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Deep Learning-Based Grading of Diabetic Retinopathy Using Semantic Segmentation

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***Abstract*: Diabetic Retinopathy is a medical condition in which damage occurs to the retina due to diabetes mellitus. The diagnosis of Diabetic Retinopathy through colored fundus images stand in need of experienced clinicians to identify the presence and significance of many small features, which makes it a time-consuming task. In this paper, we propose a Deep Learning approach to detect Diabetic Retinopathy in fundus images. Data used to train the neural network is preprocessed by a Semantic Segmentation technique which involves a different neural network architecture to impose dense predictions on the images for the purpose of blood vessel detection in the fundus images. A high-end Graphics Processor Unit (GPU) is used to train the model efficiently. The publicly available Kaggle Dataset is used to demonstrate impressive results, particularly for a high-level classification task. On the training dataset of 11,028 images, our proposed CNN achieves an accuracy of 71.88 % on 2,757 validation images.**

***Keywords*: Augmentation, CNN, Fundus, Segmentation.**

1. Introduction

Diabetic Retinopathy is found in diabetic patients and is a very common eye complication. The damaged blood vessels in the retina, a light-sensitive tissue, are the main cause of Diabetic Retinopathy. Type 1 and Type 2 diabetic patients are more prone to this complication. A prolonging case of diabetes and unsystematic control of blood sugar level increases the chances of this complication being present in the patient’s eye.

One of the principal causes of blindness in the western world is found to be Diabetic Retinopathy. Clinicians have found that great prevention for this disease in the prevailing monitoring of the patients suffering from Type 1 and Type 2 diabetes. If the condition is detected in its early stages, then due to the availability of treatment it can be controlled and in some cases be cured as well.

Millions of people suffer from Diabetic Retinopathy, the leading cause of blindness among working-age adults. In the hope to detect and prevent this disease among people living in rural areas where medical screening is difficult to conduct, Aravind Eye Hospital has launched the initiative to automatically detect Diabetic Retinopathy using Artificial Intelligence and Deep Learning.

The weighting of numerous features and the location of such features are highly involved in the classification of Diabetic Retinopathy. The task, when done by clinicians, is a highly time-consuming task. To give the clinicians the ability to aid in real-time, computers are used to make quicker classification if trained correctly. The efficacy of automated grading for Diabetic Retinopathy has been an active area of research in computer imaging with encouraging conclusions [1], [2].

Convolutional Neural Networks (CNNs), a branch of deep learning, have an impressive record for applications in image analysis and interpretation, including medical imaging. Network architectures designed to work with image data were routinely built already in the 1970s with useful applications and surpassed other approaches to challenging tasks like handwritten character recognition. However, it was not until several breakthroughs in neural networks such as the implementation of dropout, rectified linear units and the accompanying increase in computing power through graphical processor units (GPUs) that they became viable for more complex image recognition problems. Presently, large CNNs are used to successfully tackle highly complex image recognition tasks with many object classes to an impressive standard. CNN’s are used in many current state-of-the-art image classification tasks such as the annual ImageNet and COCO challenges.

In this paper, we propose a deep learning-based Convolutional Neural Network approach to grade Diabetic Retinopathy using fundus images. For the preprocessing stage, we are using a semantic segmentation technique with a neural network based on U-Net Architecture for identifying blood vessels in the fundus images. The blood vessels being a diagnostically relevant medical imaging task has been a topic of discussion in earlier studies as well. Image Augmentation methods, to increase the dataset, are used to compensate for the low number of images for the training of the model. Better training results are observed when more images are present in the training dataset [3].

2. Related data

The data used in this research paper has been collected from APTOS 2019 Blindness Detection Competition hosted on Kaggle. The data available has 2,757 RGB images comprising of fundus images labeled according to five levels of DR classification. The image is pre-processed to train the model faster.

The preprocessing stage consists of semantic segmentation of data for highlighting the blood vessel in the fundus images.

