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DIABETIC RETINOPATHY DETECTION USING DEEP LEARNING TECHNIQUES

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Abstract: The most common disorder affecting millions of people vision around the world is Diabetic Retinopathy(DR). As the population of diabetic patients is enormous early detection and diagnosis is necessary to maintain happy life.

Conventional diabetes detection method is tedious. The classification done by giving direct features are exploited. Using deep neural networks either only binary classification is done or multi classification is done on very small dataset which can not be used for deployment of DR classification application.
This project proposes an approach to create a novel dataset which can be used to perform image classification using CNN model and diagnose retina images perfectly. Which will help millions of diabetic patients to diagnose in very less time and accurately and ophthalmologists can use this in there diagnosis.

Keywords - Convolution neural network, Diabetes, Diabetic retinopathy, Microaneurysms.

I.INTRODUCTION

1.1 Introduction

Diabetes is a condition in which the body is unable to metabolize glucose effectively, which causes higher level of glucose in the blood referred as hyperglycemia in medical terminology. Diabetes can't be cured but can be managed effectively. Increase in diabetes can lead to complications and can affect many parts of the body.

This project deals with detection of effect on vision due to Diabetes which is termed as Diabetic Retinopathy. The detection of this crucial impact of diabetes is done by applying one of the deep learning techniques.

Convolution neural networks (CNNs) has demonstrated its superiority in image classification tasks. It has been proven that traditional method of DR detection is time consuming and not effective compared to CNN.

In this project, we have used retinal fungus images as a measure caused by DR, we employ CNN on images to develop a method to detect the stage and possible treatment by scanning the retinal images of patients.

1.2 Problem statement

DR is one of the leading cause of blindness. Early detection of DR, would help the affected for early diagnosis and treatment. This will not eradicate the impact of DR on vision, but slows down its impact.

The population of diabetic patients is enormous and experienced ophthalmologists are rare and distributed unevenly, indicating an urgent need for systems that diagnose DR automatically.

1.3 Existing system

During the study of DR classification we found that the research done to classify DR by giving direct features are already exploited, crafting new effective features by hand is more difficult. Deep neural networks demonstrated superiority in mage classification, but only binary (Yes/No) classification is done using large number of images. The research today for multi class is done on smaller data set which lack persuasion for real world applications.

So there is a need for a complete automatic multi class DR diagnosis with larger data set.

1.4 Proposed solution

Objective of this project is to create a larger dataset which is segregated by labelling each image with proper DR stages and create a model that takes large labelled dataset of retinal images and outputs diagnosis of DR depending on stage efficiently.

Table 1.1: Classes of DR table

Category	Class Name
0	No DR
1	Mild DR
2	Moderate DR
3	Severe DR
4	Proliferative DR

II VIEW ON CONVOLUTION NEURAL NETWORKSNTRODUCTION

2.1 Convolution Neural Network

Modern Neural networks are non-linear statistical data modeling tools used to model complex relationship between input and output to find patterns in data .The goal is to solve problem in the same way as human brain would.

CNNs are special type of Neural Networks made up of neurons that have learnable weights and biases specially used to solve image related problems. The 3 types of layers that constitute CNN are

- convolution layers
- pooling layers
- fully connected layers(FC).

In addition to this Activation Functions and Flattening also plays important role.

