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DETECTION OF DIABETIC RETINOPATHY BY VARIOUS METHODS USING DEEP LEARNING ALGORITHM A SURVEY

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ABSTRACT

DIABETIC RETINOPATHY is caused by damage to blood vessels of light sensitive tissue (retina) at the back of eye. Retina is responsible for sensing light and sending a signal to brain. Our goal was to distinguish between diabetic retinopathy (DR) and healthy controls (HC) by evaluating images using different deep learning methods. Retinal fundus image analysis (RFIA) for diabetic retinopathy screening can be used to reduce the risk of blindness among diabetic patients. We can also include other data such as thickness maps of intra retinal layers and retinal angiography using deep learning process to improve diagnostic accuracy. In our future work we can enlarge the sample size for moderate and severe DR patients.

INTRODUCTION

Diabetic retinopathy is a medical condition of the damaged retina that is caused by diabetes and lack of proper monitoring and treatment, which usually leads to blindness. However, diabetic retinopathy monitoring requires an expert ophthalmologist. Recently, automatic monitoring models with acceptable efficiency are suggested as an alternative for expert ophthalmologists. over time, too much sugar in your blood can lead to the blockage of the tiny blood vessels that nourish the retina, cutting off its blood supply. As a result, the eye attempts to grow new blood vessels. But these new blood vessels don't develop properly and can leak easily.

There are two types of diabetic retinopathy:

1.Early diabetic retinopathy or non-proliferative diabetic retinopathy (NPDR):

In this method new blood vessels aren't growing (proliferating). When you have NPDR, the walls of the blood vessels in your retina weaken. Tiny bulges protrude from the walls of the smaller vessels, sometimes leaking fluid and blood into the retina. Larger retinal vessels can begin to dilate and become irregular in diameter as well. NPDR can progress from mild to severe as more blood vessels become blocked. Sometimes retinal blood vessel damage leads to a buildup of fluid (edema) in the center portion (macula) of the retina. If macular edema decreases vision, treatment is required to prevent permanent vision loss.

2. Advanced diabetic retinopathy or proliferative Diabetic retinopathy:

Diabetic retinopathy can progress to this more severe type, known as proliferative diabetic retinopathy. In this type, damaged blood vessels close off, causing the growth of new, abnormal blood vessels in the retina. These new blood vessels are fragile and can leak into the clear, jellylike substance that fills the center of your eye (vitreous). Eventually, scar tissue from the growth of new blood vessels can cause the retina to detach from the back of your eye. If the new blood vessels interfere with the normal flow of fluid out of the eye, pressure can build in the eyeball. This buildup can damage the nerve that carries images from your eye to your brain (optic nerve), resulting in glaucoma.

Diabetic retinopathy involves the growth of abnormal blood vessels in the retina. Complications can lead to serious vision problems:

- **Vitreous hemorrhage.** The new blood vessels may bleed into the clear, jellylike substance that fills the center of your eye. If the amount of bleeding is small, you might see only a few dark spots (floaters). In more-severe cases, blood can fill the vitreous cavity and completely block your vision.

  Vitreous hemorrhage by itself usually doesn't cause permanent vision loss. The blood often clears from the eye within a few weeks or months. Unless your retina is damaged, your vision will likely return to its previous clarity.

- **Retinal detachment**. The abnormal blood vessels associated with diabetic retinopathy stimulate the growth of scar tissue, which can pull the retina away from the back of the eye. This can cause spots floating in your vision, flashes of light or severe vision loss.

- **Glaucoma**. New blood vessels can grow in the front part of your eye (iris) and interfere with the normal flow of fluid out of the eye, causing pressure in the eye to build. This pressure can damage the nerve that carries images from your eye to your brain (optic nerve).

- **Blindness**. Diabetic retinopathy, macular edema, glaucoma or a combination of these conditions can lead to complete vision loss, especially if the conditions are poorly managed.

LITERATURE SURVEY

In this paper, we survey the most recent papers related to DR classification. Overall, the focus of this paper highlights the prevalence of Deep learning techniques for DR classification and its impact on classification results.

