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AI to Predict Diabetic Retinopathy: Image Pre-Processing and Matrix Handling

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Abstract: Long durations of high blood sugar levels can cause fluid to build up in the focusing lens inside the eye in diabetics. This alters the lens's curvature, which affects how you see. However, the lens normally returns to its former shape and eyesight improves once blood sugar levels are under control. Diabetes patients with improved blood sugar management skills will delay the start and progression of diabetic retinopathy. AOA's 2018 American Eye-Q Survey found that nearly half of Americans were unaware of the existence of diabetic eye illnesses' visual signs (often which the early stages of diabetic retinopathy does not). The American Optometric Association (AOA) advises that everyone with diabetes have a comprehensive dilated eye examination at least once a year because a similar survey revealed that more than one-third of Americans were unaware that the only way to determine whether a person's diabetes will cause blindness is through a comprehensive eye exam. The risk of diabetic retinopathy causing major vision loss can be reduced with early detection and treatment. [1-3] Depending on the severity of the condition, there are many treatments for diabetic retinopathy. In order to stop blood vessels from leaking or to stop other blood vessels from leaking, people with diabetic retinopathy may require laser surgery. To reduce inflammation or inhibit the growth of new blood vessels, your Optometrist may need to inject drugs into your eye. [4-5] In this paper we will deal with image pre-processing and matrix handling. The second problem statement as mentioned in our previous introductory paper is technically dealt with in this paper.

Keywords: Image pre-processing, matrix handling, Diabetes Mellitus, American Optometric Association (AOA), Deep Learning, Convolutional Neural Networks (CNN), Diabetic Retinopathy (DR), Image Classification, retina of the eye, Optometrist, Gaussian filters, Mild DR, Moderate DR, Severe DR, Proliferate DR and NO DR.

I. INTRODUCTION

Laser treatment (photocoagulation) is used to stop the leakage of blood and fluid into the retina. A laser beam of light can be used to create small burns in areas of the retina with abnormal blood vessels to try to seal the leaks. Treatment for diabetic retinopathy depends on the stage of the disease. The goal of any treatment is to slow or stop the progression of the disease. In the early stages of non-proliferative diabetic retinopathy, regular monitoring may be the only treatment. Following your doctor's advice for diet and exercise and controlling blood sugar levels can help control the progression of the disease. Injections of medication in the eye are aimed at discouraging the formation of abnormal blood vessels and may help slowdown the damaging effects of diabetic retinopathy. If the disease advances, the abnormal blood vessels can leak blood and fluid into the retina, leading to macular edema. Laser treatment (photocoagulation) can stop this leakage. A laser beam of light creates small burns in areas of the retina with abnormal blood vessels to try to seal the leaks. Proliferative diabetic retinopathy, which causes widespread blood vessel formation in the retina, can be cured by scattering laser burns throughout the retina. As a result, aberrant blood vessels constrict and vanish. In order to protect central vision, this treatment may cause minor side vision loss.

II. LITERATURE SURVEY

[1] **Application of higher order spectra for the identification of diabetes 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.

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[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. In an operating cut point picked for high sensitivity, 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; and in an evaluation cut point selected for high specificity, the sensitivity and specificity were 90.3% and 98.1% on the EyePACS-1, while 87% and 98.5% was scored on the Messidor-2, consecutively.

[4] **Convolutional neural networks for diabetic retinopathy**. Using a training dataset of over 70,000 fundus images, Pratt et al. trained a CNN using stochastic gradient descent algorithm to classify DR into 5 classes, and it 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, and 96.8% sensitivity and 87% specificity were scored.

[5] **Deep-learning-based automatic computer-aided diagnosis system for diabetic retinopathy.** Mansour put to use the Kaggle dataset to train a deep convolutional neural network using transfer learning for feature extraction when building a computer aided diagnosis for DR. In Dutta et al. 2000 fundus images were selected from the Kaggle dataset to train a shallow feed forward neural network, deep neural network and VggNet16 model. On a test dataset of 300 images, the shallow neural network scored an accuracy of 41%, and the deep neural network scored 86.3% whiles the VggNet-16 scored 78.3% accuracy.

[6] **Comparative Study of Fine-Tuning of Pre-Trained Convolutional Neural Networks for Diabetic Retinopathy Screening.** In order to avoid the time and resource consumed during DL, Mohammadian et al. 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, reached at an accuracy score of 87.12% on the Inception-V3, and 74.49% on the Exception model.

[7] **Diagnosis of Diabetic Retinopathy Using Deep Neural.** Networks A training dataset of size 4476 was collected and labeled into 4 classes depending on abnormalities and required treatment; they resized input images into 600x600 and cut every image into four 300x300 images, and fed these images into separate pre-trained Inception-V3 models, which they called the Inception@4. After it was seen that accuracy result of the Inception@4 surpassed the VggNet and ResNet models, it was deployed on a web-based DR classification system.

