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AI to Predict Diabetic Retinopathy: CNN to Build "retina.model"

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Abstract: Diabetic retinopathy, which results from persistently high blood sugar caused by Diabetes Mellitus or simply called Diabetes, is linked to harm the microscopic blood vessels in the retina. In order to send signals to the brain via the optic nerve, the retina must first detect light. Vision distortion can result from diabetic retinopathy, which can cause blood vessels in the retina to leak fluid or haemorrhage (bleed). In its most severe form, aberrant blood vessels proliferate (grow in quantity) on the retina's surface, which may cause scarring and retinal cell loss. Due to a complex grading system and the requirement for trained doctors/ Optometrists to recognise the existence and relevance of numerous tiny characteristics, diagnosing Diabetic Retinopathy (DR) with colour fundus pictures is a challenging and time-consuming task. In this article, we suggest a CNN method for correctly identifying DR from digital fundus images and classifying its severity. We create a network with CNN architecture and data augmentation that can recognise the complex elements needed for the classification task, like micro-aneurysms, exudate, and haemorrhage on the retina, and then deliver a diagnosis automatically and without user input. On the image set as acquired in our previous papers [1] on Diabetic retinopathy, we train this network using a top-tier graphics processing unit (GPU), and the results are excellent, especially for a challenging classification test. Treatment for diabetic retinopathy is often delayed until it starts to progress to Proliferate DR/ PDR. Comprehensive dilated eye exams are needed more frequently as diabetic retinopathy becomes more severe. People with severe non-proliferative diabetic retinopathy have a high risk of developing PDR and may need a comprehensive dilated eye exam as often as every 2 to 4 months. So, in our paper we have developed such a model where even a thin line of difference between each stages of DR is well distinguished by our model "retina.model" and is 100% reusable with increasing level of cognition with time as the machine tries to learn new patterns.

Keywords: persistently high blood sugar, matrix handling, Diabetes Mellitus, American Optometric Association (AOA), Deep Learning, CNN architecture, Diabetic Retinopathy (DR), Image Classification, retina of the eye, Optometrist, Gaussian filters, Mild DR, Moderate DR, Severe DR, Proliferate DR/ PDR and NO DR.

I. INTRODUCTION

Diabetic retinopathy can affect people with any kind of diabetes, including type 1, type 2, and gestational. The duration of diabetes raises risk. Only approximately half of Americans with diabetes are aware that they have diabetic retinopathy, which affects between 40 and 45 percent of them. Diabetic retinopathy may quickly develop or deteriorate in pregnant women who develop or have diabetes. Sometimes diabetic retinopathy causes irreversible vision loss. However, early diagnosis and treatment can significantly lower the chance of blindness by 95%. People with diabetes should receive a thorough dilated eye exam at least once a year because diabetic retinopathy typically lacks early symptoms. People who have diabetic retinopathy can require more frequent eye exams. When a woman with diabetes becomes pregnant, she should get a thorough dilated eye exam as early as possible. There may be a need for additional exams during pregnancy for diagnosing gestational diabetes which may become irreversible. The image set is acquired from the American Optometric Association (AOA),[2-5] who has also given the reference dataset for training which would automate the process of detection and bring in the feature of intuition ad perception based on AI Architecture for prediction.[6-8]

II. ANATOMY OF THE DR EYE

Diabetic retinopathy does not usually cause any noticeable symptoms until it has reached an advanced stage. If it is not identified and treated, it can lead to sudden blindness. Symptoms of diabetic retinopathy mainly include: sudden changes in vision, blurred vision, slow vision loss over time, pain in the eye, double vision, floaters in vision and difficult to see at night times.[8][9] Many people with early diabetic retinopathy have no symptoms before major

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bleeding occurs in the eye as shown in figure 3. In the early stage of diabetic retinopathy i.e., non-proliferative the blood vessels in the eye are larger in certain spots, sometimes blood vessels that are blocked, small amounts of bleeding i.e., retinal hemorrhages and fluid may leak into the retina. In more advanced retinopathy i.e., proliferative we can see new blood vessels starting to grow in the eye that are fragile that can bleed, small scars develop on the retina and in other parts of the eye. Diabetic retinopathy results in microvascular retinal changes. [10-15] Hyperglycemia-induced intramural pericyte death and the thickening of the basement membrane lead to incompetence of the vascular walls. These damage the blood-retinal barrier and also make the retinal blood vessels become more permeable. Small blood vessels in the eye are especially vulnerable, the over accumulation of glucose and/or fructose damages the tiny blood vessels in the retina. During the initial stage, i.e., Non-proliferative diabetic retinopathy, most people do not notice any change in their vision. Early changes that are reversible are sometimes termed as simplex retinopathy. Some people develop a condition called macular edema. [11][16] In which the blood vessels get damaged resulting in leakage of fluid and lipids onto the macula, the part of the retina. This fluid makes the macula swell, which blurs vision. The abnormalities of a DR eye is as shown in figure 1, they are mainly[11][17]

i. Cotton wool spots
ii. Aneurysm
iii. Hemorrhages
iv. Hard exudates
v. Abnormal growth of blood vessels