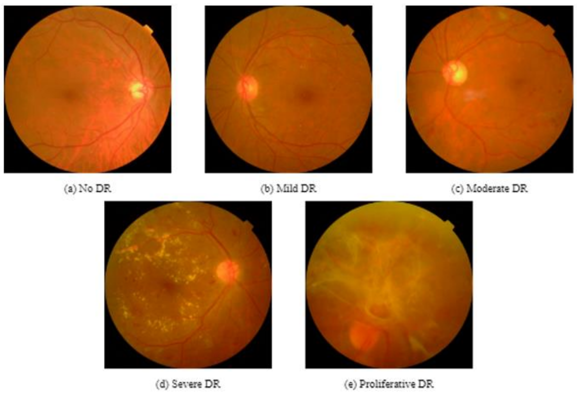

Fig. 1. Stages of diabetic retinopathy (DR) with increasing severity

The data is not adequate, so the data is augmented to increase the size of the dataset. The data is divided into two sets, 2,206 images in the training set and 551 images in the validation set.

3. Proposed Methodology

The proposed architecture for the implemented work mainly consists of five steps: Loading the data, Segmentation of the image, Augmentation of data, Training of the Model and Saving the weights of the trained model.

A. Loading the data

The dataset used is provided by Kaggle and consists of a total of 2,757 fundus images. To train and evaluate the model, the dataset is divided into Training Set, 2,206 images, and Validation Set, 551 images. The images are classified into five categories; the categorical classification is given in Table 1.

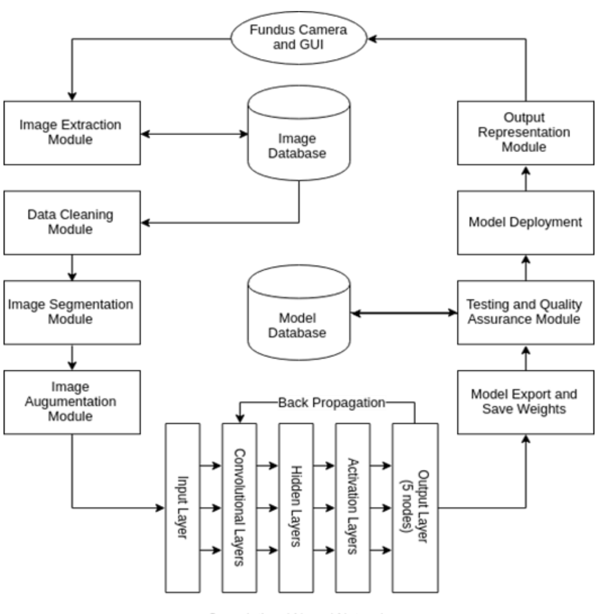

Fig. 2. System architecture

Table 1
Classification of Data

S. No.	Name of the Class	No. of Images
1	No DR	692
2	Mild DR	370
3	Moderate DR	999
4	Severe DR	401
5	Proliferative DR	295

B. Segmentation

An important aspect of determining Diabetic Retinopathy is the blood vessels in the retina. For highlighting and segmenting the blood vessels we are using a deep neural network-based semantic segmentation technique that follows,

The architecture of U-Net. The architecture of U-Net is given in the image. U-Net is found to be very intuitive and successful in the segmentation of images in the biomedical industry [4]. There are also techniques for blood vessel enhancement using Gabor filters but they were not proven better than the U-Net based blood vessel segmentation.

Another proposed work is a fully convolutional AlexNet for retinal vessel segmentation [5]. This type of network proposed to work on the STARE dataset, which consists of previously segmented training data, but the choice of U-Net over AlexNet was made due to the comparison in there F1-score. An ensemble classification-based approach is also proposed to be applied for Retinal Blood Vessel Segmentation [6].

This type of semantic segmentation requires pre-segmented images for the training of the neural network, but the absence of such images in our dataset was a problem. To solve the same we used a pre-trained model of U-Net which was trained for the STARE image dataset, which had an F1-score of 0.8373 and AUC of 0.9898[4]. The pretrained model is used to segment the images in our dataset.

C. Augmentation

There are less number of images to train the neural network so we used image augmentation techniques such as rotation, zoom, horizontal flip, vertical flip, blurring, brightness, and saturation. The augmentation module is inbuilt in the Python CV2 library. All the parameter values are randomly generated and applied using Image Data Generator in Keras Preprocessing Library.

