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Diabetic retinopathy detection using deep learning based neural network along with machine learning algorithms

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***Abstract*---**Diabetic retinopathy (DA) is an eye disease caused by retinal damage as a result of long-term diabetes mellitus. Microaneurysms (MA)are an indicator of DA and are small red spots formed on the retina caused by the ballooning of a weak blood artery.The DA is mainly classified between Proliferate diabetic retinopathy (PDR) and Non-proliferative diabetic retinopathy (NPDR). Non-proliferative is an earlier stage of DA. In our study we will classify the images into 5 stages based on their severity of DA taken from a dataset. The existing modelshave usedLogistic Regression (LR), Support Vector Machine (SVM), gradient boosting techniques such as XGBoost and Logistic Regression with Elastic-Net penalty (LR-EN), to classify wavelet features among the groups. In our project study we used theDeeplearning-based algorithmFast R-CNN (Region Convolutional Neural Network) to build the model and tested its accuracy in training as well as testing the same model with other Machine learning techniques like Decision Tree, k-nearest neighbors

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(k-NN) classifier, GaussianNaïve Bayes, Kernel-SVM. Our project study shows that Decision Tree had the best training accuracy with 99.31% whereas in case ofthe best predicted testing accuracy it is k-Nearest Neighbors (k-NN) Classifier with 71.29%.

***Keywords*---**diabetic retinopathy, neural network, machine learning algorithms.

Introduction

In 2021, the International Diabetes Federation (IDF) predicted that roughly 537 million persons aged 20 to 79 years old will have diabetes. The entire population of diabetes is anticipated to reach 643 million by 2030, and 783 million by 2045. Nearly half of the persons with diabetes are undiagnosed, and three-quarters of them reside in low- and middle-income nations. Diabetes puts everyone at danger of losing their vision.Diabetic retinopathy can be diagnosed and treated early to avoid vision loss and blindness. In case of working-age adults among the ages of 20 to 65DA appears to be the common cause of visual loss. Diabetic retinopathy affects one of out of every three people with diabetes, and one out of every ten will acquire a vison-threatening type of the illness.The retina or the back of the eye, which is a light-sensitive layer of cells gets affected due to the presence of high blood sugar in the blood vessels of the tissues thereby causing Diabetic retinopathy. The damaged blood vessels may appear leaky and bulged causing poor vision or causing the blockade of the flow of blood.It can result in visual loss and blind patches. From one day to the next, or even from sunrise to evening, your vision may alter. Many, if not all, daily activities can be hampered by this "fluctuating vision."Diabetic retinopathy (DA) is a degenerative eye disease that is categorised into Non-proliferative Diabetic retinopathy (NPDA) and Proliferative Diabetic retinopathy (PDA). Non-proliferative refers to the disease's early stages, whereas proliferative refers to the disease's mature phases, which are Mild, Moderate, Severe, and Proliferate.The goal of this research is to employ convolutional neural networks(Fast R-CNN) to build a robust model in predicting the disease more accurately and faster than beforefor that we are using a dataset which consists of the DA infected eye by their severity by analysing the retinal colour fundus images.The outcome of our project in performing with several Machine learning techniques like Kernel-SVM, Gaussian Naïve bayes, k-NN classifier, Decision tree and comparing their accuracy in detecting the DA as resultshelps the doctors by providing insights while diagnosing a diabetic retinopathy infected eye.

Literature Survey

Zhiping Liu et al [1]has proposed to differentiate between DR and healthy controls by analysing the OCTA images with the use of algorithms like Logistic Regression (LR), Support Vector Machine (SVM), gradient boosting techniques such as XGBoost and Logistic Regression with Elastic-Net penalty (LR-EN) models to classify wavelet features. They evaluated the classifiers' sensitivity, specificity, and diagnostic accuracy. They looked at 114 OCTA pictures from DA and 132 from HC. They obtained the results such that the LR-EN and LR classification algorithms' sensitivity, specificity, and diagnostic accuracyachieved maximum values, However, they acknowledge that their sample size is small, and that they did not use retinal images in their study, and that they left out components suchas hard and soft exudations, haemorrhages andmicroaneurysm while performing their experiment. Furthermore, eyes with severe and moderate DR were not included.

