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A Convolutional Neural Network Approach for Diabetic Retinopathy Classification

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***Abstract*— Diabetic Retinopathy (DR) is a kind of problem which affects diabetic patients, particularly those at their age of working, and can result in vision impairment and possibly irreversible blindness. For diagnosis and to prevent blindness or degeneration, early detection is critical. When ophthalmologists execute the diagnosis step of DR manually, it takes more time, effort, and money, and there are more possibility of misdiagnosis. The scientific community is focusing on developing a computer-aided recognition system for early identification and grading of DR severity. Ongoing AI research has highlighted the growth of the deep learning technique, which is better technique for doing medical image analysis and classification.**

Keywords*— Convolutional Neural Network, Deep Learning, Diabetic Retinopathy, IDRiD dataset

I. Introduction

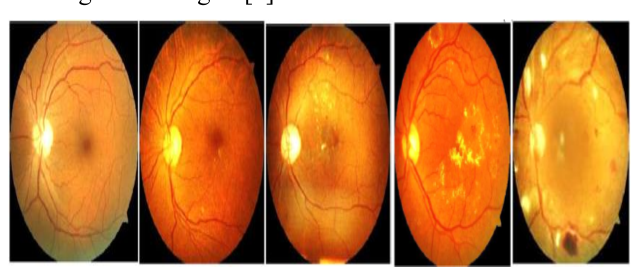
In the world of medicine, disease therapy is more feasible when diagnosed early. Diabetes develops when the body's glucose levels rise owing to a lack of insulin. The retina, kidneys, heart, and nerves are all affected by diabetes. According to a WHO report, diabetes impacted 423 million people globally in 2014, and the number expected to rise to 700 million by 2050.

Diabetic Retinopathy (DR) is a condition which affects diabetic patients, particularly those in their working years. DR is a complication of diabetes that causes the retina veins to enlarge and leakage of blood and liquids. The problem of vision is caused by DR. Patients with diabetes who have been suffering from the disease for a long time are more likely to develop DR. Patients should have their retinas screened on a regular basis for analysis and DR treatment in the early stages to reduce the risk of vision loss. The presence of several types of signs on a retina image distinguishes DR. Table 1 lists these symptoms as Haemorrhages (HM), Microaneurysms (MA), Soft exudates (EX) and Hard exudates (EX).

Early identification is critical for accurate diagnosis and the prevention of blindness or degeneration[1]. Diagnosis takes longer time and is more expensive when performed manually. Automated detection, on the other hand, makes the process simple[2]. This study investigated the Convolutional neural network for DR to overcome this issue and maximize the result. The main contributions of this work is to apply deep learning to improve DR classification results on a publically available dataset, as CNN uses less time and computation than classical machine learning[3].

- Haemorrhages (HM) shows up as huge mark on the retina and dimension range more than 125 μm with unpredictable edge. HM subdivided into two types namely blot (deeper HM) and flame (superficial HM).
- Hard exudates shows up as a bright yellow stain on the retina brought about by spillage of plasma.
- Soft exudates named as cotton wool also shows up like white markings on retina and it brought about having a round or oval shape due to irritation of the nerve fibre.
- Microaneurysms (MA), The first signs of DR appear as small red round specks on the retina. The length is less than 125m and there are sharp edges present.

No DR, mild DR, moderate DR, severe DR, and proliferative DR are the five stages of DR based on the occurrence, which are briefly listed in Table 1 and we put mild, moderate, severe and proliferative DR in one class and no DR in aother class for creating binary class. Figure 1 and 2 shows a retina image with certain anomalies and its grading into distinct stages. DR detection via automated approaches saves time and money, and it is more accurate than manual analysis. When performed manually, the risk of misdiagnosis is higher[4].



(i) (ii) (iii) (iv) (v)

Fig. 1. Retina images with grading levels (i) normal, (ii) mild, (iii) moderate, (iv) severe and (v) proliferative DR

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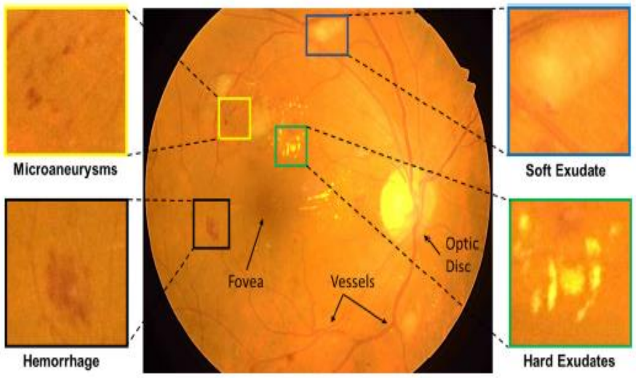


Fig. 2. Normal retinal image and DR related anomalies

Table 1
DR grading on the basis of severity and signs

DR severity grading	Signs
No DR	There are no anomalies
With DR	lesion ranging between MA and severe DR It may be any of them: • Intraretinal HM number for every 4 quadrants is more than 20. • Venous beeding in more than 2 quadrant. • More than one quadrant has a visible intraretinal microvascular problem • Pre-retinal or Vitreous HM

The following is how the paper is laid out: The second section introduces related literature. Section 3 exhibits the working model process in detail, Section 4 displays our dataset together with results, and Section 5 concludes the paper.

