

Screening and Staging of Diabetic Retinopathy using Convolution Neural Networks

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Abstract: Retinopathy is one of diabetes' main microvascular complications. The manual examination might be time-consuming. Accordingly, the deep learning model for image classification is presented in this paper. The classification involves major complexities like augmentation, prediction, etc., The model is trained using the Res-Net 50 with the resized version of the DR dataset from Kaggle. This method classifies DR into 5 grades no DR, mild DR, moderate DR, severe DR, proliferative DR. These are classified based on the type of intricate features present (microaneurysms, hemorrhages, exudates, etc.,) The proposed model shows an accuracy score of 74 percent.

Keywords— Diabetic retinopathy, deep learning, convolution neural networks, exudates, aneurysm, hemorrhage, proliferative.

I. INTRODUCTION

Diabetes is a chronic condition characterized by insufficient insulin secretion from the pancreas. Another contributing factor to diabetes is the inefficiency of the body's use of insulin.[2] As diabetes progresses, it affects the circulatory system including the retina and occurs as a result of long-term accumulated damage to the vessels, declining the vision of the patient leading to diabetic retinopathy. [15] Between 2005 and 2030, diabetes deaths are predicted to double, according to the WHO. [2] The disease is also becoming the sixth most common cause of blindness among Indians who are of working age. In order to prevent the loss, a constant eye examination is recommended.

This requires the study of fundal images of the retina, which consists of intricate features like hemorrhages, exudates, aneurysms, etc., These features are used to characterize the DR (Diabetic Retinopathy) stages. PDR (Proliferative Diabetic Retinopathy) and NPDR (Non-Proliferative Diabetic Retinopathy) are the two most common types of DR. NPDR is known as background retinopathy and it consists of 3 stages (mild, moderate, severe. As a result of NPDR, the eye does not make new blood vessels during its early stages. As NPDR progresses, it can develop into a different type known as proliferative diabetic retinopathy (PDR). The retina begins to form new blood vessels at this stage of (PDR). In most cases, these vessels are abnormal and form in the retina's center. Manual

examination of these fundal images is time-consuming. A deep learning framework for early detection and grading of DR is presented in this paper. Deep learning is part of a broader family of machine learning methods. Deep learning is applied to many fields such as speech recognition, machine translation, bioinformatics, drug design, medical image analysis, material inspection, computer vision, and board game programs. Deep learning produced results comparable to those of human experts and, in some cases, exceeded them. CNN, is also known as a feed-forward neural network and is a type of deep neural network. CNN is known as the discriminative architecture, which is a simple level model that takes a single input and produces an output which is actually the discrimination of input.

In this paper, we are using the ResNet-50 model for DR staging. In general, As the number of layers increases, so does the accuracy, at the same time there occurs a vanishing gradient problem. Res-Net stands for a residual network, where blocks of convolutional layers are skipped by using shortcut connections [1] and are helpful in overcoming the vanish gradient problem. This model consists of 50 layers, which contain convolution, pooling, and dense layers.

II. LITERATURE REVIEW

In literature, [1] Doaa K Elswah et.al did the DR grading using 2 steps, the first step is to pre-process the fundus images using intensity normalization and augmentation, the second step involves using the pre-processed images as input Res-Net model is applied. This model achieved an accuracy of 86.67%. [2] K. Verma et.al performed the experiment considering the detection and quantification of blood vessels and hemorrhages for diabetic retinopathy classification. An analysis of the area and perimeter of lesions, along with density analysis and bounding box techniques, were performed to detect hemorrhages. This model achieved an accuracy score of 90% for normal cases and 87.5% for moderate and severe NPDR cases. [10] Yijin Huang et. al conducted experiments on the publicly available dataset Eye PACS. Using the ResNet-50 framework for DR assessment they demonstrated that it is sensitive to input resolution and that the mean square error function is a more efficient loss function. However, resampling the data to overcome the problem of

imbalanced data distribution in Eye PACS leads to poorer performance. This result was obtained by combining the investigated components and using no specialized network design to achieve the subtle result (0.8631 for Kappa) on the Eye PACS test set containing 42670 fundus images with only image-level annotations. [11] D. K. Kirange et.al developed a novel system that performs early-stage detection by identifying all microaneurysms. They tested the system on the largest publicly available IDrID diabetic retinopathy dataset and achieved 77.85% accuracy with Gabor features and Naïve Bayes Classification. [13] D. Doshi et.al conducted research on diabetic retinopathy regarding the automatic diagnosis of diabetic retinopathy in various stages. To achieve the model, he implemented a model of GPU accelerated deep convolution neural networks. The accuracy obtained on a quadratic weighted kappa metric is 0.386 and assembling three similar models resulted in an accuracy of 0.3996.

III. METHODOLOGY

As shown in Figure, the proposed framework consists of three pipelined stages: a pre-processing stage that applies intensity normalization, horizontal and vertical flipping augmentation, a feature extraction stage that utilizes a Res-Net 50 model, a prediction stage, and finally the output

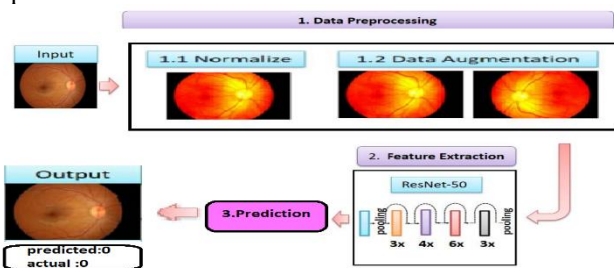


Fig. 1 Pipeline diagram of the proposed model

A. Collected Database

The data is collected from the resized version of diabetic retinopathy from Kaggle. This is composed of 35,216 fundus retinal images, with five class labels (i.e., level 0, level 1, level 2, level 3, level 4). Fig.2 shows two typical examples from the data for each class. Specifications of images are as follows: 224x224 pixel resolution and “jpeg” file format.

