e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:06/June-2022 Impact Factor- 6.752 www.irjmets.com

RETINA IMAGE AND DIABETIC RETINOPATHY: A DEEP LEARNING BASED APPROACH

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ABSTRACT

Diabetic retinopathy is one of the most threatening complications of diabetes that leads to permanent blindness if left untreated. One of the essential challenges is early detection, which is very important for treatment success. Unfortunately, the exact identification of the diabetic retinopathy stage is notoriously tricky and requires expert human interpretation of fundus images. Simplification of the detection step is crucial and can help millions of people. Convolutional neural networks (CNN) have been successfully applied in many adjacent subjects, and for diagnosis of diabetic retinopathy itself. However, the high cost of big labeled datasets, as well as inconsistency between different doctors, impede the performance of these methods. In this paper, we propose an automatic deep-learning-based method for stage detection of diabetic retinopathy by single photography of the human fundus. Additionally, we propose the multistage approach to transfer learning, which makes use of similar datasets with different labeling. The presented method can be used as a screening method for early detection of diabetic retinopathy with sensitivity and specificity of 0.99 and is ranked 54 of 2943 competing methods (quadratic weighted kappa score of 0.925466) on APTOS 2019 Blindness Detection Dataset (13626 images).

Keywords: Diabetic Retinopathy, CNN, Deep Learning, Retina Image.

I. INTRODUCTION

Millions of people suffer from Diabetic retinopathy, the leading cause of blindness among working aged adults. Aravind Eye Hospital in India hopes to detect and prevent this disease among people living in rural areas where medical screening is difficult to conduct. Currently, the technicians travel to these rural areas to capture images and then rely on highly trained doctors to review the images and provide diagnosis. DR progresses with four stages:

- Mild non-proliferative retinopathy, the earliest stage, where only microaneurysms can occur;
- Moderate non-proliferative retinopathy, a stage which can be described by losing the blood vessels' ability of blood transportation due to their distortion and swelling with the progress of the a b c https://orcid.org/0000-0002-2678-7556 https://orcid.org/0000-0001-9995-9454 https://orcid.org/0000-0001-6499-4575 disease;
- Severe non-proliferative retinopathy results in deprived blood supply to the retina due to the increased blockage of more blood vessels, hence signaling the retina for the growing of fresh blood vessels;
- Proliferative diabetic retinopathy is the advanced stage, where the growth features secreted by the retina activate proliferation of the new blood vessels, growing along inside covering of retina in some vitreous gel, filling the eye.

Each stage has its characteristics and particular properties, so doctors possibly could not take some of them into account, and thus make an incorrect diagnosis. So this leads to the idea of creation of an automatic solution for DR detection.

Deep learning is the most popular approach among researchers for detection, prediction, forecasting and classification task in various fields from few years, in medical field particularly in diabetic retinopathy it is unveiling many possibilities for the prevention of such a dreadful disease. I.Sadek et al.[1] in their work automatically detected the diabetic retinopathy using deep learning approach. They used the four convolutional neural network to classify the diabetic retinopathy into three classes as Normal, Exudates, Drusen. This method outperforms the Bag of words approach and achieved an accuracy of 91%-92%. G.Zago et al.[2] in their study designed a lesion localization model using a deep network specifically convolutional neural network approach

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with an aim to address the models complexity so, that the performance can be improved. Instead of segmentation localization process of regions were used. Two convolutional networks were used for training purpose on a Standard Diabetic Retinopathy Database and DIARETDB1 where 94% - 95% of sensitivity was obtained. D.Doshi et al.[3] in their work used a GPU based convolutional neural network to classify the retinal images severity level into 5 stages. This approach used 3 models of CNN architecture and an ensemble model of the three to evaluate the results on kappa metrics. The best result were achieved by ensembling method with a score of 0.3996. The work of P.Kaur et al.[4] Presents a Neural network technique for the classification of retinal images using MATLAB. The results obtained were compared with the machine learning approach like SVM where better results were achieved. M.Voets et al.[5] in their study used a kaggle dataset EyePACS for detection of diabetic retinopathy from retinal fundus images. However, this study is the re-implementation of already existing work but on different data set which provided 95% of AUC. The difference of AUC between the original and the re-implemented method tend to be very large