LifengQiao et al[2]has employed deep learning-based CNN techniques that includes accelerating the GPU by performing a medical image recognition and a high performance and low-latency inference of segmentation to detect the existence of microaneurysm in fundus images. The fundus image is classified as normal or diseased using the semantic segmentation technique, for the identification of microaneurysm features semantic segmentation is used in splitting the pixels of images based on their same connotation. This gives an automated technique to help ophthalmologists by analysing the grade fundus images earlier for severity of DA, however the feature space can explode with high cardinality

Xiaomeng Li et al [3] has employed CANet to jointly assess DR and DME using only image-level supervision to investigate the intrinsic link between the disorders. It's an attention module that gives important aspects on both individual disease and two diseases and also the inter relations between them. They then use a deep network to combine these two attention modules as well as to achieve higher overall performance for grading both of them, however this study has to be looked into further.Cam-Hao Hua et al [4] proposes a deep learning-based technique that uses fundus pictures paired with SS-OCTA in evaluating DR severity recognition performance. They have proposed a TFA-Net architecture linked with a neural network. Their model achieved a 90.2% Kappa rate on KHUMC dataset. The single-modal Messidor dataset is used to assess the resilience of the RCA stream; 94.8% achieved as mean accuracy indicating a high performance, but inaccuracy leads to systems that under or overperform.M. A. Zahranet al [5] has proposed an early detection of DR by using OCTA images for diagnosing earlier stage of DA with SVM technique in improving the accuracy, they achieved 98.5% accuracy on their model; however, it couldn't control complicated systems' behavior patterns.I. P. Okuwobi et al [6] has proposed in SD-OCT with Diabetic Retinopathy, an automated measurement of Hyperreflective Foci to be studied. The advancement of retinal disease is linked to the appearance of HFs, for this they studied 40 individuals with different severities of DA using 3D SD-OCT (DME). They achieved dice similarity coefficient as 69.70% ,70.31% ,71.30% and correlation coefficient as 0.99,0.99,0.99 for NPDR, PDR and DME.

Francisco Nunes et al [7] proposed EyeFundusScopeNEO which can be used as an alternative to existing pupil dilation by users with little training and it is a hand held device for screening the patients. Studies suppot that the device appears to be fine when after a few training period the users can take quick capture of images.Yuanyuan Peng et al [8] presents a 5-level ROP staging network based on deep neural networks. The feature extractor is proposed as a three-stream parallel framework that can produce rich and various high-level features. Second, concatenation and convolution are utilized to deeply merge the features from three streams and to the end a classification step which can significantly increase the ROP staging performance. Even though they got the desired result, they had a lot of calculations to do while training the model.A. Umamageswari et al [9] proposed an efficient method for retinal vascular disorder analysis by recognising exudates and vessels in retinal pictures. They employed classification algorithm and CNN on Region of Interest to compare their test findings to existing methods for early disease detection. Pre-processing, Gaussian blurring, Bilateral Filtering, Image Blurring, and grey conversion techniques have all been used. When compared to existing systems, they were able to attain greater accuracy, specificity, and sensitivity.Yi Zhou et al [10] has used a dataset to examine 2,842 images with 1000 being labelled by ophthalmologists and the rest having DR annotations. They have three tasks to evaluate that is by grading them together for classification and segmentation, lesion segmentation and transfer learning. They discovered that joint classification and segmentation methods performed better on the DR grading job, despite the fact that their method is time-consuming.

