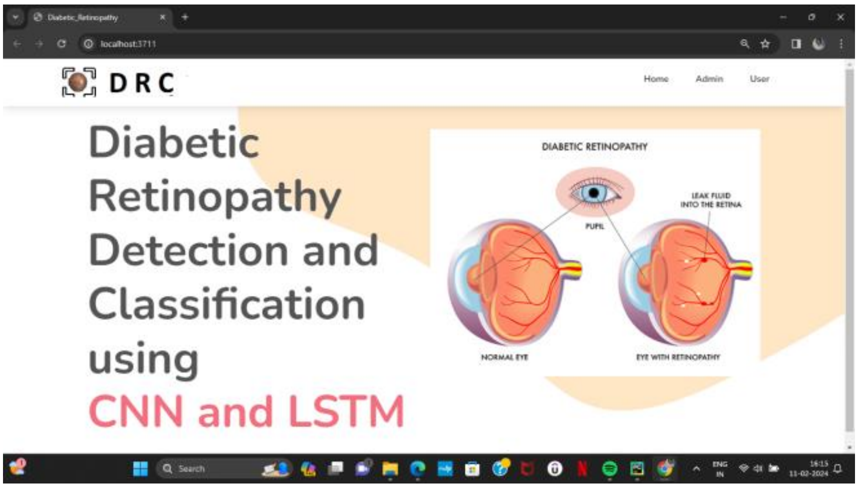


Figure 3:

In above screen click on 'Admin' button to get below output

Admin:

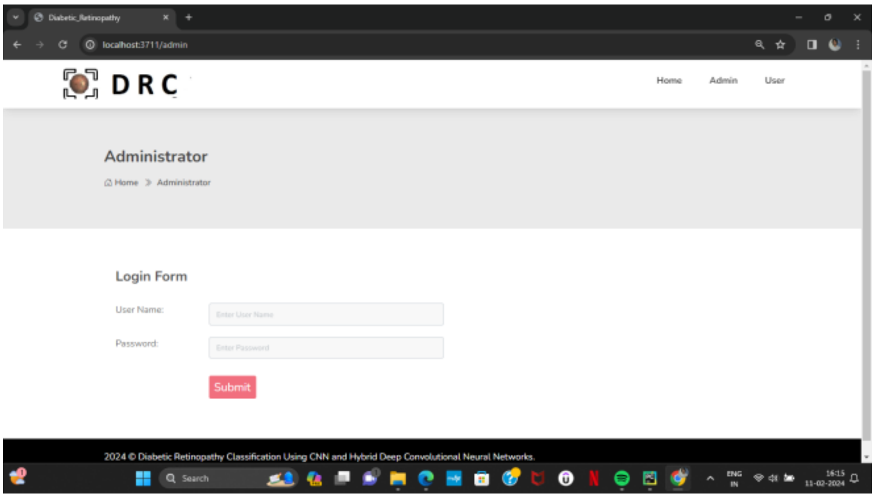


Figure 4:

The admin can login using this page and when he logged in, the following page appears.

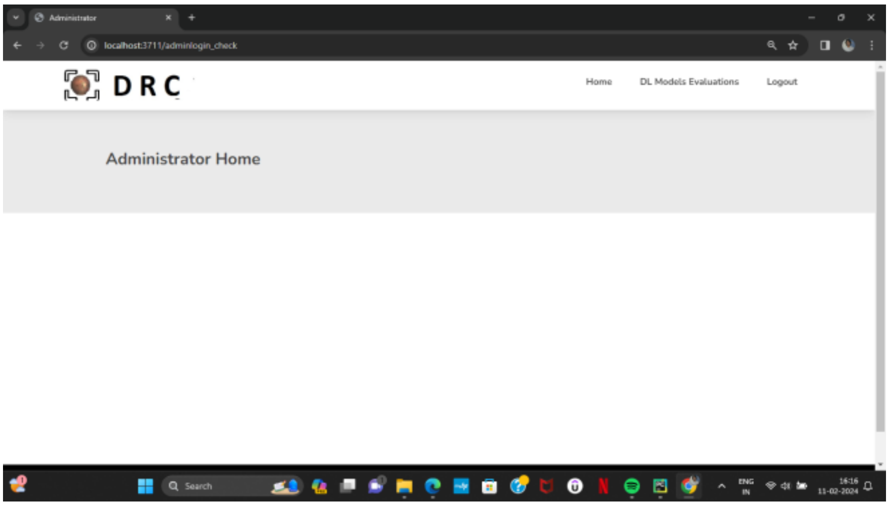


Figure 5:

In the above screen, if we click on DL Model Evaluations, we can see the accuracy of the CNN+LSTM model.