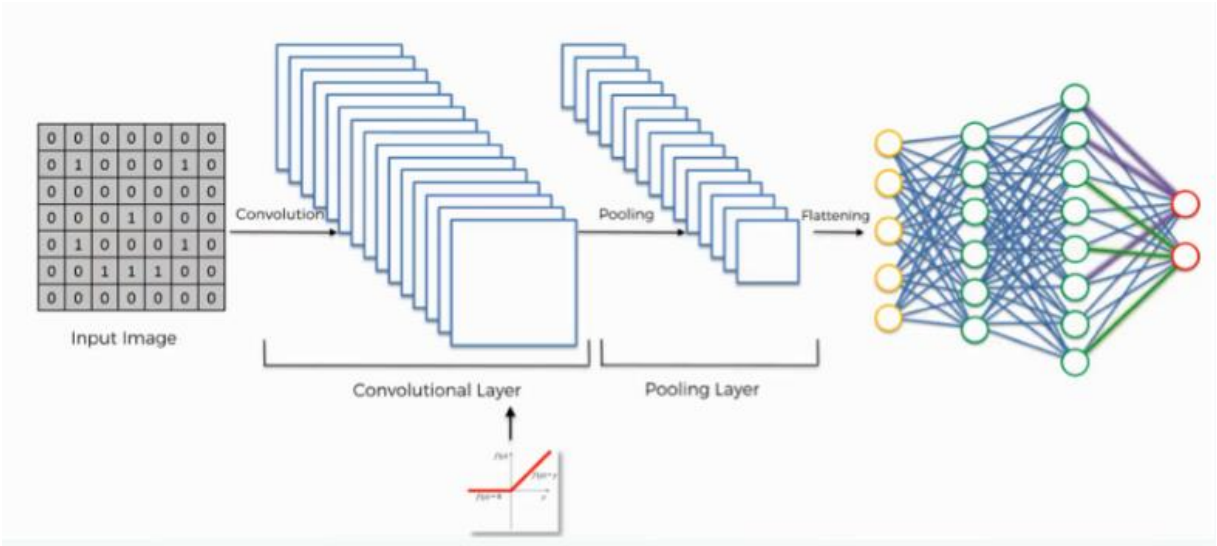


Fig. 1 Steps of CNN

2.1.1 Image channels

This step is to make image capable with the CNN algorithm by representing the mage in a numerical format, each pixel in the image is mapped to a number from 0 to 255 based upon the RGB intensity of the pixel. The image is represented as a 3D array with each channel representing red green and blue values respectively.

2.1.2 Convolution Layer

In this step key features are identified within the image. This is extracted using a method known as convolution, a filter is an array that represents the feature to be extracted, filter is stride over the input array, and output array is feature map. The resulting image contains just edges present in the original input.

2.1.3 Pooling Layer

To further reduce the size of the feature map generated as a result of convolution, apply pooling focusing on each feature map separately and minimizing the interaction between the layers. The pooling layer usually acts as a link between the convolution layer and the FC layer, a process of summarizing the features within a group of cells in the feature map by using Pooling operations. There are several types of Pooling operations depending on the method used.

- Max Pooling: In Max Pooling, the largest element from the feature map is selected.
- Average Pooling: Average Pooling is calculated by taking the average of the elements within a predefined image section.

2.1.4 Flattening

In this step pooled feature map is converted into a column to make it compatible with an Artificial Neural Network (ANN) as ANN needs inputs in the form of Vector.

2.1.5 Fully Connected Layer

The Fully Connected (FC) layer consists of the weights, biases, neurons, and is used to link neurons between two different layers. The output layer is usually placed after these layers, which constitute the final few layers of a CNN architecture. Input images from previous layers are flattened before being fed to

the FC layer. After flattening the vector, it passes through a few more FC layers where mathematical functions are applied. A classification process will be carried out at this stage.

2.1.6 Activation Function

Activation function decides whether neuron should be active or not using simple mathematical operation. The primary role of the this function is to transform the summed weighted input from the node into an output value to be fed to the next hidden layer or as an output and adding nonlinearity to a network. ReLU, Softmax, tanH and Sigmoid are some of the most commonly used activation functions.

III. LITERATURE SURVEY

Literature survey is mainly conducted to summarise related works on datasets, type of features extracted and to find research gaps in the existing system that need to be addressed. This adds as a major input to develop a better solution.

In paper[1] Swapna G,et al.[2]has implemented binary classification of DR using Deep learning algorithms. The author has presented a methodology using heart rate variability (HRV) signals. In this work long short-term memory (LSTM), CNN and its combinations are used to extract complex temprol dynamic features of the input HRV data. These features are passed into support vector machine (SVM). This cites it has achieved a high accuracy value of 95.7% employing CNN 5-LSTM architecture with SVM using 5-fold cross-validation.