III. EXISTING CNN MODELS

i. Inception V3: Szegedy et al proposed the Inception architecture in 2014. The original architecture was called GoogleLeNet. All the subsequent versions were called Inception Vn (n is the version number). Batch Normalization was added in Inception V2 as an improvement over Inception V1. In InceptionV3 model factorization methods were introduced as an improvement over V2.[6-9]

ii. ResNet50: In 2015 He et al proposed ResNet - The Residual Networks architecture. It has 50 convolutional layers with skip connections that help in improving the learning accuracy of the model. Also, it uses global averaging pooling instead of fully connected layers thereby reducing the model size.[10]

iii. MobileNet: In 2017 another CNN architecture called MobileNet was proposed by Howard et al. In this separable convolution have been arranged depth-wise and they apply the convolution operation on each color channel separately instead of taking them as a whole. The cost of computation gets reduced in this architecture.[11]

iv. Xception: François Chollet developed Xception in 2017. This model can be considered as an improvised version of Inception as modules of Inception have been replaced with depth wise separable convolutions. This latest and accurate model scores upon speed and accuracy.

IV. PROBLEM STATEMENT

Using the Keras_h5 model of CNN, we predict the stage of diabetic retinopathy using fundus photograph images. The project's major goal is to diagnose diabetic retinopathy early enough to prevent blindness. Using Deep transfer learning and classification techniques, we detect the Complication of the disease by classifying the images of the patient's retina

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into five labels numbered from 0 to 4, where each label named Normal, Mild DR, Moderate DR, Severe DR, and Proliferate DR represents the disease complication. For the given input fundus image, one of these five steps is detected as an output label. Realtime images or new images of newer subjects has to be predicted for Normal, Mild DR, Moderate DR, Severe DR, and Proliferate DR. Also, the model obtained out of CNN needs to be re-validated for better accuracy through feedback method. This research work is divided into four parts

First. Image Acquisition, categorization and applying Gaussian filters.
Second. Image Pre-processing, Image to array formation and image matrix handling.
Third. Applying CNN and creating and validating retina.model for Prediction.
Fourth. Testing on real time images and verification.

V. METHODOLOGY

After reviewing the literature for other image identification tasks, we chose the structure of our neural network, which is multilayer CNN. It is believed that adding more convolution layers will enable the network to learn more detailed information. For instance, the last convolutional layer of the network, which is the deepest layer, should learn the characteristics of DR classification, such as hard exudate, whereas the first layer learns edges. After each convolution layer, the network does batch normalisation. Convolution blocks with activation are the first step. We switch to one batch normalisation each block as the number of feature maps rises. The kernel size is 3x3 and the strides are 2x2 for all maxpooling operations. The network is flattened to one dimension following the last convolutional block. We utilise weighted class weights relative to the number of photos in each class to prevent overfitting. Similarly, we dropout dense layers to lessen overfitting until we reach the dense five node classification layer, which predicts our classification using a softmax activation function. To prevent over reliance on certain network nodes, the leaky rectified linear unit 13 activation function was utilised, applied with a value of 0.01. Similar to this, weight and biases in the convolution layers were regularised using L2. To cut down on initial training time, Gaussian initialization was also used to initialise the network. The popular categorical cross-entropy function was employed as the loss function during optimization. Figure 1 shows different retinal images classified as [12-14]

(a) No DR
(b) Mild DR
(c) Moderate DR
(d) Severe DR
(e) Proliferative DR

The dataset contained images from patients of varying ethnicity, age groups and extremely varied levels of lighting in the fundus photography. This affects the pixel intensity values within the images and creates unnecessary variation unrelated to classification levels. To counteract this, colour normalisation was implemented on the images using the OpenCV (http://opencv.org/) package. The result of this can be seen in Fig 2 (b). [15] The images were also high resolution and therefore of significant memory size. The dataset was resized to 512x512 pixels which retained the intricate features we wished to identify but reduced the dataset to a memory size the NVIDIA K40c could handle. [16]