II. RELATED WORK

Early DR research relied on measurements of optic circle and veins manually, as well as the presence of flaws such as microaneurysms, haemorrhages soft exudates and hard exudates. Then, utilization of several machine learning approaches such as k-nearest neighbour and support vector machines (SVM), grading was done by hand built features (KNN). With the use of support vector machine and K-nearest neighbour classifier, Jaykumar et al. [5] proposed a procedure for microaneurysms detection and exudates from the retina. GLCM feature extraction is used for further classification after preprocessing. The SVM classifier outperforms the KNN classifier. Patton et al. [6] investigated and established standards for retinal imaging evaluation, as well as the approach for recognizing retinal marker and indications associated with DR. Jordon et al. [7] provides a brief introduction to quantifiable methodologies for reviewing fundus photographs, with a focus on identifying retinal symptoms and examine retinal illness using automatic algorithms.

Deep learning reduces the requirement for human intervention in feature engineering by immediately learning data depiction at a low level with high level parameters. Recep et al. [8] proposed a strategy on the basis of AlexNet, GoogleNet and CNN to improve the outcome of DR identification using mobile phone and traditional fundus camera retina photos. The result of emloying photos from diverse groups is examined by retraining these frameworks on datasets such as EyePACS, Messidor and IDRiD. On independent test datasets, these approaches exhibit great accuracy. Alyoubi et al. [9] revealed state-of-the-art solutions for DR colour fundus picture localization and categorization using deep learning process. Furthermore, the colour fundus retina DR datasets were examined. They also take on contrast testing difficulties that require greater investigation. Using a cross disease attention network, Xiameng et al. [10] described a new approach for rating DR and DME together. With only picture level inspection, it analyses the inner links between the diseases. They created two independent attention modules for disease dependent and disease specified aspects learning, then combined them for grading DR and DME to improve grading outcomes. For testing, they use the Messidor and IDRiD datasets.

III. PROPOSED METHODOLOGY

This part presents the organization of the used deep learning. Deep learning is a part of Artificial Intelligence that gets its inspiration from the human brain structure[11]. Different layers of hierarchy exist in DL, each of which includes indiscriminate processing steps for pattern classification and unsupervised feature learning. Segmentation, classification and image registration are just a few of the uses of DL in medical image analysis. DL performs features extraction from the system using training set photos to learn the structure. Although this learning ability eliminates the need for creating particular features, the strategy is based on comprehensive end-to-end DL training[12].

CNNs are more commonly employed for analysis in clinical image than other approaches, and are quite efficient.

Convolution layers, pooling layers, and fully connected (FC) layers are the three primary layers in the CNN architecture[13]. The CNN's number of layers, size, and filters are all determined by the vision of author. Every layer in the CNN architecture has a distinct function. Various filters performs convolution of an image in the CONV layers to extract the features[14]. To minimize the feature maps size, after CONV layer pooling layer is applied. Various pooling techniques are there but the most popular are average pooling and maximum pooling. FC layers are used to characterize the input image entirely. The frequently utilized classification function is the SoftMax activation function[15]. The model summary of CNN is illustrated in figure 3.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 148, 148, 64)      1792

 conv2d_1 (Conv2D)           (None, 146, 146, 64)      36928

 max_pooling2d (MaxPooling2D  (None, 48, 48, 64)       0
 )

 conv2d_2 (Conv2D)           (None, 46, 46, 64)        36928

 conv2d_3 (Conv2D)           (None, 44, 44, 64)        36928

 max_pooling2d_1 (MaxPooling  (None, 14, 14, 64)       0
 2D)

 max_pooling2d_2 (MaxPooling  (None, 7, 7, 64)         0
 2D)