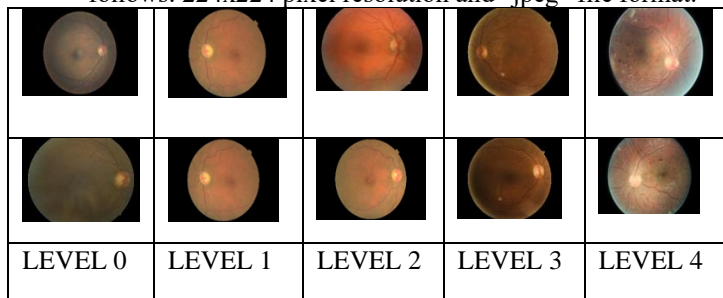


Fig.2 Fundus images from the dataset representing different levels

B. Image pre-processing

It is implemented in 2 steps; normalization and data augmentation. First, the images are resized, and then a Gaussian filter with sigmoid as activation function is used to detect the edges. These images

after edge detection are normalized and data augmented. The data augmentation step is performed to increase the training samples. Here, it is done by horizontal and vertical flipping the input images.

C. Deep Learning CNN Model

The proposed framework applies transfer learning using the pertained Res-Net50 [1] CNN model, consisting of 50 weighted layers. Res-Net50 has four stages, each stage consists of three convolutional layers (convolution, normalization, and activation) and is replicated n times. This feature can assist the Res-Net model to learn the data-specific global features. Hence, the intricate features present in the fundus images are identified and are used for the characterization of DR staging.

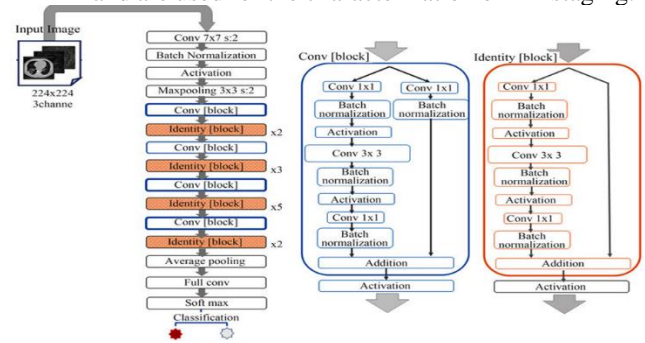


Fig. 3. Res-Net 50 Architecture

D. Prediction

Prediction of the level of the image is performed as the final step. The accuracy of the model is calculated.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Here, we will observe the result obtained for the proposed model and the analysis on them. The model is carried out in a google colab environment and the code is written in python language. The model is trained using the dataset from Kaggle with 35,126 samples. The epoch and batch sizes are initially set to 1 and 32. When the training samples are reduced it shows a decrease in accuracy.

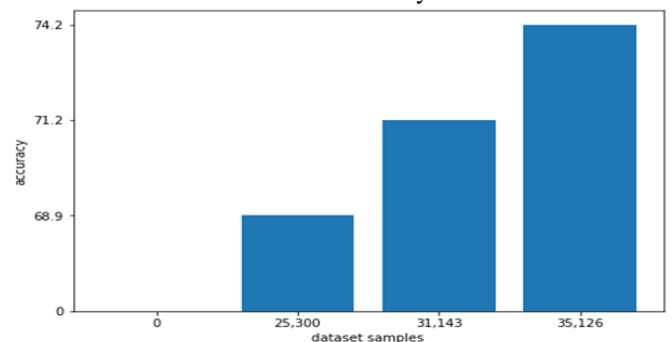


Fig.4 Accuracy Analysis

It can be seen from the figure that accuracy increases with an increase in the number of samples. The above result is taken when the batch size is 32, epoch value 10, and steps per epoch as 93.

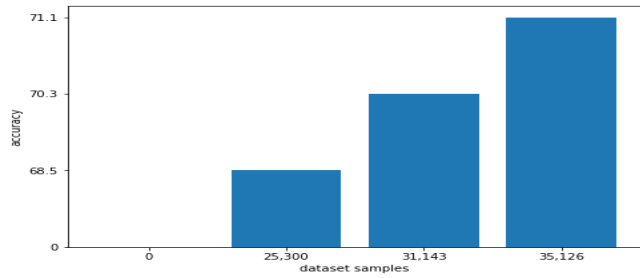


Fig 5. Accuracy Analysis part 2

The above result is considered when the batch size is 32, the epoch value is 2 and the steps per epoch is 500. So, in order to increase the accuracy, the parameters like batch size, epoch, and steps per epoch are varied accordingly. To verify this accuracy the model is trained with other pre-trained models and their accuracies were observed.

TABLE I COMPARISON OF DR STAGING ACCURACY

Model	Accuracy
Res-Net 50	74.2%
Alex Net	57%
E Net	66%

Below shown is the image of how the prediction result is displayed.

predicted: 0
actual: 0

Fig.6 Predicted output

V. CONCLUSION

This paper presents a three-stage framework for automated DR grading. The proposed framework is composed of preprocessing, feature extraction, and prediction. Experimental results show that having more samples can significantly improve the system’s performance. Whereas the training time increases. So, data augmentation needs to be performed only on the particular samples and hence this causes data balancing and achieves better accuracy. This better accuracy will result in better prediction of the images. Comparison results with other pre-trained models confirm the accuracy of the proposed framework for DR grading

VI. FUTURE SCOPE

In the future, we plan to investigate using other deep learning models and also look forward to working on data balancing to improve the performance and other databases to check the robustness of the proposed system [1].

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