Diabetic Retinopathy Blindness Detection

Rohit Rajendra Kadam[1] , Prathmesh Sukhadev Pujari[2] , Mayur Sanjay Chakre [3] ,

Vishwajeet Anil Gaikwad[4] , Prof. Yogendra Patil[5]

Student, Dept. of Computer Engineering, JSPM's Bhivarabai Sawant Institute Of Technology & Research Wagholi, Maharashtra, India

Assistant Professor, Dept. of Computer Engineering, JSPM's Bhivarabai Sawant Institute Of Technology & Research Wagholi, Maharashtra, India

Abstract: *Diabetic retinopathy is one of the most dangerous consequences of diabetes, resulting in lifelong blindness if ignored. One of the most difficult issues is early diagnosis, which is critical for therapeutic effectiveness. Unfortunately, determining the exact stage of diabetic retinopathy is notoriously difficult and needs experienced human interpretation of fundus pictures. Simplifying the detecting phase is critical and can benefit millions of individuals. Many neighbouring subjects, as such as the detection of diabetic retinopathy, have shown progress using denset convolutional neural networks (CNN). However, the costly expense of large labelled datasets, as well as doctor unreliability, hinder the efficacy of these approaches. In this research, we offer an autonomous deep-learning-based technique for detecting diabetic retinopathy stages using single photographs of the human fundus. Furthermore, we present a multistage strategy to transfer learning that use similar datasets with varied labelling. The provided approach, with sensitivity and specificity of 0.99, may be utilised as a screening tool for early identification of diabetic retinopathy and is rated 54 out of 2943 competing methods (quadratic weighted kappa score of 0.925466) on the APTOS 2019 Blindness Detection Dataset (13000images). Diabetic Retinopathy is an eye illness that mostly affects the retina. It is the outcome of long-term Diabetes, which causes blood to leak from the retinal blood vessels onto the retina. It is now one of the top causes of blindness in the globe. To save people's sight, early detection and treatment are essential. It is extremely difficult to recognise the illness at each stage since symptoms do not appear until there is severe retinal damage.*

1. Introduction

Diabetes is a common condition around the world, with over 422 million people suffering from diabetes as of 2014. Diabetic retinopathy (DR) is a potentially preventable illness caused by long-term diabetes. DR impacts the blood vessels of light-sensitive tissue (i.e. retina). It is now the main cause of visual impairment and blindness in working-age individuals worldwide [8], and almost half of all diabetics have this illness to some level. One well-known issue with DR is that there is no early warning sign, even for diabetic macular edoema. As a result, it is critical that DR be discovered in a timely manner. Unfortunately, in practise, this DR detection technique is insufficient to meet this need. This technique, in particular, necessitates a well-trained physician physically evaluating digital colour fundus pictures of the retina, and DR is discovered by detecting lesions associated with vascular anomalies caused by diabetes. While the existing technique is successful, it is time intensive and heavily reliant on the knowledge of well-trained practitioners. To address this issue, significant attempts have been made recent years to provide an autonomous solution for DR detection. Figure 1 depicts an image of the retina with diabetic retinopathy.

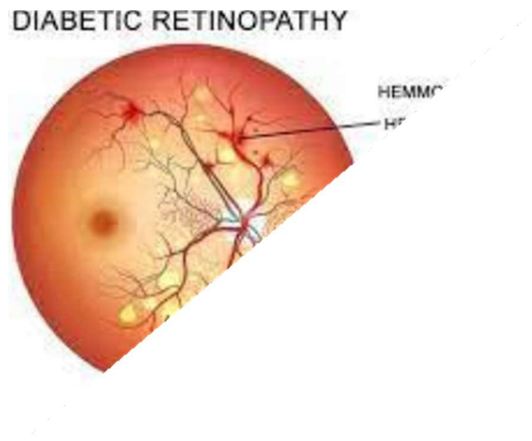

Fig.1 Diabetic Retinopathy

However, Deep Learning has gained popularity in recent years in various fields like sentiment analysis, handwritten recognition, exchange prediction, medical image analysis, etc. CNN in deep learning tends to supply constructive results when it involves the work of image classification. Such a ramification of processing units can yield an efficient nonlinear representation of the local salience of the signals.