Prognosis of Microaneurysm and early diagnosis system for non – proliferative diabetic retinopathy (PMNPDR) system that is capable to train effectively a deep convolution neural network for semantic segmentation of fundus images which can increase the efficiency and accuracy of NPDR (non-proliferated diabetic retinopathy) detection. In pathological retinal images, the texture of red lesions and bright blobs may be transient EXs or smooth can be modeled on the step edges in the retinal image while MAs display gaussian axial curves. Prognosis of Microaneurysm and early diagnostics system for non-proliferative diabetic retinopathy (PMNPDR) capable of effectively creating a deep-convolutional neural network for the semantic segmentation of fundus images which can improve NPDR detection efficiency and accuracy. The input images entered will be fed into convolutional layers for analysis A unit of a convolutional layer in an input image binds to a small area called the receptive field, always extends to the entire image range. The units are placed in the feature maps in a convolutional layer. The unit on the same map of features is on the same filter bank. If flattened and analyzed with a fully connected layer that contains several class neurons, then the output of the last normally dual module built to become a 336 dimensioned function vector

in our job. Finally, the output of the fully associated layer is translated to the likelihood of every class by a SoftMax function. The network will learn deeper features through increased convolutional layers. The convolution neurons are triggered by ReLU and the final layer connects to a SoftMax feature that transforms the performance in input image probabilities from different categories. The true label joins the expected Loss Calculation groups in training employing the objective function which in our case cross-entropy. The losses are then propagated back to the weights of the convolutional filter and fully connected layer by the network where stochastic gradient descent for weight updates has been used. The semantic segmentation of the diabetic retinopathy image has been performed.

Traditional screening of retinal diseases requires multiple stages of scans followed by filtration techniques. Optical coherence tomography (OCT) and spatial domain optical coherence tomography (SD-OCT) are examples of scans performed during the screening stage. The resulting fundus images are then sent for analysis by an ophthalmologist. There have been multiple efforts to classify OCT images.

For instance, OCT fundus images can be classified using the local binary pattern (LBP) proposed in 1990 and enhanced in 2015 by Silva *et al.* [11], but such images are not sufficient for distinguishing between proliferative and non-proliferative DR cases. In retinal imaging, multi-color laser and infrared are used to enhance OCT outputs, as a result the fundus images can be classified with much higher accuracy. This technique allows the detection of lower-level abnormalities such as optic discs, but is still not enough for proper DR classification. Emphasis has also been put towards effective image processing techniques as proposed by Gharaibeh *et al.* to further enhance model performance. In computer aided diagnosis (CAD), features of exudates and hemorrhages are highly detectable. This allows fundus images to be clustered into proliferative and non-proliferative cases, where mild and severe vessel abnormalities are distinguished from low level less critical lesions. CAD is one of the fundamental diagnosis techniques in the medical industry and has paved the way for digital medicine.

IMAGE PREPROCESSING TECHNIQUES IN SELECTED ARTICLES

Images are subjected to numerous image preprocessing steps for visualization enhancement. Once the images are brighter and clearer, a network can extract more salient and unique features. A brief description of the preprocessing techniques used by the researchers addressed in this section. Green channel on the RGB color space provides a better contrast when compared to the other channels. In most of the image preprocessing techniques, green channel extraction is employed. The green channel image produces more information than blue and red channels.

Another popular image preprocessing technique is contrast enhancement. The application of contrast enhancement further improves the contrast on a green channel image. To improve the contrast of the image, contrast enhancement is employed to the green channel of the image. The resizing of an image is another popular method
of image preprocessing.