Juan Wang et al [11] proposes to diagnose DR severity and their features by developing using the deep learning model. The suggested technique was evaluated on two independent testing sets in the experiments for kappa coefficient. When detecting DR severity levels, it performs better than general ophthalmologists of certain years of experience but it is not an easy-to-use method.De-Kuang Hwang et al [12] has proposed to deploy a software that can provide medical care using electronic interface. To accomplish the diagnosis, they employed a dataset labelled with OCTA pictures of 35,900 individuals with AMD and trained on three types of CNN. They were able to obtain picture discrimination that was comparable to that of a retina specialist. More than 90% of the time, the AI system was correct.MenglinGuo et al [13] has presented an additional brightness and contrast forms based on deep learning using sFAZ images of OCTA. They employed OCTA photos from 45 subjects that were manually segmented. When compared to ground truth (GT), they were able to attain DSC of 0.976 with an error of 0.011. It also outperformed sFAZ segmentation in terms of brightness and contrast.

Elaheh Imani et al [14] has proposed a system for automatic screening of DA and also a quality assessment of retina. It uses the Morphological Component Analysis (MCA) technique for distinguishing the normal and infected retinal components. On the Messidor dataset, their system achieved a sensitivity rate of 92.01 percent and a specificity rate of 95.45 percent after they employed pre-screening methods to measure image quality.Sheikh Muhammad Saiful Islam et al [15] developed a unique CNN for early diagnosis by recognising microaneurysms, which are the initial indicator of DR, and classified them into five levels of DA severity. They used a Kaggle dataset and got a score of 0.851 and 0.844 on kappa measure and AUC measure respectively which is the best on severity grading. They attained a sensitivity of 98 percent and a specificity of over 94 percent in the early stages.Jonathan Krause et al [16] has proposed employing individual graders to quantify diabetic retinopathy (DR) errors and to build a better automated grading system. Retinal fundus pictures were obtained using screening programmes for DR. They compared performance on manual grading and different DR severity cutoffs by measuring the kappa score between graders.

System Architecture & Proposed Methodology

In the Dataset we are separating the images for testing and training in 25% to 75% ratio, before training the data the images are converted to numpy array and iterated over them until all images are trained, we then constructed a Fast-RCNN Algorithm baseddeep neural network using sequential model from keras to predict the testing and training accuracy based on this model we apply other Machine Learning algorithms for classification and using the better predicted model will lead to a better detection of DA.

