Transfer Learning-Based Approach for Diabetic Retinopathy Classification using Fundus Images

Abhishek Kumar Pandey¹, Santosh Kumar Mishra²
¹,²CSE, VNS Group of Institution Bhopal

Abstract: Diabetic retinopathy (DR) is a major microvascular complication of diabetes. Around 95 million individuals worldwide suffer from DR. Regular testing of fundus images and early identification of initial diabetic retinopathy symptoms, namely microaneurysms and hemorrhages, are essential to decrease vision impairment possibilities. This research work is focused on the detection and classification of fundus images of diabetic retinopathy.

In this research work, we have proposed a deep learning-based method to classify diabetic retinopathy fundus images into positive (diabetic) class and negative (normal) class. The convolutional neural network is recently most popular in the computer vision for pattern recognition and classification. In this work we have used pre-trained ResNet50 for the fundus image classification. ResNet50 has amazing power to extract robust and discriminating features from the images for diagnosis. The evaluate the performances of the proposed approach we use publically available Messidor dataset. The proposed approach achieves accuracy of 91.78 % and sensitivity of 94.68 %.

Keywords: Deep learning, Convolutional Neural Network (CNN), ResNet50, Diabetic Retinopathy, Fundus Image, Transfer learning.

I. INTRODUCTION OF DIABETIC RETINOPATHY

An essential sensory organ that provides us the feeling of sight is the human eye. In our daily lives, it plays a very significant role. In almost every activity, we use our eyes because the eye enables us to see and interpret the world's items by processing the light that they reflect or emit. It moves through the cornea and the lens when light enters the eye and is refracted; Concentrate the image on the retina. The retina is a complicated transparent tissue that consists of several layers that cover two-thirds of the eyeball inside the back, where light stimulation happens and causing visual sensation. The retina is effectively a brain extension created by embryos of nerve tissue and linked through the optic nerve to the brain.

Diabetic Retinopathy (DR) is a complication of diabetes mellitus, including stroke, cardiac illness, diabetic nephropathy, and diabetic neuropathy. Damage to the retinal capillaries happens in mellitus diabetes. Only the retina, which is a tissue layer, can visualize diabetic retinopathy. Diabetic retinopathy occurs through lasting damage to the retina by tiny blood vessels, which ultimately leads to blindness. Effective diabetic retinopathy screening is therefore essential for early treatment as well as efficient risk factor management to avoid diabetic complications [1].

The incidence of diabetes recorded in 2014 by the World Health Organization (WHO) was estimated at 9% among adolescents aged 18 and over [2]. Diabetes adds approximately one percent of worldwide blindness. Overall, 4.8% of the 37 million instances of blindness are caused by diabetic retinopathy and in 2030 around 366 million globally will be impacted by diabetes mellitus. It has also been anticipated that diabetes will be the seventh major cause of death by 2030 [3].

DOI:10.23883/IJRTER.2019.5084.CGA0R
A broad variety of sensitivity and specificity will be produced by distinct screening modalities conducted by distinct professionals. The screening instruments are the direct and indirect ophthalmoscope, the biomicroscope of the slit lamp, the mydriatic fundus camera, and the non-mydriatic fundus camera. The non-mydriatic fundus camera has, among other benefits, elevated sensitivity and specificity. For instance, there is no need for pupillary dilatation, particularly if the room is properly darkened, supporting adherence, effectiveness, and security trained primary care clinicians are needed to screen diabetic retinopathy to improve interpretation and grading precision.

In this research work, we have developed a deep learning-based approach, specifically, residual network for diabetic retinopathy detection and classification fundus images. The proposed method is based on the residual learning-based convolutional neural network named as ResNet50 [4] which is consist of 177 layers, 5 residual blocks. ResNet is a pre-trained network that is trained on the ImageNet database by considering millions of images of large varieties, containing about 1.4 million images and 1000 classes. The name ResNet50 is a short form of Residual Neural Network. In this work transfer learning, in which network architecture and networks weigh of pre-trained network ResNet50 is directly used for fundus image classification.

II. RELATED WORK

Jagatheesh and Jenila [5] used the Bag of Visual Words (BOVW) model to develop a technique for detecting DR lesions. The model converts descriptors of local images into depictions of images that are regarded in the classification. These models are designed to identify a big amount of feature vectors around the image's points of interest. Visual words based on a visual dictionary are then allocated to the identified characteristics. The work of Jagatheesh and Jenila accomplished precision of 84.21 percent and sensitivity of 76.62 percent for exudate detection. It accomplished precision of 75.2 percent and sensitivity of 74.57 percent for detection of hemorrhages. BOVW-based DR detection and classification is still undergrowth.

Welikala et al. [6] suggested a methodology to use a dual classification strategy to detect and classify PDR. Using the standard line operator and a modified line operator, the blood vessel was segmented into two images. Then from each picture 21 characteristics were obtained and used in the classification phase. The final choice was based on mixing the two classifiers’ outcomes by removing in each classifier the fake fresh ship answers. PDR is a very developed level of DR and may not be efficient in curing PDR with present medicines. Welikala’s and colleagues’ research results, however, assist ophthalmologists to find fresh treatments.