Image augmentation is applied when there is an image imbalance. Images are mirrored, rotated, resized and cropped to produce cases of the selected images for a class where the number of images is lower than the other large proportion of healthy retina images in comparison with DED retina images. Augmentation is a common strategy for enhancing outcomes and preventing overfitting. Under the employment of newly developed model, data augmentations were exhibited to enhance the dataset and limit the over-fitting. When data augmentation has been improvised, then numbers of samples are maximized with implementing geometric transformation to the image data sets by applying delicate image processing approaches. The exterior of various DR lesions varies, for example, because they are dark spots, and MA and hemorrhages are mostly undividable from the background while Exudates are a high-contrast yellow color. Therefore, some kind of edge improvement is required to distinguish between dark and background lesions. In contrast, pre-processing is not about edge processing, it rather about enhancing contrast. The curve transform is efficient to define a horizontal, diagonal point and vertical, directional information, contours, missing, curvatures, and inaccurate boundary data, etc. The picture is first decomposed into several sub bands with a curve transformation. The approximate sub band is suppressed and some amplification factor increases the remaining sub strip. This reinforces the borderline of the dark lesions that enhances their separation from the background. Morphological closures are carried out on the image under consideration to preserve the luminous regions. It smoothes the substrate suppresses and components the thin vascular networks so that light lesions remain virtually unchanged. This closing process, however, it reduces the picture contrast. The image is transferred via an optimal wideband bandpass filter structure to enhance the contrast of the Exudates. Exudates often cover a wide range of retinal picture frequency spectrums.

We used data augmentation techniques to magnify the retinal dataset at multiple sizes and remove noise from fundus images. The primary data augmentation processes we performed are listed below.

- Rotation: Images were rotated from 0 to 360 degrees at random.
- Shearing: Sheared at a random angle ranging from 20 to 200 degrees.
- Image flipping: Images were flipped horizontally and vertically.
- Zoom: Images were randomly stretched in the (1/1.3, 1.3) range.
- Cropping: At random, images were shrunk to 85–95% of their original length.
- Image translation: Images were randomly moved between -25 and 25 pixels.

DATASET:

Retinal fundus images (RFI) are obtained from publicly available standard sets such as DRIVE, EyePACS, APTOS, STARE, DIARETDB, HEIMED, ROC, Messidor, e-ophtha, DDR, and RFMiD. The 9 sets are used for comparing different DR classification techniques. In more focused studies, private datasets are leveraged to enhance the accuracy of pre-trained models. The DIARETDB0 dataset is publicly accessible in DR detection and classification. The DIARETDB0 dataset contains 130 fundus images, 110 classifieds with DR and 20 deemed normal FIs. Images were taken using a digital FI camera with a 50-degree field view and unknown camera settings. The data relate to real-world scenarios and can be used to assess the overall performance of diagnostic techniques.

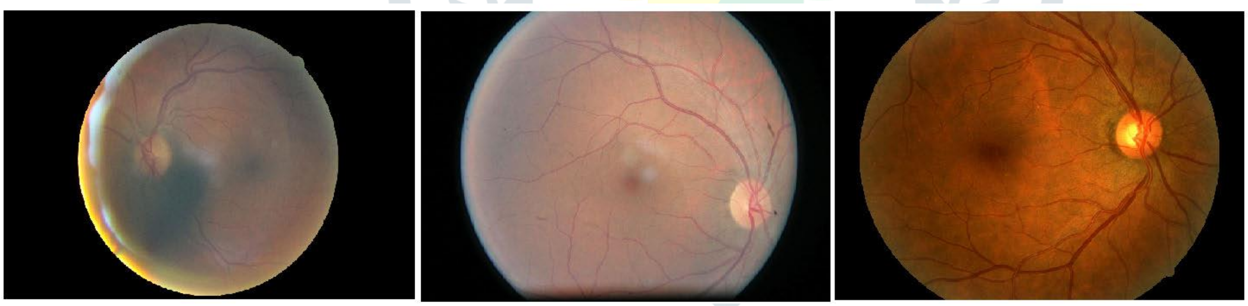


Fig.1 A sample of retinopathy images from EyePACS data set

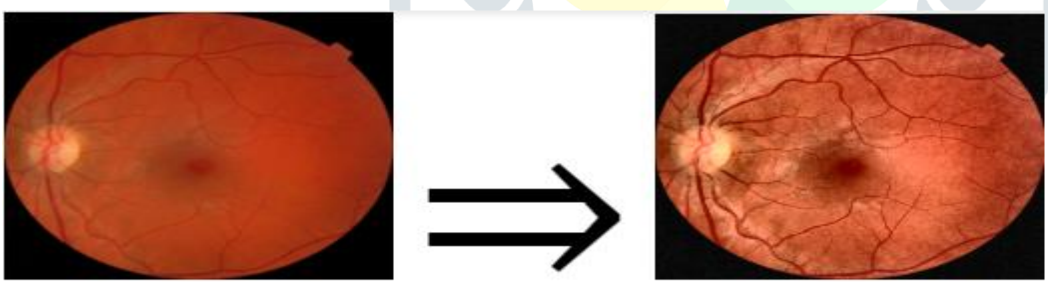
Fig.2 A sample of retinopathy images from APTOS data set