The ECG of 20 people each from the diabetes and normal group were collected for 10 min.71 datasets each were extracted from the recorded data. Each dataset contains 1000 number of samples.

Further improvement in accuracy can be obtained using a very large sized input dataset.

In paper [2] J.R Dinesh Kumar,et al.[1] has implemented work on DR detection using Electrooculogram (EOG), system is constructed based on CNN to classify DR in to non proliferative DR(NPDR), proliferative DR(PDR)& Normal Retina (NR).The proposed model ensures minimum accuracy of 93% .

In paper[3] Dinal Utami Nurul,et al.[2] has developed a model using large pre-trained transfer learning models like Alexnet, VGGnet, InceptionNet, GoogleNet, Densenet on millions of natural images, the feature vector obtained from CNN is used for classification using SVM as normal and severe NPDR.

They have tested using 77 and 70 retinal images from Messidor dataset of base 12 and 13 and got minimum of 95% accuracy.

They have concluded that using a combination of feature extraction from CNN transfer learning and SVM can provide good result, the training process can be expanded for a bigger amount of data and classes.

In paper[4] Zhentao Gao,et al.[2] have built new dataset of DR fungus images and labelled them by proper treatment method. Trained this dataset with CNN by using Inception-V3 network and proposed modification to it. The authors are able to achieve an accuracy of 88.72% for four degree classification and deployed the models on cloud computing platform and provided pilot DR diagnosis services to few hospitals .

The results are obtained on small datasets which is not enough for clinical applications and data from more equipments have to be included and broader pilot study have to be launched in band accumulated data have to be further used to improve the accuracy of the models.

In paper[5] Wanghu Chen,et al.[2] have implemented shallow CNN based approaches to detect DR. When there are not enough high-quality labelled samples available, with such a measure, they made the model simpler and reduced the computation cost and over fitting.

In this model they focused on the scenario of lacking high-quality labelled training samples, explored shallow neural networks can also get good performance on the classification of medical images, even if labelled dataset is not so big, by combining multi-scale shallow CNNs with performance integration is introduced to the early detection of Diabetic Retinopathy through the classification of retinal images.

More effective approach to integrating shallow CNNs has to be explored to further improve the classification accuracy. The transformation of image samples and the repeatable sampling of the dataset have to be combined to improve the performance of integrated shallow CNN model.

IV. PROPOSED ARCHITECTURE

It describes the different components of the system and outlines the various products as well as advanced systems that will make the whole thing work. When the query image is given as an input to the CNN model, the features of that image will be extracted and compared with the global features of the images that are present in the global feature database.