Architecture Diagram

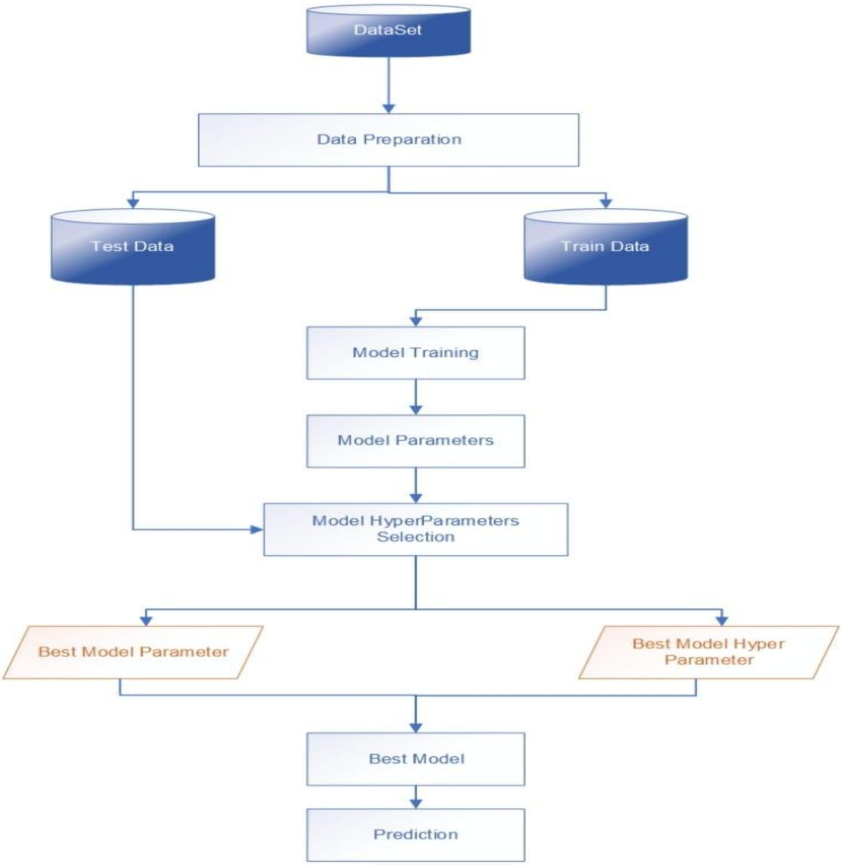

Fig 1: System Architecture diagram

Module Explanation

- Dataset
  We obtained our dataset from the Kaggle website, which has a lot of useful datasets and is particularly popular for machine learning and deep learning research.The photographs show a gaussian filtered retina scan done with fundus photography to diagnose diabetic retinopathy. There are 3662 images in the.PNG format, each of which is 224x224 pixels in size and has

been shrunk to 150x150 pixels to allow them to be easily conducted on numerous pre-trained deep learning models. The photos are divided into two categories: testing and training, with 25% for testing and 75% for training.The dataset has an export.pkl file which is a ResNet34 model trained on the dataset for 20 epochs using the FastAI library. Using the train.csv file, all of the images have already been saved into their relevant folders based on the severity/stage of diabetic retinopathy. There are five categories present in the dataset which will have the imagesin the corresponding labels:0- No_DR, 1- Mild, 2- Moderate, 3- Severe, 4- Proliferate_DR.

- Execution Environment
  This project was executed on a Jupyter-Notebook based editor and Python programming language for writing the codes.
- Libraries
  Several Machine learning, Deep learning libraries and libraries involved in python environment for numerical, mathematical, graphical and manipulation techniques were used such as Tensorflow, Keras, Sklearn, Imutils, CV2, Seaborn, Numpy, Pandas, Scikitplot, Matplotlib etc.
- Algorithms Used

  a) FastRegion Convolutional Neural Network (Fast R-CNN)algorithmis an object detectorwhich solves a number of R-CNN problems. It has been trained from end to end on a single stage model whichis able to generate the region proposals with the help of novel region proposal network, which saves time over classic methods like Selective Search, rather than doing calculations for each proposal separately it shares computation calculations across all the proposals which it achieves by having a new Region of Interest pooling layer which is a main advantage over R-CNN.
  b) Linear Kernel SVMas a technique that is used when our data can be linearly separable which means a single line is used for separating the data. This technique is mainly preferred when the dataset contains many large numbers of features.
  c) Decision Treealgorithm is applicableto solve classification and regression type of problems. The idea behind this algorithm is by constructing a model which learns simple decision-based rules from the properties of data thereby allowing us in predicting the value for a target variable. It is simple to comprehend and implement. The classifier can do multi-class classification on the dataset.
  d) k-NN classifieris technique that stores the available data to classify a new data point which is based on the similarity with the existing data, thus it helps in getting the new data into a defined category which can be sorted quickly.This technique is appliedin solving both regression as well asclassification-based problemand is widelypreferred for classification-based problems.
  e) Gaussiannaive bayes classifieris used when the predictor values are continuous and are predicted to follow a Gaussian distribution. It is a type of Naïve bayes and is a classification technique.

- Data Visualization

We need to explore how the data is present in dataset and how it is categorised. To this we need to obtain the number of images in each category of DA as well as the different retinal fundus image.To this we plot a graph as shown in Fig 2 and we can see random retinal images as shown in Fig 3.