Recently deep learning-based approaches have been used in diabetic retinopathy detection and classification. Carson Lam at el [7] presents the use of convolutional neural networks (CNNs) for the recognition of diabetic retinopathy staging assignment on color fundus images. They have achieved a validation sensitivity of 95%. Shorav Suriyal at el. [8] focus is on elements of identification of a mobile application created for real-time DR screening. These pictures are preprocessed in order to remove noise and prepare it for feeding into the neural network. Pre-processing steps require averaging all pictures with a 5x5 filter to enhance image quality. The input dataset is transmitted into the neural network after preprocessing. MobileNets, which is used for mobile devices, is the convolutional neural network model used in this project. Asti Herliana at el. [9], their research was carried out using the technique of particle swarm optimization (PSO) to select the best feature of Diabetic Retinopathy based on the dataset of diabetic retinopathy. The chosen descriptor is then further classified using neural network classification method. They achieved accuracy 76.11%.
III. PROPOSED METHODOLOGY

In the proposed method transfer learning is used, in which network architecture and networks weights of retrained network ResNet50 is directly used for fundus image classification. To improve the performance of the proposed approach the data augmentation method has been applied. Then the network is fine-tuned according to our application on the fundus images. The following section gives the details descriptions of the proposed method:

A. Data augmentations

We use affine transformation based data augmentation technique to improve the performance of the network by overcoming the problem of network overfitting [10]. Data augmentation method is only applied to the training set and for validation set and testing set real-world data have used. For training set augmentation first we rotated the images by $90^0$, $180^0$ and $270^0$, then flip operation is applied in which pixels are flip with level and vertical direction and at last translation is applied.

B. Network Fine-tuning

To fine-tune the network following algorithm 1 is applied:

**Algorithm 1:** Fine-tuning pre-trained ResNet50 network

**Input:** Train set and validation set

**Output:** a Trained model for diabetic retinopathy image classification

**Begin**

**Step 1.** Remove fully connected layer, softmax layer and an output layer of the network

**Step 2.** Add a new fully-connected layer with two neurons (for two binary classifications), softmax layer and output layer.

**Step 3.** Set a high learning rate for newly added layers and very low learning rate for the remaining.

**Step 4.** Re-trained the network on the new application dataset (Fundus image dataset).

**End**

C. Diabetic retinopathy detection and classification algorithm

We have use the concept of transfer learning to detection and classification the diabetic retinopathy from the fundus images. In the proposed approach pre-trained ResNet50 model is fine-tuned by using train set of the fundus images dataset. Test set images are given as the input to the trained model, which produces classify images into the malignant and non-malignant classes. Proposed approach algorithm is given as follows:

**Algorithm 2:** Classification of fundus images in malignant and non-malignant

**Input:** Query and database images

**Output:** Retrieved Images

**Begin**

**Step 1.** Read all images from database.

**Step 2.** Divide dataset into train set, test set and validation set.

**Step 3.** Apply data augmentation approach on the train set.

**Step 4.** Fine-tuned pre-trained ResNet50 model by applying Algorithm 1 (pass train set and validation set in the input).

**Step 5.** Now read test images.

**Step 6.** Test images are given as input to the trained model and get the label for each input image as output.

**End**
IV. IMPLEMENTATION AND RESULTS

A. Diabetic Retinopathy Dataset

The Messidor project database, which contains 1200 retinal images, is the large publically available database. This data set is provided by the partners of the Messidor program [11]. Sample of fundus images from the Messidor dataset is depicted in figure 1. Three ophthalmological services obtained the pictures using a 3CCD color video camera on a non-mydriatic Topcon TRC NW6 camera with a 45 FOV.

![Sample images from the Messidor dataset](image)

**(a) Non-diabetic**

**(b) Diabetic**

_Fig. 1: Sample images from the Messidor dataset; (a) represents non-diabetic image and (b) represents diabetic images._

The pictures were recorded using 8 bits per color plane at 1440X960, 2240X1488 or 2304X1536 pixels images. With pupil dilation (one drop of Tropicamide at 0.5%) and 400 without dilation, 800 pictures were obtained. The reference standard given includes the grading of diabetic retinopathy in each picture and the risk of macular edema. This database contains no other annotations and is used to promote computer-assisted retinopathy diagnosis research.

B. Network Training Setup

To train the network first, the dataset is randomly divided into training and test sets in the ratio of 0.7 and 0.3 for each magnification. The training set is further divided in train set and validation set in ratio of 0.8 and 0.2. The train set is used for network training and validation set is for selecting the best parameter for the model. Test also divided into five subtest sets such as Test #1, Test #2, Test #3, Test #4 and Test #5. This test set is used for performance evaluation of the proposed methods.
Second, the train set is augmented by applying data augmentation approach mentioned in chapter 4. Third, Kernel's initial weight has been initialized with standard deviation 0.01 by the Gaussian distribution and hyper parameters are initialized as learning rate to 0.001, regularization parameter to 0.005, gradient decay factor to 0.9 and mini-batch size to 128. We found these hyper parameter values experimentally that are well suited to our issue. Network is train for 50 epochs and 250 iterations. Network training performance is given in the fig. 5.2 and fig. 5.3.