II. METHODOLOGY

The image data used in this research was taken from several datasets. We used an open dataset from Kaggle Diabetic Retinopathy Detection Challenge 2015 (EyePACs, 2015) for pretraining our CNNs. This dataset is the largest available publicly. It consists of 35126 fundus photographs for left and right eyes of American citizens labeled with stages of diabetic retinopathy: • Nodiabetic retinopathy (label 0) • Mild diabetic retinopathy (label 1) • Moderate diabetic retinopathy (label 2) • Severe diabetic retinopathy (label 3) • Proliferative diabetic retinopathy (label 4) In addition, we used other smaller datasets: Indian Diabetic Retinopathy Image Dataset (IDRiD) (Sahasrabuddhe and Meriaudeau, 2018), from which we used 413 photographs of the fundus, and MESSIDOR (Methods to Evaluate Segmentation and Indexing Techniques in the field of Retinal Ophthalmology) (Decencies et al., 2014) dataset, from which we used 1200 fundus photographs. As the original MESSIDOR dataset has different grading from other datasets, we used the version that was relabeled to standard grading by a panel of ophthalmologists (Google Brain, 2018). As the evaluation was performed on Kaggle APTOS2019Blindness Detection (APTOS2019) dataset (APTOS, 2019), we had access only to the training part of it. The full dataset consists of 18590 fundus photographs, which are divided into 3662 training, 1928validation, and 13000 testing images by organizers of Kaggle competition. All datasets have similar distributions of classes; distribution for APTOS2019 is shown in Figure 2. As different datasets have a similar distribution, we considered it as a fundamental property of this type of data. We did no modifications to the dataset distribution (under sampling, oversampling, etc.). The smallest native size among all of the datasets is 640x480. Sample image from APTOS2019 is shown in Figure 1.

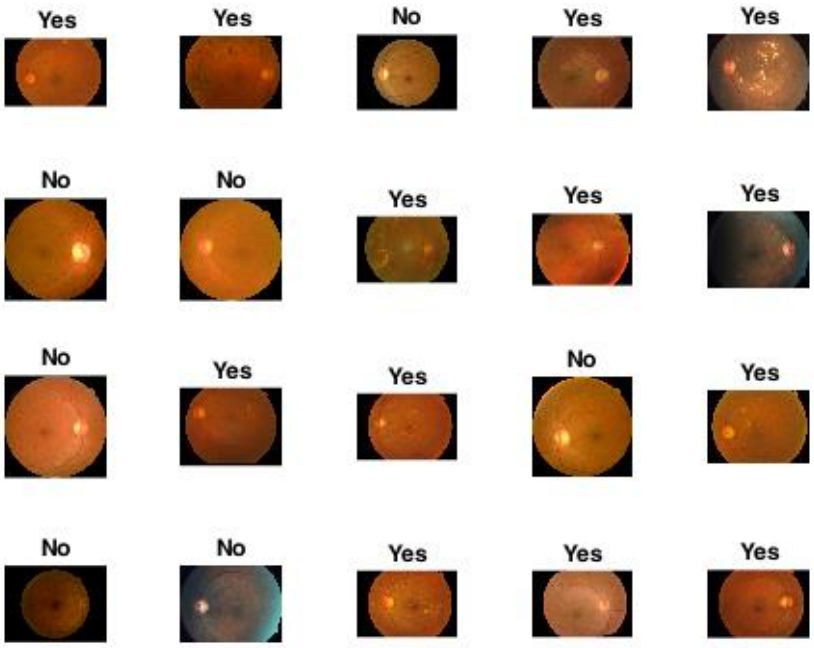

Fig 1: Image samples from the dataset

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The diabetic retinopathy detection problem can be viewed from several angles: as a classification problem, as a regression problem, and as an ordinal regression problem (Ananth and Kleinbaum, 1997). This is possible because stages of the disease come sequentially.