Then, the deep architecture allows multiple layers of those processing units to be stacked, so thisdeep learning model can characterize the salience of signals on numerous scales. Also, in CNN, feature extraction and prediction algorithm are unified joimodelsodel. Thus, the extracted featuresown more discriminative power, since the complete CNN model is trained under the supervisionof output labels.

2. Motivation

- Approximately one-third of 285 million people with diabetes mellitus worldwidehave signs of Diabetic Retinography.
- If we provide timely service to this disease the we can recover it.
- Diabetic Retinography Detection using image processing
- Even we can rate it on how much it is affected on eyes.

2. Literature Survey

1. Application of higher order spectra for the identification ofdiabetes retinopathy stages.

Feature extraction based classification and DL has been used to classify DR. In Acharya et al. higher order spectra technique was used to extract features from 300 fundus images and fed to a support vector machine classifier; it classified the images into 5 classes with sensitivity of 82% and specificity of 88%. Different algorithms were developed to extract DR lesions such as blood vessels, exudates, and microaneurysms. Exudates have been extracted for DR grading. Support vector machine was used to classify the DIABETDB1 dataset into positive and negative classes using area and number of microaneurysms as features.

2. Rethinking the inception architecture for computer vision.

Feature extraction based classification methods need expert knowledge in order to detect the required features, and they also involve a time consuming process of feature selection, identification and extraction. Furthermore, DL based systems such as CNNs have been seen to outperform feature extraction based methods .DL training for DR classification have been performed in two major categories: learning from scratch and transfer learning.

3.Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs.

A convolutional neural network (CNN) was trained to classify a dataset of 128,175 fundus images into 2 classes, where the first class contains images with severity levels 0 and 1, and the second class contains levels 2, 3 and 4 [27]. In an operating cut point picked for high sensitivity, [27] had a sensitivity of 97.5% and specificity of 93.4% on the EyePACS-1 dataset which consists of 9963 images; it scored a sensitivity of 96.1%and a specificity of 93.9% on the Messidor-2 dataset.

4. Convolutional neural networks for diabetic retinopathy.

Using a training dataset of over 70,000 fundus images, Pratt et al. [28] trained a CNN using stochastic gradient descent algorithm to classify DR into 5 classes, andit achieved 95% specificity, 75% accuracy and 30% sensitivity. A DL model was trained from scratch on the MESSIDOR-2 dataset for the automatic detection of DR in [29], and a 96.8% sensitivity and 87% specificity were scored**.**

5. Automated identification of diabetic retinopathy using deep learning.

A CNN was trained from scratch to classify fundus images from the Kaggle dataset into referable and non-referable classes, and it scored a sensitivity of 96.2%and a specificity of 66.6% [30]. A dataset of 71896 fundus images was used to traina CNN DR classifier and resulted in a sensitivity of 90.5% and specificity of 91.6%[31]. A DL model was designed and trained on a dataset of 75137 fundus images and resulted in a sensitivity and specificity scores of 94% and 98%, respectively.

6.Comparative Study of Fine-Tuning of Pre-Trained Convolutional NeuralNetworks for Diabetic Retinopathy.

Screening In order to avoid the time and resource consumed during DL, Mohammadian et al. [33] fine-tuned the Inception-V3 and Exception pre-trained models to classify the Kaggle dataset into two classes. After using data augmentation to balance the dataset, [33] reached at an accuracy score of 87.12%on the Inception-V3, and 74.49% on the Exception model.