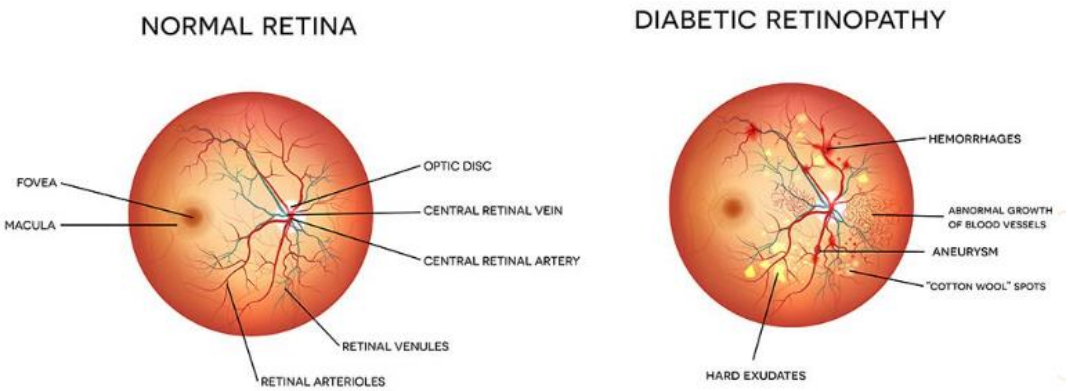

Figure 1 shows the anatomy of a normal eye and Diabetic Retinopathy eye.

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][12]
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.[18]

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,[12] we detect the Complication of the disease by classifying the images of the patient's retina 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,

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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.[29]
Second. Image Pre-processing, Image to array formation and image matrix handling.[1]
Third. Applying CNN and creating and validating retina.model for Prediction.
Fourth. Testing on real time images and verification.

V. METHODOLOGY

When we train a deep convolutional neural network on a dataset of pre-processed images, the images are passed through the network by applying a number of filters at each layer as part of the training process. The activations of the image at each layer are multiplied by the values of the filter matrices. The last layer's activations are utilised to determine the class to which the image belongs. In order to successfully identify the class to which an image belongs, it is important to determine the best values for each of these filter matrices when training a deep network. This way, the output activations of the network can reliably identify the class to which an image belongs. Gradient descent is the method used to determine these filter matrix values. When we train a conv net on the ImageNet dataset and then examine what each filter on the conv net has learned to recognise or what triggers it, we can see something really interesting based on perception. Colours and certain horizontal and vertical lines are recognised by the filters on the convolutional network's initial few layers. [19-22] The next few layers slowly learn to recognize trivial shapes using the lines and colours learnt in the previous layers. Then the next layers learn to recognize textures, then parts of objects like legs, eyes, nose etc. Finally, the filters in the last layers get activated by whole objects and gives the output. By using a pretrained network to do transfer learning, we are simply adding a few dense layers at the end of the pretrained network and learning what combination of these already learnt features help in recognizing the objects in our new datasets.[23][24][29]

```
# Building the model

model = tf.keras.Sequential([
    layers.Conv2D(8, (3,3), padding="valid", input_shape=(224,224,3), activation = 'relu'),
    layers.MaxPooling2D(pool_size=(2,2)),
    layers.BatchNormalization(),

    layers.Conv2D(16, (3,3), padding="valid", activation = 'relu'),
    layers.MaxPooling2D(pool_size=(2,2)),
    layers.BatchNormalization(),

    layers.Conv2D(32, (4,4), padding="valid", activation = 'relu'),
    layers.MaxPooling2D(pool_size=(2,2)),
    layers.BatchNormalization(),

    layers.Flatten(),
    layers.Dense(32, activation = 'relu'),
    layers.Dropout(0.15),
    layers.Dense(2, activation = 'softmax')
])

model.compile(optimizer=tf.keras.optimizers.Adam(lr = 1e-5),
              loss=tf.keras.losses.BinaryCrossentropy(),
              metrics=['acc'])

history = model.fit(train_batches,
                    epochs=12,
                    validation_data=val_batches)
```

Figure 2 shows the process of building the keras model.

In a neural network, the activation function is responsible for transforming the summed weighted input from the node into the activation of the node or output for that input. The rectified linear activation function or ReLU for short is a piecewise linear function that will output the input directly if it is positive, otherwise, it will output zero. It has become the default activation function for our model "retina.model" because a model that uses it is easier to train and often achieves better performance. Softmax is often used as the activation for the last layer of a classification network because the result could be interpreted as a probability distribution.[25-28] Figure 2 shows the process of building the model and setting up of the initial activation units with ReLU [29] and the final layers with softmax. The epoch is set at 12 (can also be 25). An epoch is training the neural network with all the training data for one cycle. In an epoch, we use

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all of the data exactly once. A forward pass and a backward pass together are counted as one pass. An epoch is made up of one or more batches, where we use a part of the dataset to train the neural network. We call passing through the training examples in a batch an iteration. Figure 3 shows the functions during an epoch and an iteration. Figure 4 shows validation with 81 iterations in each of 12 epochs.