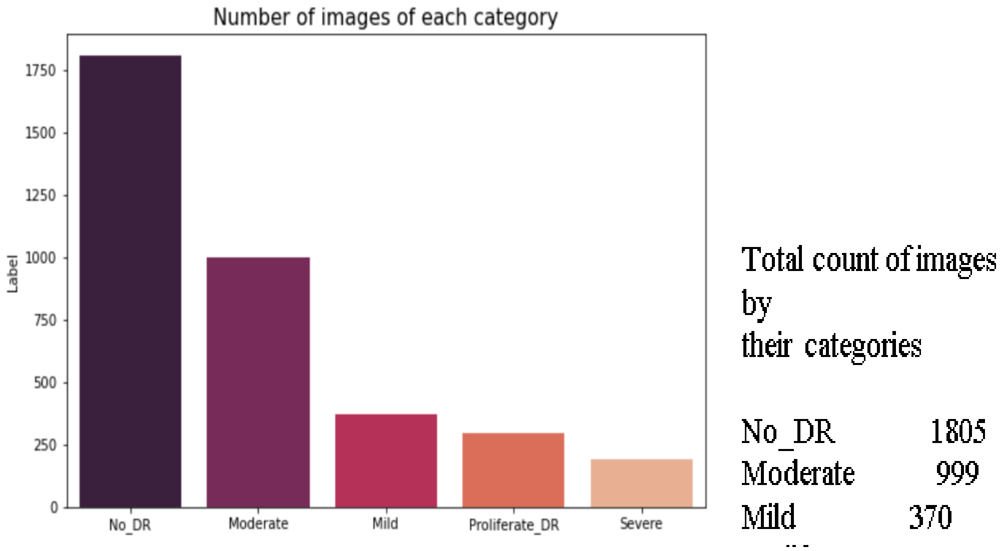

Fig 2: No of images in each category

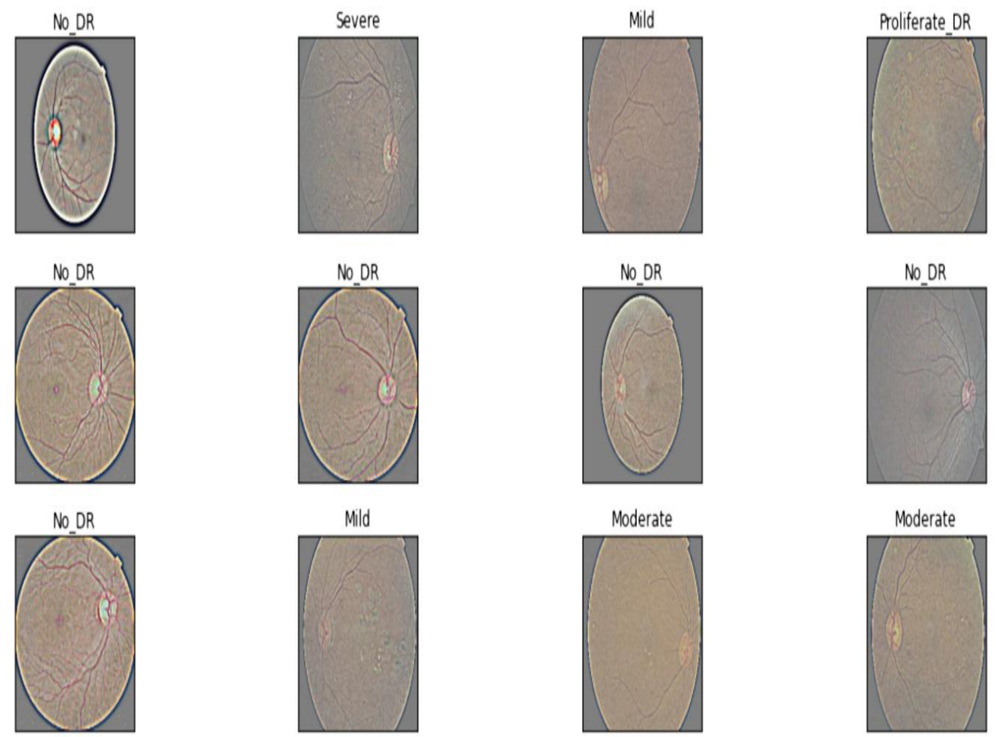

Fig 3: Severity of Diabetic Retinopathy in randomly displayed images in Dataset

- Training of RCNN - The Fast R-CNN is a deep learning technique designed in Sequential model and the neural network consists of 4 hidden layers and several functions like Relu, Sigmoid, Flatten, Dense, Adam optimizer, Maxpooling and Batch Normalization were used to design. The model is then displayed with its parameters and now the training of this model is done as peraccuracy level and then its testing and training accuracy were displayed.
- Comparing On Other Machine Learning Techniques - The Deep learning trained RCNN model is now applied with Machine Learning techniques like Linear-KernelSVM, Decision Tree,k-nearest neighbors (k-NN) classifier, Gaussian Naïve bayes, and their test and training accuracy are displayed for better analysis and comparison on various techniques for better prediction of DA.