 flatten (Flatten)           (None, 3136)              0

 dense (Dense)               (None, 160)               501920

 dense_1 (Dense)             (None, 500)               80500

 dropout (Dropout)           (None, 500)               0

 dense_2 (Dense)             (None, 2)                 1002

=================================================================
Total params: 695,998
Trainable params: 695,998
Non-trainable params: 0
_________________________________________________________________
```

Fig 3. CNN model summary

In general, dataset collection and the necessary pre-processing to enhance and upgrade the images is the prior step in the process of detection and classification of DR using DL. Then, DL technique is applied, which performs feature extraction and classification of the images as shown in figure 3.

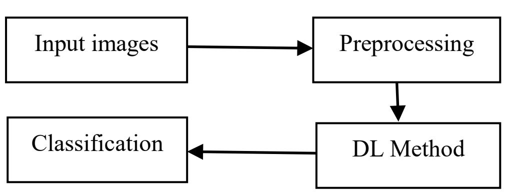


Fig 4. Classification of DR using DL method

IV. EXPERIMENTAL RESULT

Using the IDRiD dataset, we compare and evaluate the model's performance in this section.

A. Dataset

The IDRiD dataset was created using real clinical data from an eye hospital in Maharashtra (Nanded), India. The whole dataset contains 516 photos with different DR classes which we have taken as binary class[16]. DR is graded into classes based on disease severity and here taken as one without DR and other with DR. There are 413 photos for training and 103 images for testing. Table 2 shows the statistics labelling inside the IDRiD dataset. The IDRiD dataset is related with three types of ground truth, which are listed below:

- *Annotation at the pixel size*- This type of notation is used to locate specific lesions within a photograph, as well as to split and pinpoint region of interest in data. A total of eighty one colour fundus pictures with DR signs and 164 with no sign of DR are included in the dataset. Color fundus images are available in the format of .jpg, with binary masks for each lesion type in .tif format, as well as a specific optic disc mask (OD) for entire eighty one colour fundus images[17]. These annotations are significant in study because they allow researchers to examine how lesion segmentation is computed inside an image.
- *Diseases Grading of DR*- It consists of data that indicates the risk factor associated with the entire image. The 516 pictures with varying pathological stages of DR and DME were rated by a clinical specialist. The CSV record allows to grade all photos on a DR severity level. By retaining the desired ratio of disease stratification, the train and test data consists of 413 and 103 photos, respectively.
- *Optic disc and Fovea centre co-ordinates*- For the entire 516 image data, the fovea centre and OD co-ordinates are stated, and is presented as a CSV record

B. Evaluation Metric

There are various performance standard measurements for assessing Deep Learning algorithms categorization performance. The area under the curve (AUC), sensitivity, accuracy and specificity are the most commonly used standard measurements[18]. The number of correctly categorized photos, expressed as a percentage, is used to determine accuracy. Specificity is the percentage of normal images that are classified as normal, whereas sensitivity indicates the percentage of abnormal images which are labelled as aberrant by the classifier[19]. AUC is a graph that shows the relationship between specificity and sensitivity.

$$Accuracy = \frac{TN + TP}{TP + FP + FN + TN} \tag{1}$$

$$Sensitivity = \frac{TP}{FN + TP} \tag{2}$$

$$Specificity = \frac{TN}{FP + TN} \tag{3}$$

Where, TP stands for True Positive which means correctly classified diseased images. True Negative (TN) refers to occurrences of non-diseased images that are categorized as such. False Positive (FP) images are non-diseased images that are classified as sick, whereas False Negative (FN) images are diseased images that are classified as normal[20].

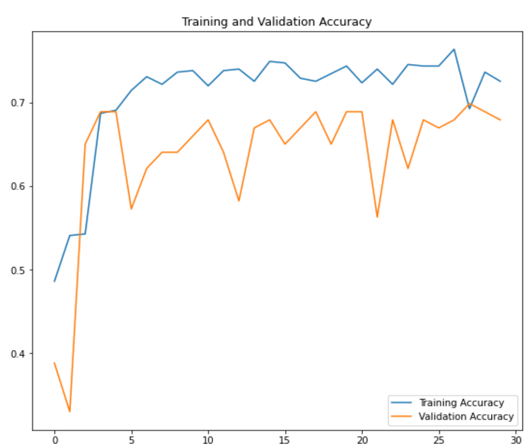
C. Result

CNN framework is employed for DR classification. The system is trained using the ADAM optimizer with a 1e-4 learning rate and a batch size of 10 for 30 epochs, a dropout layer with a dropout rate of 0.5 is applied after that sparse categorical loss is used as a loss function[21][22]. Accuracy of CNN model for DR classification is shown in Table 2. Here train accuracy is 73% and test accuracy is 68%.

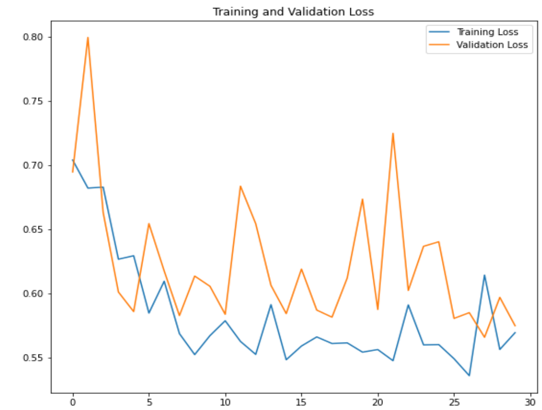
Table 2. Train and test accuracy for DR classification

Grading	Train Accuracy	Test Accuracy
DR	73%	68%

Accuracy and loss in training and validation of DR grading is given in Fig.5.



(a)



(b)

Fig 5. (a) Accuracy in training and validation (b) Loss in Training and validation

V. CONCLUSION

Deep learning is used for DR classification based on its binary grading to increase study in the medical domain, particularly for the diagnosis of diabetic retinopathy. Diabetic Retinopathy is a condition that affects diabetic patients, particularly those in their working years, and causes vision impairment and, in some cases, permanent blindness. For diagnosis and to prevent blindness or degeneration, early detection is critical. Ongoing AI research has highlighted the growth of the deep learning technique, which is the best technique for doing medical picture analysis and classification. And here, the CNN model classifies DR based on binary class on the public benchmark dataset IDRiD, achieving higher training and testing accuracy.

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