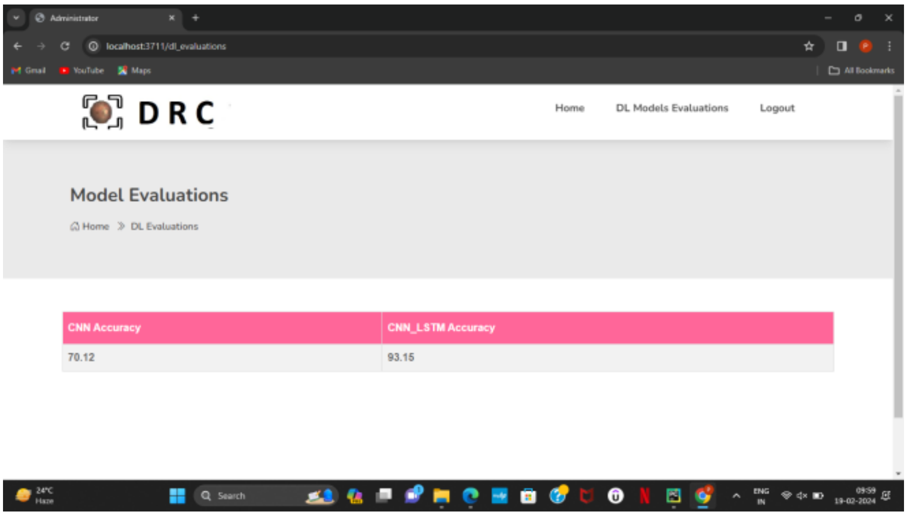


Figure 6:

User

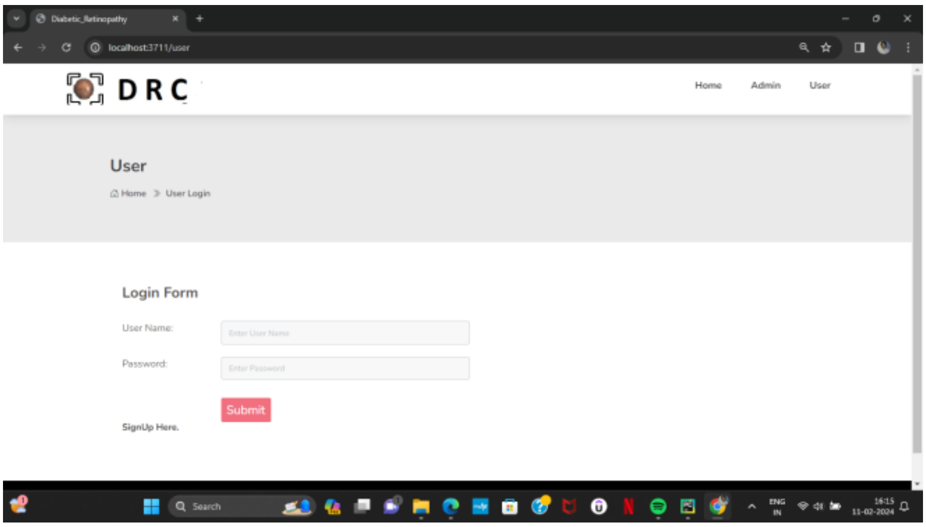


Figure 7:

The user can either Signup or login in order to detect the level of Diabetic Retinopathy

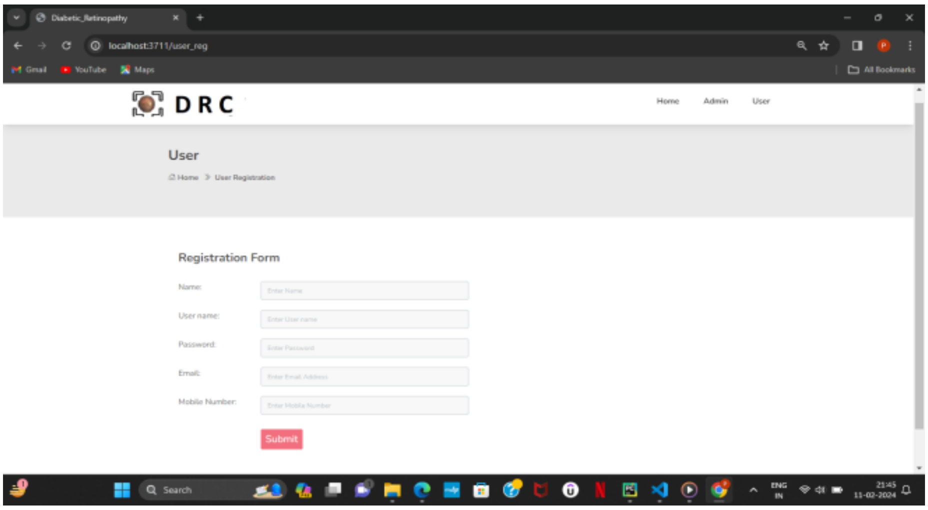


Figure 8:

Uploading the image:

The user can upload the image to detect and the model will classify the DR into different stages

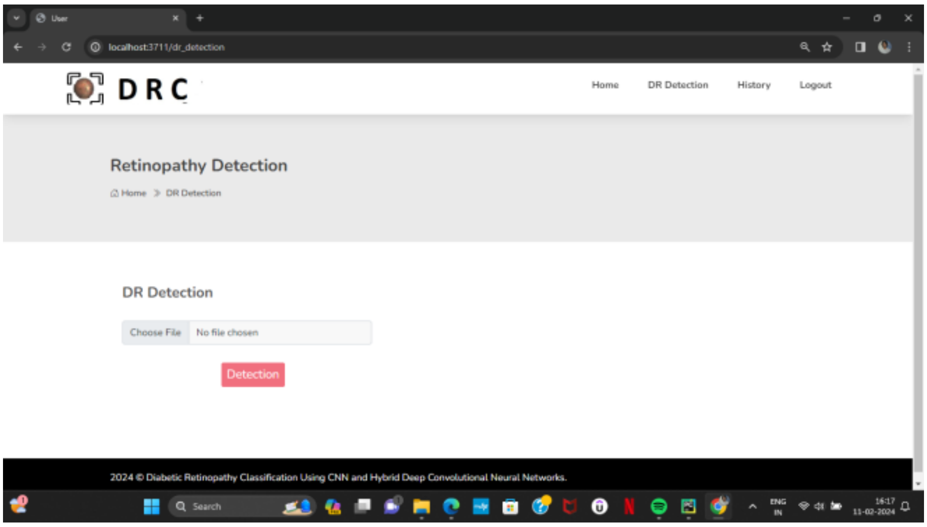


Figure 9:

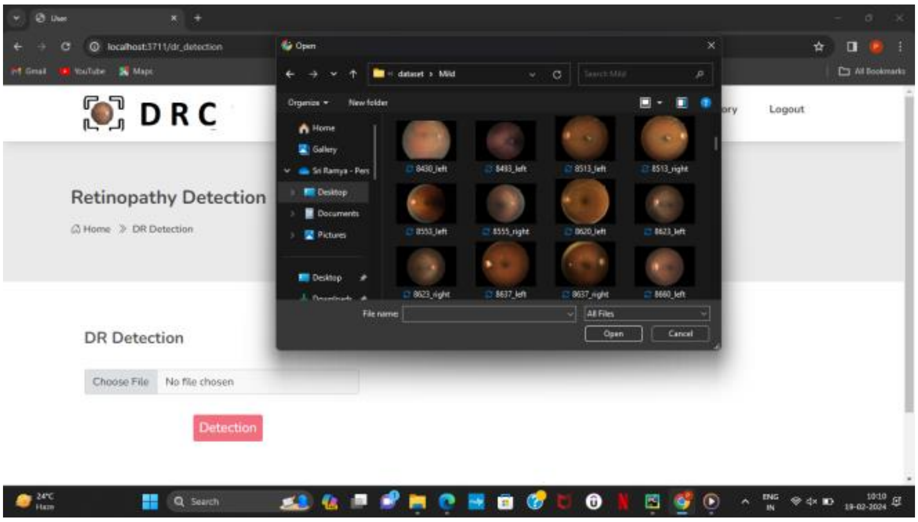


Figure 10:

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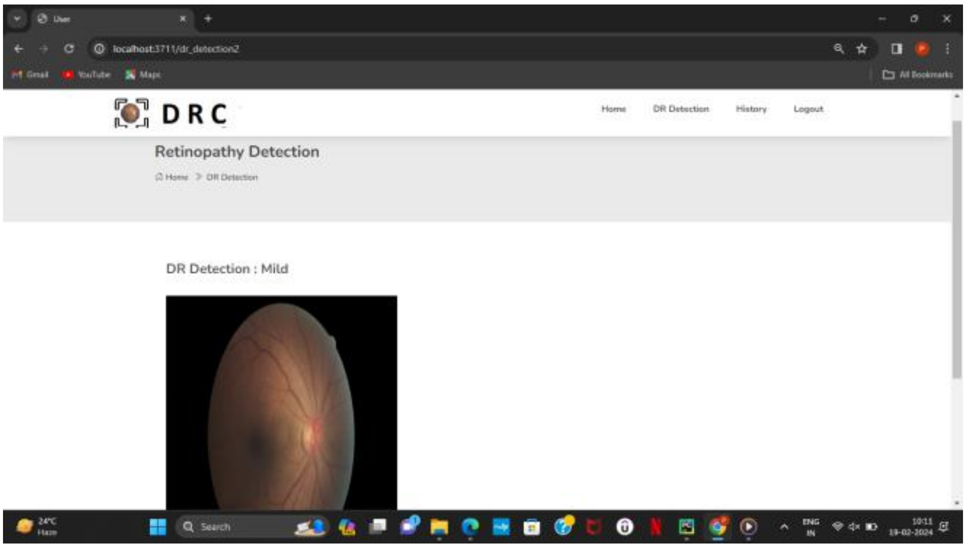

Figure 11:

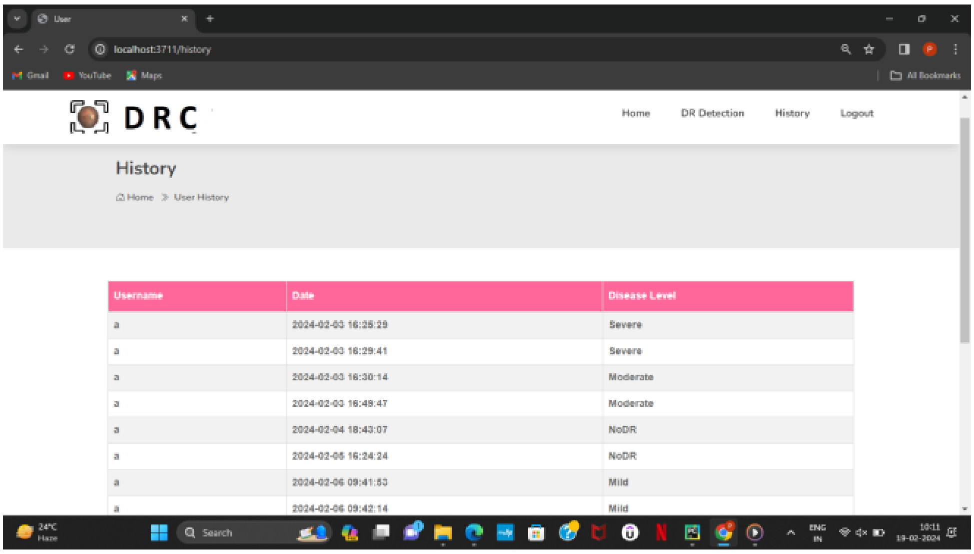

Figure 12:

The user also see their previous detection history by clicking on 'History' button in User's Home page.

VII. CONCLUSION

The huge population of diabetic patients and the prevalence of DR among them have fostered a great demand in automatic DR diagnosing systems. So far, a lot of achievements have been made and satisfactory results have been achieved in many sub problems like vessel segmentation, lesion detection. However, these results are obtained on datasets relatively small and are steps away from real world applications. For clinical application, systems that can give DR severity directly are more favourable and practical. However, current results for multi-class severity grading are still not good enough for clinical application. In this work, we investigated the automatic grading of DR using deep neural networks. We proposed a novel dataset that is moderate in size and annotated with a new labeling scheme that is more useful for clinical practice. We proposed a preprocessing pipeline to change fundus images into a uniform format. We used the Inception-V3 network and a proposed medication of it as our diagnostic models and evaluated the performance of them with several mainstream CNN models. The experimental results demonstrate the efficiency of the models in diagnosing DR. Visualization and analysis of the trained models provide insights into how the models make diagnoses using given fundus images and justify the diagnostic ability of the models from a different viewpoint. For clinical applications, the trained models are deployed on a cloud computing platform and provide pilot diagnostic services to several hospitals

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via the internet. The performance of the system in the clinical evaluation demonstrates the efficiency of this work.

In the future, data from more equipment's will be included, and a broader pilot study will be launched. The accumulated data will be further used to improve the accuracy of the models.

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