Experimental Results

The images are divided into 25 percent for testing and 75 percent for training, resulting in 2746 images to be trained and 916 images to be testedin dataset. The Fast RCNN was designed in sequential model to be trained with various other techniques. The Deep learning based neural network while training for sufficient number of times (in our case no of epochs = 5)in getting the desired accuracy of the model.The neural network is also displayed with its parameters and 4 hidden layers that were designed as shown in Fig 4. The Training accuracy along with testing accuracy of this model is displayed and a graph is also plotted for the training loss/accuracy of this model as shown in Fig 5.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 148, 148, 16)	448
max_pooling2d_5 (MaxPooling 2D)	(None, 74, 74, 16)	0
conv2d_6 (Conv2D)	(None, 72, 72, 32)	4640
max_pooling2d_6 (MaxPooling 2D)	(None, 36, 36, 32)	0
conv2d_7 (Conv2D)	(None, 34, 34, 64)	18496
max_pooling2d_7 (MaxPooling 2D)	(None, 17, 17, 64)	0
conv2d_8 (Conv2D)	(None, 15, 15, 128)	73856
max_pooling2d_8 (MaxPooling 2D)	(None, 7, 7, 128)	0
conv2d_9 (Conv2D)	(None, 5, 5, 256)	295168
max_pooling2d_9 (MaxPooling 2D)	(None, 2, 2, 256)	0
batch_normalization_1 (BatchNormalization)	(None, 2, 2, 256)	1024
flatten_1 (Flatten)	(None, 1024)	0
dropout_1 (Dropout)	(None, 1024)	0
dense_2 (Dense)	(None, 1024)	1049600
dense_3 (Dense)	(None, 5)	5125

Total params: 1,448,357
Trainable params: 1,447,845
Non-trainable params: 512

Fig 4: Sequential Model of the designed neural network

```
model = create_rcnn_model()
model.summary()
```

Fast R-CNN Results: -

Training Accuracy Score:56.91915513474144

Testing Accuracy Score:54.69432314410481

Fig 5: Plotting the graph between Training Loss and Accuracy vs No of Epochs

Now after the Fast R-CNN model is predicted we have to test it on machine learning techniques that is discussed earlier. The results of all these techniques will be observed in a table and compared for analysing the best prediction model for detection of DA.

Table 1: Observing the Training and Test accuracies of different Techniques used

S.NO	TECHNIQUES USED	TRAINING ACCURACY %	TESTING ACCURACY %
1.	FAST R-CNN	56.92	54.69
2.	LINEAR KERNEL SVM	96.18	68.23
3.	DECISION TREE	99.31	65.50
4.	K-NEAREST NEIGHBORS (k-NN)	78.62	71.29
5.	GAUSSIAN NAÏVE BAYES	42.86	42.36

Conclusion and Future Works

After the successful execution of the project, we get a clear observation of different techniques based on their testing and training accuracy in Table 1. So, it can be inferred from the observation table that Decision Tree has the best training accuracy with 99.31% followed closely by Linear kernel SVM with 96.18% whereas the best predicted testing accuracy is K-Nearest Neighbors (k-NN) Classifier with 71.29% followed by Linear kernel SVM with 68.23%. Thus K-Nearest Neighbors (k-NN) Classifier has the bestpotential in detection of Diabetic Retinopathy from our observed model.In Future enhancements we propose a combinations of classification models like a multi stage which might be used to identify the extend of severity of the disease present in the eyes of an infected person. This study can be furtherextendedto other diseases such as identifying cancer cells from digital images etc.

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