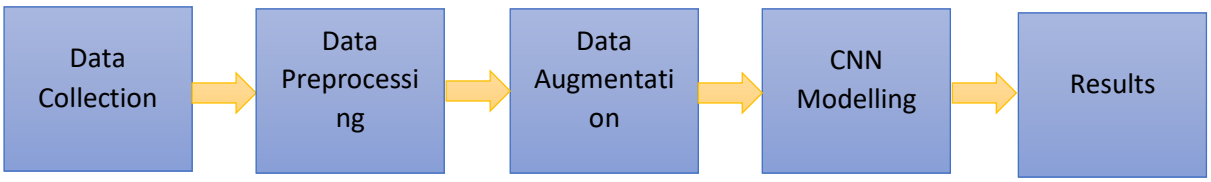

Fig 2: Proposed Methodology

A. Training: The main training is performed on 2019 data, IDRID, and MESSIDOR combined. Starting with weights obtained in the pretraining stage, we performed 5-fold cross-validation and evaluated models on the holdout set. At this stage, we change loss functions for heads: Focal Loss (Lin et al., 2017) for classification head, binary Focal Loss (Lin et al., 2017) for ordinal regression head and mean-squared error for regression head. We trained each fold for 75 epochs using Rectified Adam optimizer (Liyuan Liu, 2019), with cosine annealing learning rate schedule. To save pretrained weights while new heads are in a random state, we disabled training (froze) of the encoder for five epochs while training heads only. During the main training, we monitor separability in feature space generated by the encoder. We generate 2-dimensional embeddings with T-SNE (van der Maaten and Hinton, 2008) and visualize them in the validation phase for manual control of training performance. Figure 6 shows T-SNE of embeddings labeled with ground truth data and predicted classes. From the picture, it can be seen that images with no signs of DR are separable with a large margin from other images that have any sign of DR. Additionally, stages of DR come sequentially in embedding space, which corresponds to semantics in real diagnoses.

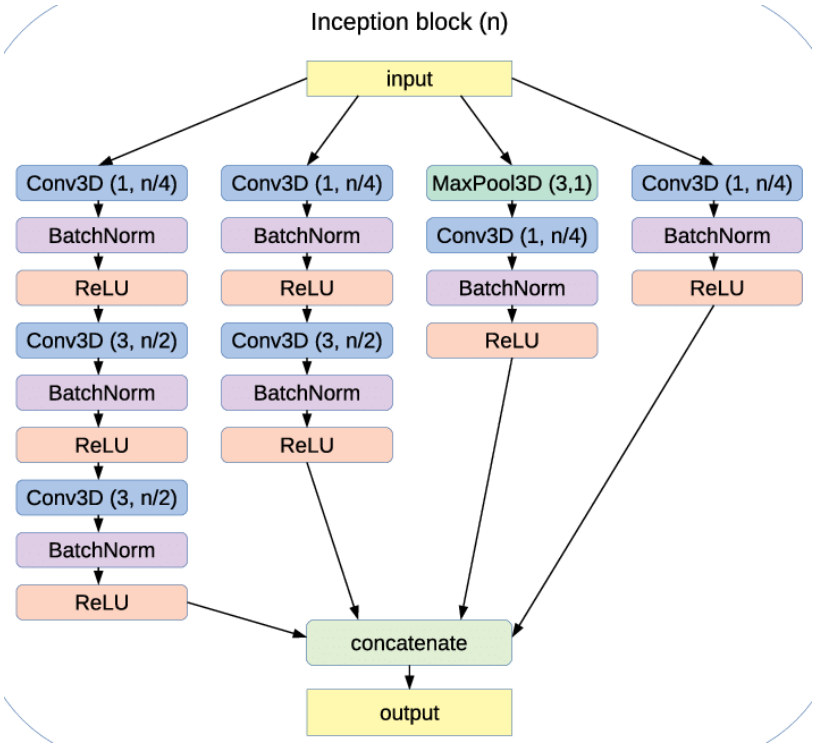

Fig 3: Block diagram of Inception-V3 CNN

III. RESULTS AND DISCUSSION

After done with the experiments, we got the experiment results in which we show the accuracy of our project. We used two architectures for same dataset and see the accuracies of each. As we seen clearly in the above table VGG16 is used without ImageNet and QWK and DenseNet is used with ImageNet and QWK. So without ImageNet VGG16 gives the less accuracy and with ImageNet DenseNet gives better accuracy than VGG16. Now

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will see the accuracy and loss graph of VGG16 and DenseNet respectively. We trained our proposed model using DenseNet-169 on a combination of dataset from Diabetic Retinopathy Detection 2015[21] and APTOS 2019 blindness detection[22] from kaggle. There was a lot of noise associated with the images provided by the dataset therefore, preprocessing was needed. For preprocessing, we first removed the black border of the images in order to focus more on the fundus image only, black corners of images was also removed, then the images were resized to a standard format of 256*256 of width and height. At last a Gaussian blur was applied to the images in order to remove the Gaussian noise. After preprocessing we analyze that the data is highly unbalanced among the severity classes, majority of data belonged to the class '0'i.e. No DR. in order to address this issue, we used data augmentation, which gives us 7000 images from each severity class and made the data balanced. After preprocessing and augmentation of images, data was finally fed to the DenseNet-169 for training the model. After evaluating our model the training accuracy of 0.953 was obtained, while as validation accuracy of 0.9034 was achieved. We also calculated the Cohen Kappa score which comes out to be 0.804. We also applied a regression model to our dataset and compute its validation saccuracy which is 0.789. Our proposed model outperforms the regression model.