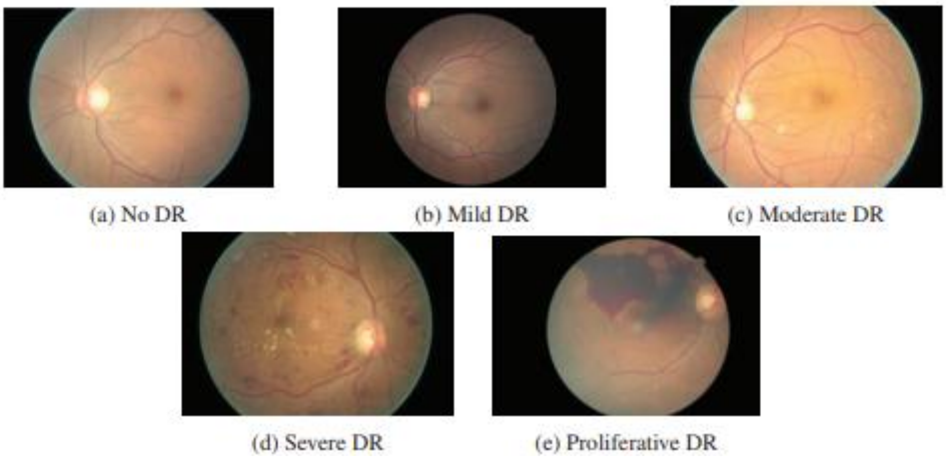

Figure 1 shows different types of retinal images.

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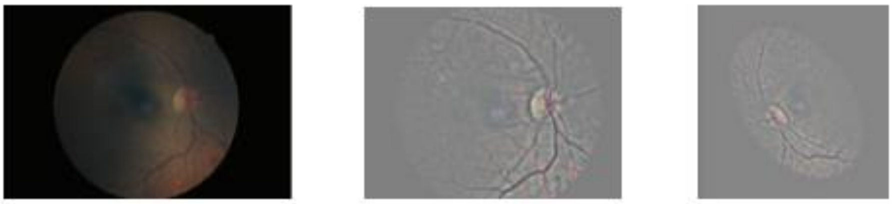

(a) Original image (b) Preprocessed image (c) Augmented image

Figure 2 shows the image pre-processing techniques.

The network was only trained once using the original pre-processed images. After then, training was conducted using real-time data augmentation to enhance the network's localization capabilities. Each image was randomly enhanced during each epoch with random rotations of 0–90 degrees, random yes–or–no flips of the horizontal and vertical axis, and random shifts of the horizontal and vertical axis. The result of an image augmentation can be seen in Fig 2 (c). Figure 3 shows the normalized array of images. Figure 4 shows image to matrix conversion. [17-18]

```
data

array([[[[ 0.00787401,  0.00787401,  0.00787401],
         [ 0.03937006,  0.03937006,  0.03937006],
         [ 0.00787401,  0.00787401,  0.00787401],
         ...,
         [ 0.00787401,  0.00787401,  0.00787401],
         [ 0.00787401,  0.00787401,  0.00787401],
         [ 0.00787401,  0.00787401,  0.00787401]],

        [[ 0.00787401,  0.00787401,  0.00787401],
         [ 0.03937006,  0.03937006,  0.03937006],
         [ 0.00787401,  0.00787401,  0.00787401],
         ...,
         [ 0.00787401,  0.00787401,  0.00787401],
         [ 0.00787401,  0.00787401,  0.00787401],
         [ 0.00787401,  0.00787401,  0.00787401]],

        [[ 0.00787401,  0.00787401,  0.00787401],
         [ 0.00787401,  0.00787401,  0.00787401],
         [ 0.00787401,  0.00787401,  0.00787401],
         ...,
         [ 0.03937006,  0.03937006,  0.03937006],
         [ 0.00787401,  0.00787401,  0.00787401],
         [ 0.00787401,  0.00787401,  0.00787401]],
```

Figure 3 shows the normalized array of images.

```
[[128, 128, 128],
 [132, 132, 132],
 [128, 128, 128],
 ...,
 [124, 124, 124],
 [128, 128, 128],
 [128, 128, 128]],

[[128, 128, 128],
 [130, 130, 130],
 [128, 128, 128],
 ...,
 [128, 128, 128],
 [127, 127, 127],
 [128, 128, 128]],
```

Figure 4 shows image to matrix conversion.

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VI. CONCLUSIONS AND FUTURE WORK

Automated screening methods drastically cut down on the time needed to make diagnoses, saving ophthalmologists' time and money while also enabling patients to receive treatment sooner. Automated DR detection systems are crucial for spotting DR at an early stage. The stages of DR are determined by the kind of lesions that develop on the retina. This article has examined the most recent deep learning-based automated methods for detecting and categorising diabetic retinopathy. We have detailed the publicly accessible common fundus DR datasets and provided a quick introduction to deep learning methods. Due to its effectiveness, CNN has been adopted by the majority of researchers for the detection and classification of DR pictures. This review has also discussed the useful techniques that can be utilized in image pre-processing to detect and to classify DR using DL. The matrix handling techniques used are making our study more sophisticated and our model more robust.

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BIOGRAPHY

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