3. System Design

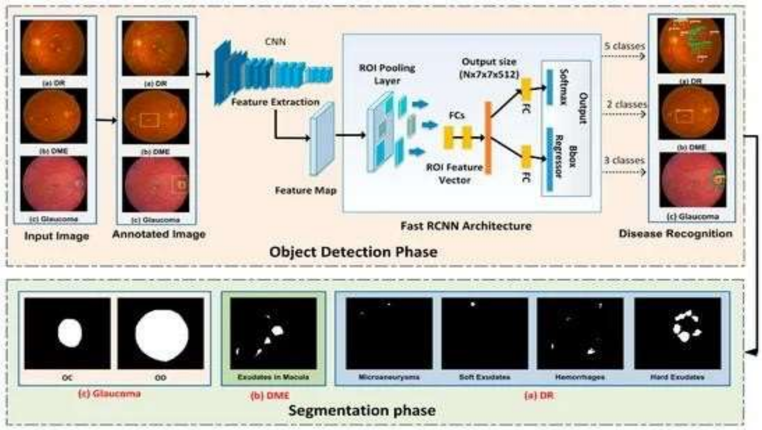

Fig.2 System Architature

We used a DenseNet-169 (Densely connected convolutional neural network) and Regression model for training purpose. In DenseNet-169 weights are loaded into the network without the top or last layer. When modelling the network, initially there is no last layer. We design this layer by using Global Average Pooling 2D, a Dropout layer set at 0.5 and an output comprisingof five nodes for each class. Global Average Pooling 2D is same as that of 2D average Pooling in operation, but it considers the entire input block size as pool size.

Module:

Preprocessing

Model training and validation were performed with preprocessed versions of the originalimages. The preprocessing consisted of image cropping followed by resizing. Due to theway APTOS2019 was collected, there are spurious correlations between the disease stageand several image meta-features, e.g., resolution, crop type, zoom level, or overall brightness. Correlation matrix is shown in Figure 4. To make CNN be able not to overfitto these features and to reduce correlations between image content and its meta-features,we used a high amount of augmentations. Additionally, as we do not have access to the test dataset both in the competition and in real life, we decided to show as much data variance as possible to models.

Data augmentation

We used online augmentations, at least one augmentation was applied to the training image before inputting to the CNN. We used following augmentations from Albumentations (A. Buslaev and Kalinin, 2018) library: optical distortion, grid distortion, piecewise affine transform, horizontal flip, vertical flip, random rotation, random shift, random scale, a shift of RGB values, random brightness and contrast, additive Gaussian noise, blur, sharpening, embossing, random gamma, and cutout(Devries and Taylor, 2017).

Network architecture

We aim to classify each fundus photograph accurately. We build our neural networks using conventional deep CNN architecture, which has a feature extractor and smaller decoder for a specific task (head). However, training the encoder from scratch is difficult,especially given the small amount of training data. Thus, we use an imagenet-pretrained CNNs as initialization for encoder (Iglovikov and Shvets, 2018). We propose the multi- task learning approach to detect diabetic retinopathy. We use

three decoders. Each is trained to solve its task based on features extracted with CNN backbone:classification head,regression head,ordinal regression head.

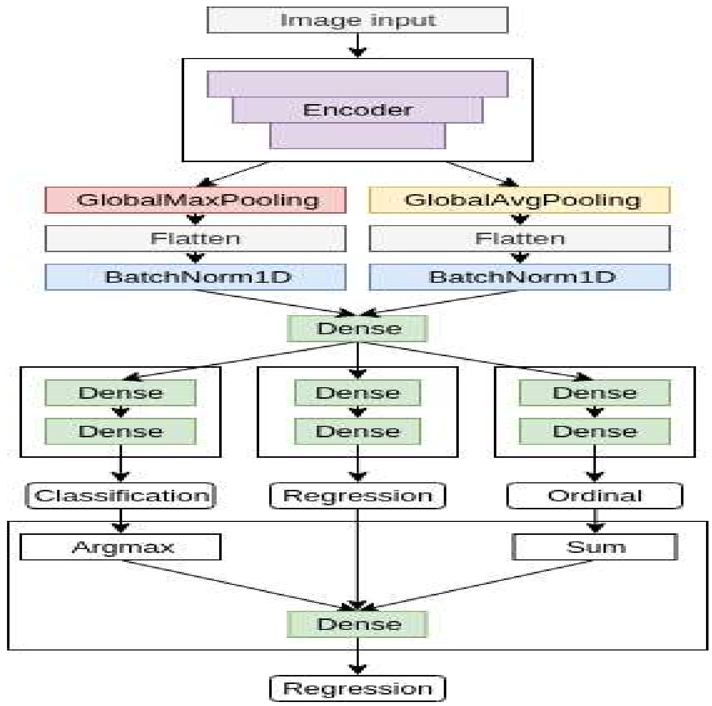

Fig.3 Module

4. Conclusion And Future Work

Conclusion:

Thus we've got developed sort of a model to detect blindness before it happened. We will be achieving this by building a Convolutional neural network model that may automatically examinea patient's eye image and estimate the severity(severity scale which is one among [0,1,2,3,4].) ofblindness within the patient. The traditional method for detection of DR is prolonged, challenging,and dear, thus many types of research were remarked to automate the detection process by usingmachine learning and deep learning approaches. During this work, we presented a comprehensivestudy of assorted methodologies for detecting diabetic retinopathy automatically and attempted to propose our deep learning approach for the first diagnosis of retinopathy by employing a DenseNet169(which could be a new CNN architecture, having many deep layers). Two datasets: 'Diabetic Retinopathy Detection 2015'and 'APTOS 2019 blindness detection' from Kaggle were used together for this study. Plenty of preprocessing and augmentation was done to standardize the information in an exceedingly desired format and to get rid of the unwanted noise.

Future Work:

We've used two datasets in our study, using more no of datasets or a mix of assorted datasets mayimprove the generalizability. The deployment of such systems will be done by using the Mobile Net, which could be a convolutional neural network for developing mobile applications. The netapplications will be developed which will work for Windows, Linux, and Android operating systems as a diabetic retinopathy diagnostic tool.

5. References

1. S. R. Sadda et al., “Quantitative assessment of the severity of diabetic retinopathy,” Am.J. Ophthalmol., 2020, doi: 10.1016/j.ajo.2020.05.021.
2. J. Amin, M. Sharif, and M. Yasmin, “A Review on Recent Developments for Detection of Diabetic Retinopathy,” Scientific, vol. 2016. 2016, Doi: 10.1155/2016/6838976.
3. Y. Kumaran and C. M. Patil, “A brief review of the detection of diabetic retinopathy in human eyes using pre-processing & segmentation techniques,” International Journal of Recent Technology and Engineering, vol. 7, no. 4. pp. 310–320, 2018. [15] M. Chetoui,
4. M. A. Akhloufi, and M. Kardouchi, “Diabetic Retinopathy Detection Using Machine Learning .
5. “Diabetic Retinopathy Detection Identify signs of diabetic retinopathy in eye images,” 2015. Av.
6. Harry Pratt, Frans Coenen, D. M. B. S. P. H. Y. Z. (2016). Convolutional neural networksfor diabetic retinopathy.https://www.health.harvard.edu/a_to_z/retinopathy-a-to-z
7. J. De Calleja, L. Tecuapetla, and M. A. Medina, “LBP and Machine Learning for Diabetic Retinopathy Detection,” pp. 110–117, 2014.
8. N. Silberman, K. Ahrlich, R. Fergus, and L. Subramanian. The case for automated detection of diabetic retinopathy. In AAAI Spring Symposium: Artificial Intelligence forDevelopment. AAAI, 2010.
9. U. R. Acharya, C. M. Lim, E. Y. K. Ng, C. Chee, and T. Tamura, “Computer-based detection of diabetes retinopathy stages using digital fundus images,” Proc. Inst. Mech. Eng. Part H J. Eng. Med., vol. 223, no. 5, pp. 545–553, 2009, doi: 10.1243/09544119JEIM486.
10. K. A. Anant, T. Ghorpade, and V. Jethani, “Diabetic retinopathy detection through imagemining for type 2 diabetes,” in 2017 International Conference on Computer Communication and Informatics, ICCCI 2017, 2017, doi: 10.1109/ICCCI.2017.8117738.
11. M. Gandhi and R. Dhanasekaran, “Diagnosis of diabetic retinopathy using morphological process and SVM classifier,” Int. Conf. Commun. Signal Process. ICCSP 2013 - Proc., pp. 873–877, 2013, doi: 10.1109/iccsp.2013.6577181.
12. J. I. Orlando, E. Prokofyeva, M. del Fresno, and M. B. Blaschko, “An ensemble deep learning based approach for red lesion detection in fundus images,” Comput. Methods Programs Biomed., vol. 153, pp. 115–127, 2018, doi: 10.1016/j.cmpb.2017.10.017.
13. S. Preetha, N. Chandan, K. Darshan N, and B. Gowrav P, “Diabetes Disease Prediction Using Machine Learning,” Int. J. Recent trends Eng. Res., vol. 6, no. 5, 2020, doi: 10.23883/IJRTER.2020.6029.65Q5H.