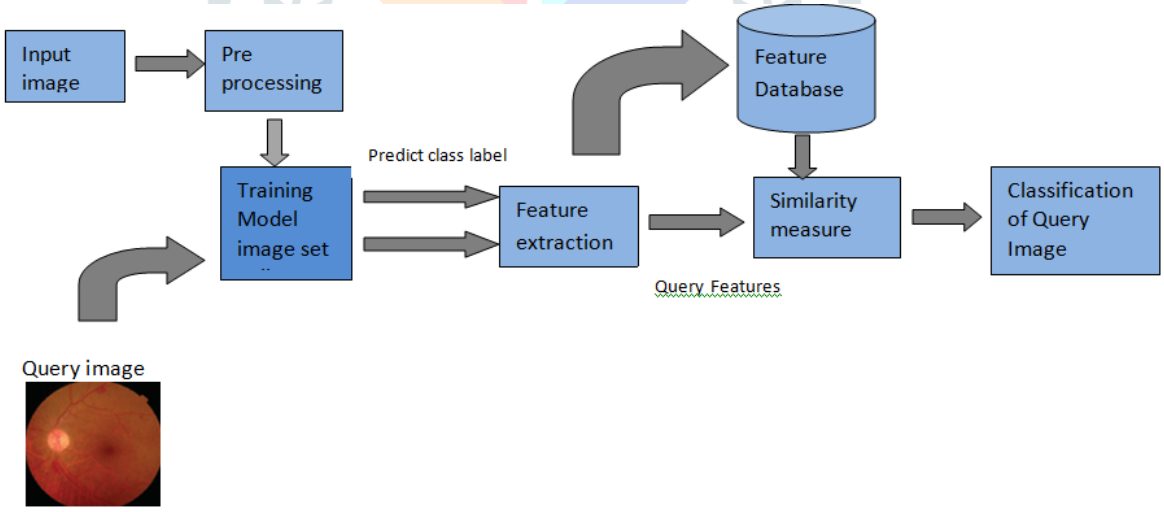


Fig 2. System Architecture of DR Detection

4.1. Dataset Construction

We have constructed a novel dataset of fungus images by creating the folders of each label and moving images from missed images of Kaggle using a read CSV file which contains name of the image followed by label number (0/1/2/3/4), our dataset is contains around 8000 test images.

4.2 Pre-processing

1. Resize different images into a uniform scale so that all fungus a read in all images have same diameter
2. Color Normalization, colors must be tunes because different devices may convert the color images into gray scale images
3. For medical image application to mitigate shortages in data and fully utilize the data that are available certain data augmentation techniques must be carried out, following techniques are used for augmentation
    a. Flip the image horizontally
    b. Flip the image vertically
    c. Randomly rotate the image
    d. Randomly zoom in or out.