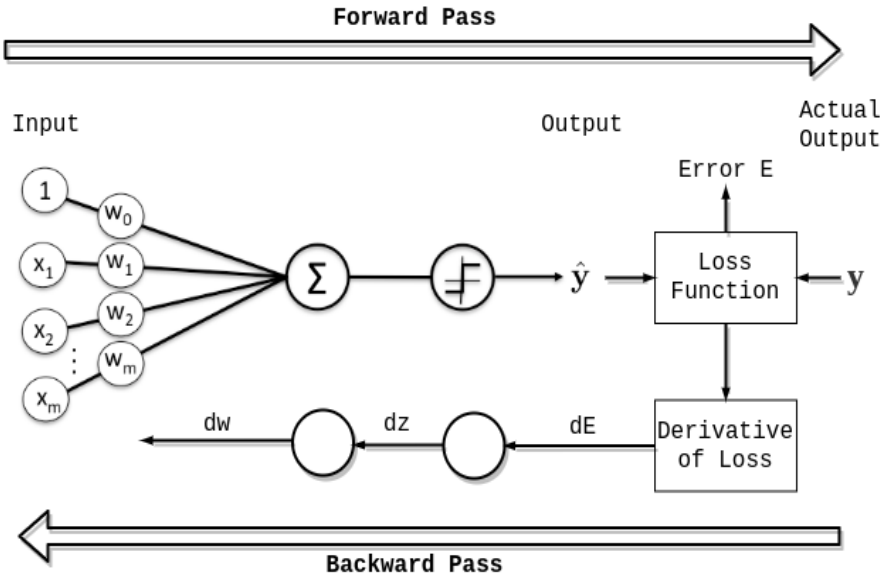

Figure 3 shows the functions during an epoch and an iteration.

```
Train for 81 steps, validate for 18 steps
Epoch 1/12
81/81 [==============================] - 45s 556ms/step - loss: 0.3958 - acc: 0.8271 - val_loss: 0.6725 - val_acc: 0.5073
Epoch 2/12
81/81 [==============================] - 41s 505ms/step - loss: 0.2544 - acc: 0.9044 - val_loss: 0.6653 - val_acc: 0.5073
Epoch 3/12
81/81 [==============================] - 40s 494ms/step - loss: 0.2192 - acc: 0.9235 - val_loss: 0.5842 - val_acc: 0.5909
Epoch 4/12
81/81 [==============================] - 40s 494ms/step - loss: 0.1994 - acc: 0.9301 - val_loss: 0.5047 - val_acc: 0.7145
Epoch 5/12
81/81 [==============================] - 40s 496ms/step - loss: 0.1805 - acc: 0.9360 - val_loss: 0.3540 - val_acc: 0.8764
Epoch 6/12
81/81 [==============================] - 40s 499ms/step - loss: 0.1700 - acc: 0.9411 - val_loss: 0.2802 - val_acc: 0.9073
Epoch 7/12
81/81 [==============================] - 40s 500ms/step - loss: 0.1572 - acc: 0.9450 - val_loss: 0.2337 - val_acc: 0.9127
Epoch 8/12
81/81 [==============================] - 40s 500ms/step - loss: 0.1469 - acc: 0.9504 - val_loss: 0.2217 - val_acc: 0.9164
Epoch 9/12
81/81 [==============================] - 40s 496ms/step - loss: 0.1377 - acc: 0.9520 - val_loss: 0.2139 - val_acc: 0.9200
Epoch 10/12
81/81 [==============================] - 40s 499ms/step - loss: 0.1281 - acc: 0.9563 - val_loss: 0.2140 - val_acc: 0.9236
Epoch 11/12
81/81 [==============================] - 40s 495ms/step - loss: 0.1205 - acc: 0.9586 - val_loss: 0.2143 - val_acc: 0.9200
Epoch 12/12
81/81 [==============================] - 40s 495ms/step - loss: 0.1129 - acc: 0.9637 - val_loss: 0.2185 - val_acc: 0.9218
```

Figure 4 shows validation with 81 iterations in each of 12 epochs.

VI. CONCLUSIONS AND FUTURE WORK

Since our trained CNN can categorise thousands of photos per minute, utilising it in real-time whenever a new image is obtained has the potential to be advantageous. In reality, when a patient comes in for screening, photos are forwarded to physicians for grading and are not appropriately rated. A swift diagnosis and an immediate response to a patient are made possible by the trained CNN. These outcomes were likewise accomplished by the network using just one image per eye. The network easily picks up on an image of a healthy eye. This is probably because the dataset has a lot of healthy eyes. To classify the photos at the extreme ends of the scale during training, much less learning was needed. The network may have had difficulty learning detailed enough features to recognise some of the more complex components of DR, as evidenced by the low sensitivity, which mostly came from the mild and moderate classes. Over

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10% of the photos in our collection are declared ungradable by national UK standards, [24] which was a related problem that was discovered and confirmed by a clinician. Since these photos have at least a specific amount of DR, they were classified as a class. Considering that the photos were incorrectly categorised for both training and validation, this may have seriously hampered our results.

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OUR GUIDE

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