C. Results

It could be said that there is a two-class classification engaged in diabetic retinopathy. The categorization is based on two instances called "normal" and “retinopathy with diabetes.” In Table 1, we present the results of experiments of the proposed method in terms of accuracy, sensitivity, specificity, precision, recall and F-score. As we can see from the table 1 this approach achieves 91.78%, 94.62%, and 87.65% mean accuracy, Sensitivity and specificity respectively. The proposed approach given high sensitivity toward the malignant class (positive class).

The Fig. 2 represents the confusion matrix for overall test set.

| Test set | Accuracy | Sensitivity | Specificity | Precision | F-Score |
|----------|----------|-------------|-------------|-----------|---------|
| Test #1  | 81.82    | 88.46       | 72.22       | 82.14     | 85.19   |
| Test #2  | 95.45    | 96.15       | 94.44       | 96.15     | 96.15   |
| Test #3  | 90.70    | 92.31       | 88.24       | 92.31     | 92.31   |
| Test #4  | 95.45    | 96.15       | 94.44       | 96.15     | 96.15   |
| Test #5  | 95.45    | 100.00      | 88.89       | 92.86     | 96.30   |
| Mean     | 91.78    | 94.62       | 87.65       | 91.92     | 93.22   |

Fig. 5.5: Confusion matrix on the test set.
Fig 3: ROC curve.

Table 2: Comparison of the proposed approach with the existing method

| Method             | Accuracy (%) | Sensitivity (%) |
|--------------------|--------------|-----------------|
| Lam at el. [42]    | -            | 95              |
| Suriyal at el. [43]| 73.3         |                 |
| Asti at el. [44]   | 76.11        |                 |
| Proposed Approach  | **91.78**    | **94.62**       |

Receiver operating characteristic curve of the proposed approach is shown in the figure 3. This work is also compared with the existing methods that presented their results over the Messidor database. Comparison is shown in table 2 with the recently published method. As we can see from the table, proposed method is outperforming on the Messidor database compare to other matching methods.

V. CONCLUSION AND FUTURE WORK

In this research work, we have proposed a deep learning-based method to classify diabetic retinopathy fundus images into positive (diabetic) class and negative (normal) class. In this work we have used pre-trained ResNet50 for the fundus image classification. ResNet50 has amazing power to extract robust and discriminating features from the images for diagnosis. The proposed approach achieves accuracy of 91.78 % and sensitivity of 94.68 %. The performance of the proposed approach very effective and it outperformed most the state-of-the-art methods. The proposed method gives a significant improvement in terms of precision, recall, f-score, and accuracy. Intended for which an image was chosen as of coral image database and method was useful on it.

The proposed method also need to test on the large dataset before going to use in the clinical purpose. In future work, we want to develop a new deep learning model, which trained from the scratch and also try it with the combination of some other classifier algorithm for the further improvement of the proposed methodology.

REFERENCES

I. World Health Organization (2005) Prevention of Blindness from Diabetes Mellitus, Report ofWHO Consultation. Geneva: WHO

II. World Health Organization (2012a) Global status report on non-communicable diseases 2014. Geneva: WHO

III. World Health Organization (2012b) Global data on visual impairments 2010. Geneva: WHO
IV. C. Jagatheesh and C. Jenila, “Automatic Detection and Classification of Diabetic Retinopathy Lesion Using Bags of Visual Words Model,” International Journal of Scientific and Research Publications, Vol. 5, September 2015.

V. He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

VI. R. Welikala, M. Fraz, T. Williamson and S. Barman, “The Automated Detection of Proliferative Diabetic Retinopathy using Dual Ensemble Classification,” International Journal of Diagnostic Imaging, Vol. 2, 2015.

VII. Carson Lam, Darvin Yi, Margaret Guo, and Tony Lindsey. "Automated detection of diabetic retinopathy using deep learning." AMIA Summits on Translational Science Proceedings 2018 (2018): 147.

VIII. Suriyal, Shorav, Christopher Druzgalski, and Kumar Gautam. "Mobile assisted diabetic retinopathy detection using deep neural network." 2018 Global Medical Engineering Physics Exchanges/Pan American Health Care Exchanges (GMEPE/PAHCE). IEEE, 2018.

IX. Herliana, Asti, et al. "Feature Selection of Diabetic Retinopathy Disease Using Particle Swarm Optimization and Neural Network." 2018 6th International Conference on Cyber and IT Service Management (CITSM). IEEE, 2018.

X. Q. Geng, Z. Zhou, and X. Cao, “Survey of recent progress in semantic image segmentation with CNNs,” Sci. China Inf. Sci., vol. 61, no. 5, p. 051101, Nov. 2017.

XI. MESSIDOR: Methods for evaluating segmentation and indexing techniques dedicated to retinal ophthalmology. [Online].