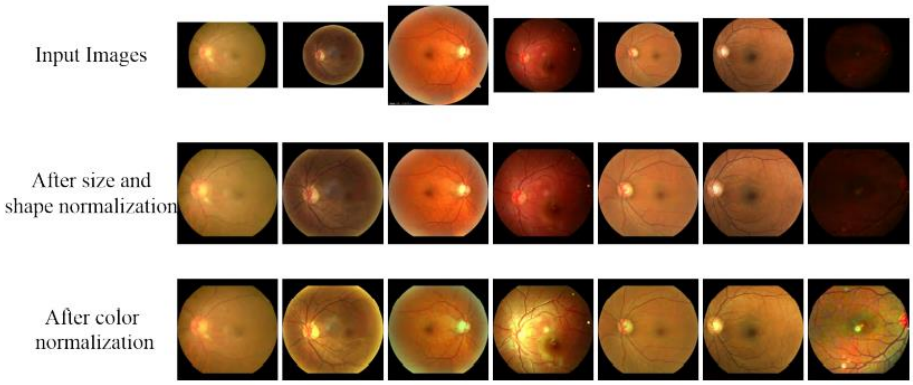


Fig. 3: Uploaded Input images

The above Figure 2 represents the input image which is chosen for DR detection

4.3. CNN model architecture

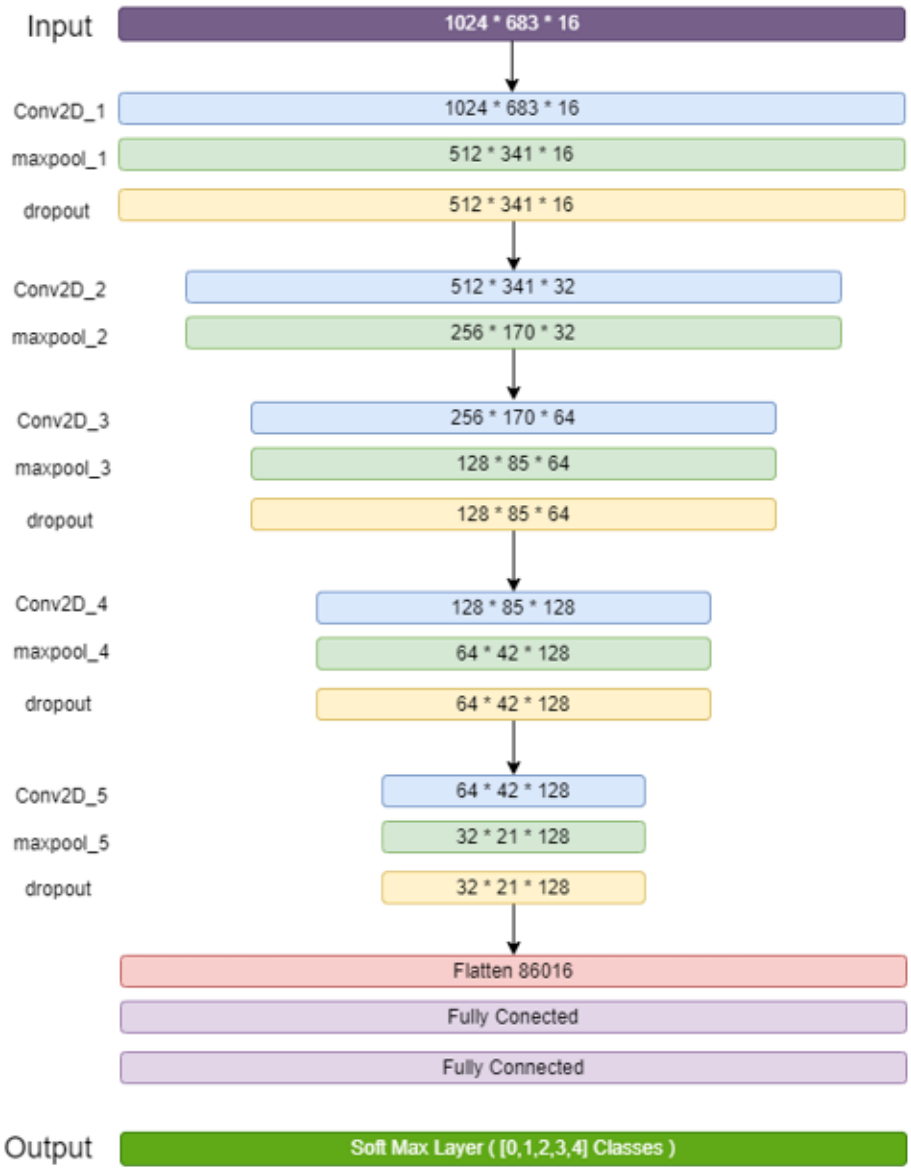


Fig 4 CNN Model Architecture

Fig 4 Shows the custom neural network designed to determine the class of DR. Image dataset of size 10k DR images with 80% training data and 20% testing data. Training on such large dataset can not be done on local system or laptop, so we used VM within Google Collab with a Nvidia TESLA T4 Tensor Core GPU with 16GB vRAM. Training was done on 20 and 50 epochs and the results are discussed below.