METHODS:

A. THE CLAHE METHOD

The Histogram Equalization (HE) enhances image contrast. This method can keep the brightness of the background, but it does not work well when we work with color images. The Brightness Preserving by Histogram Equalization (BBHE) method is another image enhancement method. This approach is useful when brightness conservation is needed. The problem with this method is that it needs more time for calculation. In the Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDHE) method, the mean intensity of the output and input images are approximately equal. The problem with this method is that transparency of the image contrast cannot be achieved. Adaptive Histogram Equalization (AHE) divides the image into tiles and then applies HE in each of these tiles. Although doing this way augments the contrast in near-constant areas of the image, it may cause augmented noise in these areas. Also, with this method, when there are areas in the image that are darker or brighter than most parts of the image, the contrast is low. The CLAHE is one of the ways of image quality increasing that improves the contrast and the visible surface of the dark image. Also, it reduces the noise amplification of the tiles by limiting the contrast. Although the CLAHE method does not completely eliminate artifacts, it is better from AHE. Block size (BS) and clip limit (CL) are the two main parameters of CLAHE, which control the image quality and are determined by the users. CL is the amount at which the histogram is clipped, and it depends on two factors of the normalization of the histogram and the size of the neighborhood area. Generally, before computing the Cumulative Distribution Function (CDF), the CLAHE restricts the augmentation by clipping the histogram at a predetermined amount. If the user defines improper parameters for CLAHE, the results may not be even as good as compared to HE.

we use CLAHE to improve image contrast and to equalize intensities uniformly. Using this method, the image is divided into continuous tiles without overlap. Then the histogram above a threshold is clipped, and clipped pixels distribute to each grey level. Finally, HE is applied to each of the tiles, and the mapping is interpolated between the neighboring tiles. The resulting mapping to each pixel is interpolated from the intensity mappings of eight neighboring tiles. Therefore, by doing this method, the vessels are displayed better in the image, and the network can better learn.



After using the CLAHE method

Figure 3 Depicts the increase in image contrast with the CLAHE method.

B. CNN MODEL

Recently, CNNs are applied to various problems, which have obtained excellent results. They significantly improved the image processing results in terms of accuracy and generalization. However, designing the proper CNN architecture for such problems is a vital, yet complex task.

There are three scalable dimensions for CNNs: depth, width and resolution. Depth is the number of layers in a network. Width is the number of channels in a convolutional layer, whereas the resolution is the same as the input image resolution. Generally, network all dimensions scaling improves accuracy compared to network one-dimensions or two-dimensions scaling. There are lots of CNN models with state-of-the-art results in computer vision problems. To the best of our knowledge, one of the most successful CNN models, which is proposed recently is Efficient Nets. The advantages of Efficient Nets compared to the most popular CNNs are in terms of reducing the number of parameters and FLOPS, furthermore, increasing accuracy, and speed. First, we experiment with the efficient-B0 network and then scale all three dimensions of our network by an effective compound factor. Also, our scaling is uniform, because arbitrarily scaling needs tedious manual settings, and sometimes results in less accuracy and efficiency [2].