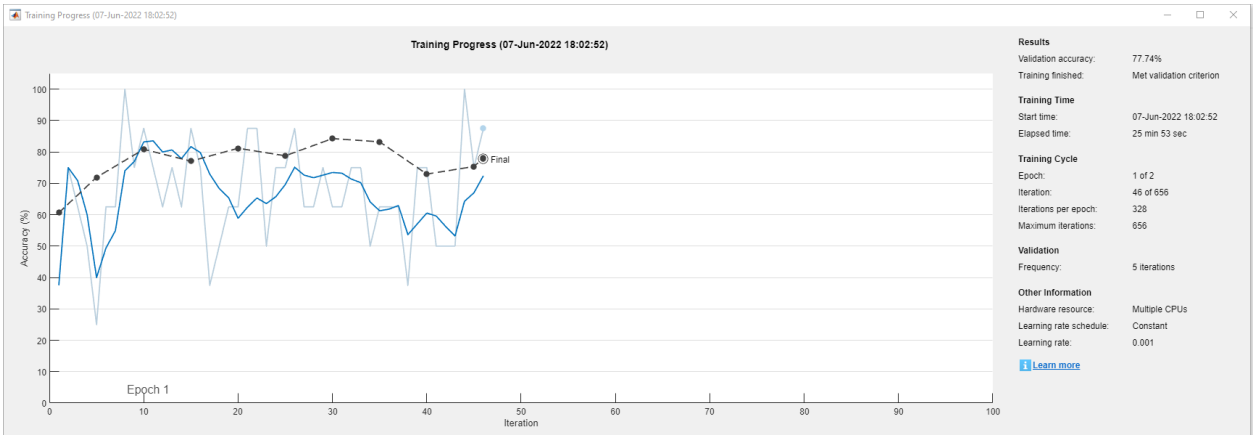

Fig 4(a): Training of the proposed model

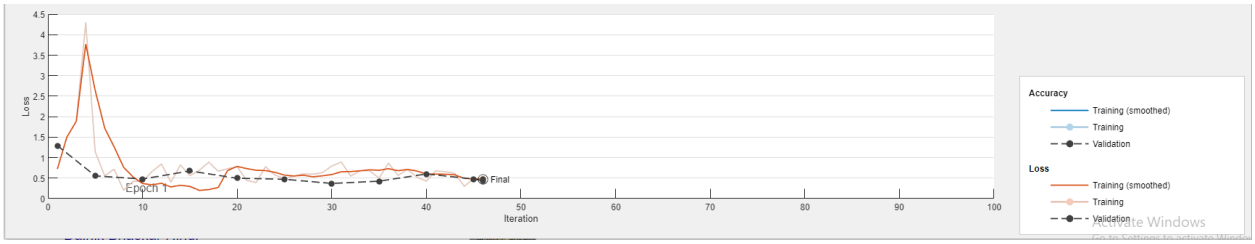

Fig 4(b): Validation Curve of the proposed model

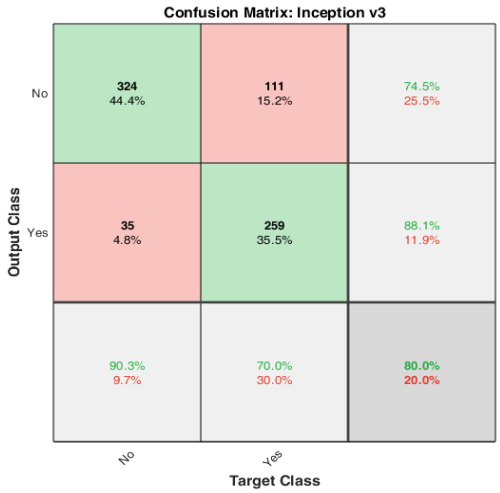

Fig 5: Confusion matrix of the classification result

IV. CONCLUSION

As we know that the DR (Diabetic Retinopathy) is primary concern for the diabetes patients, and manually it took a long time to detect DR. So we developed a architecture for automatic detection of DR, here we took two architectures to compare them that which architecture is best at what condition. The two architectures are VGG16 and DenseNet121 and the accuracies are 0.7326 and 0.9611 respectively. The QWK helped us to give the confidence of accuracy which we got from DenseNet architecture.

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