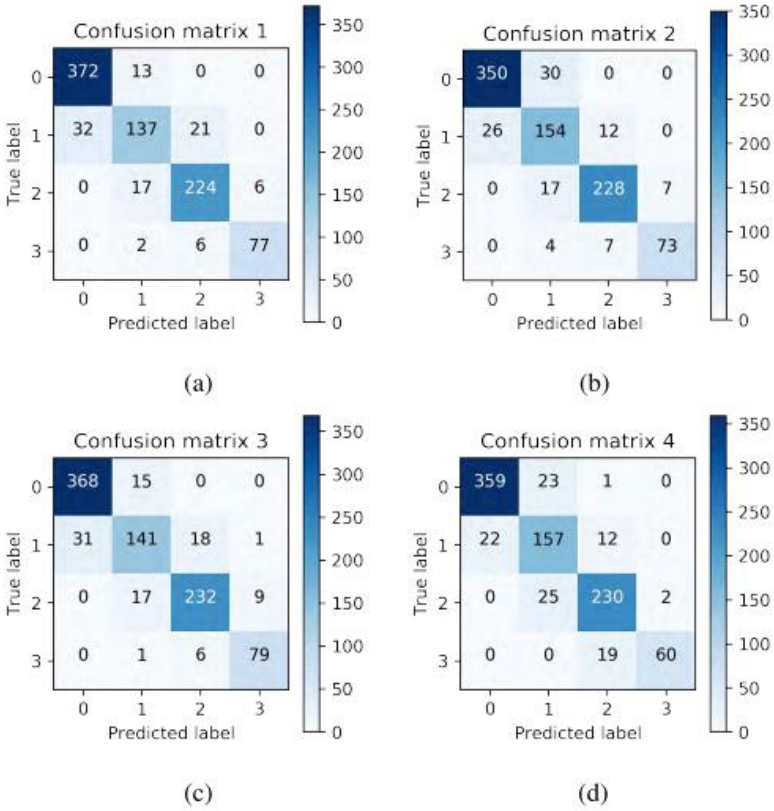
4.4. Training Dataset

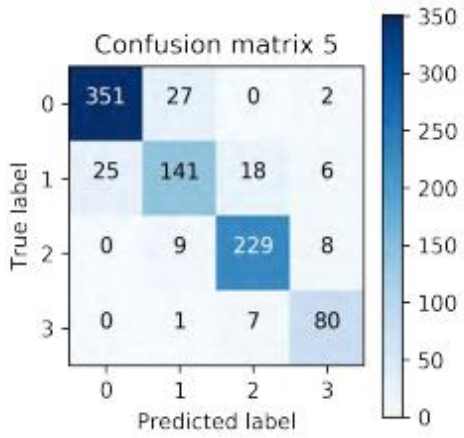
Dataset	Set	Normal	Moderate	Heavy	Severe	Total
Dataset 1	Training	1513	760	975	321	3569
	Test	385	190	247	85	907
Dataset 2	Training	1518	758	970	322	3568
	Test	380	192	252	84	908
Dataset 3	Training	1515	759	964	320	3558
	Test	383	191	258	86	918
Dataset 4	Training	1515	759	965	327	3566
	Test	383	191	257	79	910
Dataset 5	Training	1518	760	976	318	3572
	Test	380	190	246	88	904

Fig. 5: Testing/Training set Statistics

Fig. 5 Shows that We separated our data randomly into a training set and a test set at a ratio of 4:1; fungus images that are captured on each eye (one or two images per eye) are treated as a single sample. Random separation is carried out five times independently to prevent poor randomization. This results in five pairs of training and test sets. Because we separate the data by eye rather than image, the number of samples in each category varies slightly in different training/test set pairs. The statistics of each training/test set pair are listed in Fig 3

V. RESULTS AND DISCUSSION





(e)

Fig 6. The confusion matrix for each dataset shown in Fig 5

From the confusion matrices, we can see that most misclassification is between adjacent categories, indicating such images are hard to classify for the model because progression of DR is continuous.

VI. CONCLUSION

In our project we have a built a novel dataset of 10K images from a cumulative dataset of 88K mixed images. The images are segregated to the class to which it belongs, which is much needed for accurate detection of DR. This trained dataset uses CNN model to achieve an accuracy of 88%.

After pre-processing and augmenting the dataset to enhance prediction our project resulted in the following outcomes. This work solves the problem of unavailability of segregated cumulative dataset problem, needed to achieve 100% accuracy in DR detection by creating 3.5 million imges dataset

References

[1] https://www.sciencedirect.com/science/article/pii/S2405959518304624

[2] https://ieeexplore.ieee.org/document/9478121

[3] https://ieeexplore.ieee.org/document/8850940

[4] https://ieeexplore.ieee.org/document/8581492

[5] https://ieeexplore.ieee.org/abstract/document/9208666

[6] https://www.kaggle.com/pouryaayria/a-complete-ml-pipeline-tutorial-acu-86/notebook

[7] https://www.youtube.com/watch?v=YxQYvhap3kE

[8] https://www.hindawi.com/journals/jhe/2022/8100697/

[10]https://www.superdatascience.com/blogs/convolutional-neural-networks-cnn-summary/