The data is augmented and the resulting dataset consists of 11,028 images in the training dataset and 2,757 images in the validation dataset.

D. Training the model

There are a vast number of image classification architectures that are very successful in image classification tasks. After carefully studying different architectures of Convolutional Neural Network we applied the architecture of multiclass ResNet50, which was previously shown to be useful in medical image classification scenarios [7].

ResNet50 is a 50-layer Residual Network, which consists of 5 stages each with a convolution and identity block. The network is 50 layer deep and uses the softmax activation function to predict our classification. The learning rate is kept at 0.0005 and Categorical Cross entropy loss is used.

The network is also initialized with Gaussian initializations to reduce the initial training time. The network is trained for 200 epochs to get the documented results.

4. Results

2,757 images from the dataset were saved for validation purposes. Running the validation images on the network took 776 seconds. In this classification problem, specificity is defined as the number of images which are predicted as not having DR correctly in association with the total number of images not having DR. Accuracy is defined as the total number of images on which DR is detected correctly in association with the total number of images. The Accuracy of 71.88 % is achieved on the final neural network. The classification in the network was defined numerically as: 0 – No DR, 1 – Mild DR, 2 – Moderate DR, 3 – Severe DR and 4 – Proliferative DR.

Table 2
Confusion Matrix

	[0]	[1]	[2]	[3]	[4]
[0]	599	5	20	0	60
[1]	0	369	1	0	0
[2]	3	37	408	211	340
[3]	2	8	12	379	0
[4]	5	23	15	25	227

Table 3
Classification Report

Class	Precision	Recall	F1-score	Support
0	0.98	0.87	0.92	692
1	0.83	1.00	0.91	370
2	0.89	0.41	0.56	999
3	0.62	0.95	0.75	401
4	0.36	0.77	0.49	295

5. Conclusion

The majority of images classified as proliferative DR are detected accurately by our neural network. To classify the fundus images, encouraging signs are shown by our network in learning the features required. A trade-off between lower sensitivity and higher specificity is observed in other studies including large datasets [2]. In the future, we have plans to test other image classification models. We will also try another blood vessel segmentation technique which can lead to better results. If possible then we will also try to gather more images to train the model on a better dataset. To conclude, we have shown that CNNs can be trained to detect Diabetic Retinopathy in fundus images. An ophthalmologist can use CNNs for a second opinion in the classification problem.

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References

[1] Fleming A.D., Philip S., Fonseca S., Goatman K. A., Mcnamee P., Scotland G.S., et al. "The efficacy of automated disease/no disease grading for diabetic retinopathy in a systematic screening programme," *Brit J Ophthalmol* 2007; 91(11):1512–1517.

[2] J. U. Duncombe, "Infrared navigation Part I: An assessment of feasibility" *IEEE Trans. Electron Devices*, vol. ED-11, no. 1, pp. 34–39, Jan. 1959.

[3] Goatman K.A., Fleming A.D., Philip S., Sharp P.F., Prescott G.J., Olson J. A, "The evidence for automated grading in diabetic retinopathy screening," *Current Diabetes Reviews*, 2011; 7:246 – 252.

[4] Shorten, C., Khoshgoftaar, T. M., "A survey on Image Data Augmentation for Deep Learning," *J Big Data*, 6, 60 (2019).

[5] Olaf R., Philipp F., and Thomas B, "U-Net: Convolutional Networks for Biomedical Image Segmentation,"

[6] Zhexin Jiang, Hao Zhang, Yi Wang, Seok-Bum Ko. "Retinal blood vessel segmentation using fully convolutional network with transfer learning," *Computerized Medical Imaging and Graphics*, 2018; 1 – 15.

[7] Muhammad M.F., Paolo R., Andreas H., Bunyarit U., Alicja R.R., Christopher G. O., et al., "An Ensemble Classification-Based Approach Applied to Retinal Blood Vessel Segmentation," in *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 9, pp. 2538-2548, Sept. 2012.

[8] Muhammed Talo, "Convolutional Neural Networks for Multi-class Histopathology Image Classification."