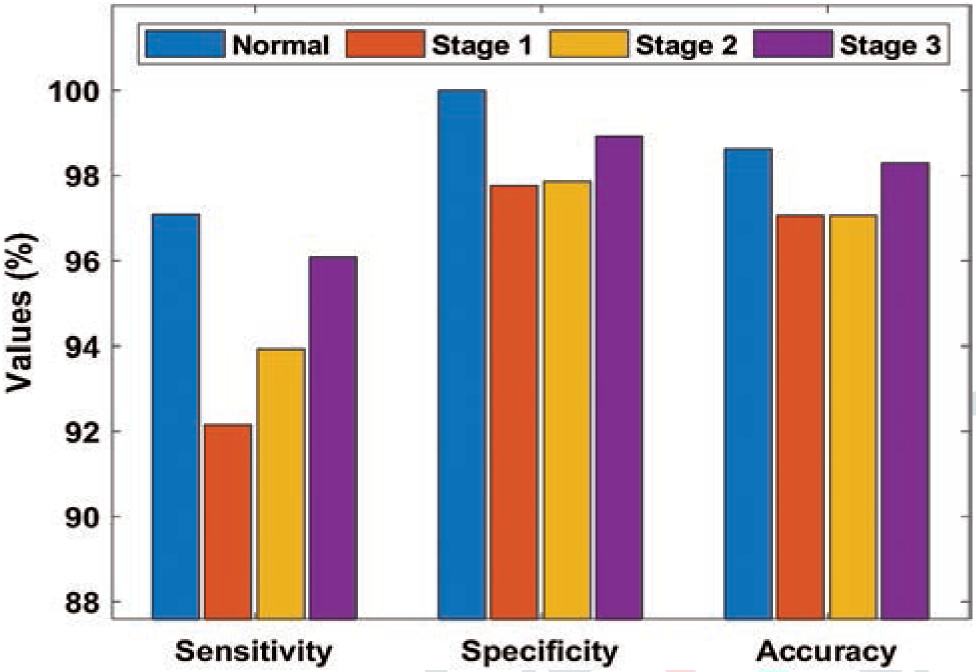


Figure 4 show the classifier results analysis of the PSO-CNN model on the applied dataset. The table values pointed out that the normal images are categorized correctly with 97.07% sensitivity, 100% specificity and 98.62% accuracy. Also, the Stage 1 images are categorized correctly with 92.16% sensitivity, 97.76% specificity and 97.04% accuracy. Equally, the Stage 2 images are categorized correctly with 93.03% sensitivity, 100% specificity and 98.62% accuracy. At last, the Stage 3 images are categorized correctly with 96.06% sensitivity, 98.90%
specificity and 98.29% accuracy.

C. MULTI-CLASS CLASSIFICATION

Multi-task learning approach to classify DR classes, by using a deep CNN architecture with a small decoder, namely, head and a feature extractor. Kaggle EyePACS dataset was used for pre-training of the CNN. Other datasets that were combined for the training set were the IDRiD dataset containing 413 photographs of the fundus and the MESSIDOR dataset which contains 1200 fundus images. Augmentations that were performed on the images include optical distortion, grid distortion, piecewise 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. This model uses ImageNet pre-trained CNNs for the initialization of the encoder. They use three decoders in which each decoder is trained to solve its own task virtue of the extracted features using the CNN backbone with classification, regression, and ordinal regression heads. Whereas the classification head output is a one-hot encoded vector were a value of 1 represents the existence of each respective stage. The Regression head's output is a real number in the range from 0 to 4.5 rounded to indicate the different disease stages.

D. TRANSFORMER METHODS

Transformer-based technique through pre-training on a large number of fundus images followed by fine-tuning on a classification task. The model uses a multiple instance learning (MIL) based `MIL head' that is attached to the ViT in a plug-and-play manner to improve on the downstream classification task. The private dataset used for training mainly was obtained from a tele- ophthalmology platform, which contains a total of 345,271 fundus images with the most common retinal conditions labeled namely normal, diabetic retinopathy, glaucoma, cataract and macular degeneration, but since some conditions occur simultaneously the pretraining is set as a multiclass classification task with 95 and 5 percent split for training and validation, respectively and images resized to (384,384).

CONCLUSION

As DR cannot be cured, it is important to detect it in its early stages to prevent further damage. For example, non-proliferative DR stages will almost always contain early indicators of DR and the ability to detect and classify those stages using a proper evaluation technique could mean saving one's eyesight. DL based approaches to enhance and classify the DR stage using lesion detection techniques across multiple fundus images. The main issue addressed in the reviewed studies is the manual diagnosis that has to occur after screening, which is typically a lengthy process prone to ophthalmologists. Efficiency of Deep Learning techniques, the analysis of retinal scans has become faster. With these advancements, it is possible to generalize DL based models and assess a wider range of symptoms and indicators that could help us to get a better understanding of the causes of retina-based diseases.

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