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DIABETIC RETINAL ANOMALY PREDICTION USING KERAS MODEL OF NEURAL NETWORKS

Rohan S, Rekha Lavanya, Akshay S Katti, Srinivas B V
Student, student, student. Asst Professor
Atria Institute of Technology

I. ABSTRACT

Diabetic retinopathy, a complication of diabetes mellitus caused by elevated blood sugar levels, can cause harm to the retina located at the back of the eye. Failure to detect and treat this condition appropriately may result in loss of eye sight. Electrical signals are being formed from the light rays with the help of the retina located behind the eye it contains Light-sensitive radiation. The brain receives the signals and converts them into the visuals you see. Continual blood flow is necessary for the retina, which is provided through a system of tiny blood capillariesIn severe cases of diabetic retinopathy, surgical removal and replacement of the vitreous, a substance which is gel like located behind the eye, may be necessary. Additionally, surgery may be required for a retinal detachment. Rear separation is being done here. We offer a CNN method for accurately determining the degree of DR from digital fundus pictures. [1-4] Through the use of CNN architecture and data augmentations, we have created a network that has the ability to identify the intricate components of the classification task, such as Tiny dilation or outpouchings of small blood vessels, Abnormal fluid or protein accumulation in tissues or body cavities, and Bleeding within the layers of the retina, the light-sensitive tissue located at the back of the eye. This network can provide automatic diagnosis without any input from the user. The training data consisted of images that had undergone Gaussian filters. Our research demonstrates the accuracy of the proposed CNN was recorded at 98%, while the sensitivity was over 95% on a set of 3500 validation photos. The implementation of this method removes the necessity for a retina specialist and enhances accessibility to retinal treatment, while offering a reliable and objective diagnosis and grading of diabetic retinopathy. Early disease detection and objective disease progression tracking are made possible by this method, which may help the improvement of medical treatment to lessen vision loss. [5]

Index Terms – Diabetes mellitus, Convolution Neural Networks (CNN), data augmentations, Image Classification, , Diabetic Retinopathy(DR).

II. INTRODUCTION

Prolonged high blood sugar levels in individuals with diabetes may lead to accumulation of fluid in the eye's lens used for focusing, resulting in a change in the lens's curvature and a shift in vision. Vision typically returns to normal once blood sugar levels are regulated, but delayed and advanced diabetic retinopathy may still occur. The AOA's 2018 American Eye Q Survey revealed that nearly half of Americans are unaware of the visual symptoms associated with diabetic eye diseases, which are often absent in the early stages of diabetic retinopathy.

Failure to treat diabetic retinopathy can lead to significant vision loss if left unchecked. Treatment options for diabetic retinopathy vary depending on the severity of the condition. Laser surgery may be necessary to seal or stop the leaking of blood vessels, while medication may be prescribed to reduce inflammation or prevent the growth of new blood vessels. In advanced cases, the vitreous, a gel-like fluid at the back of the eye, may need to be surgically removed and replaced. Retinal detachment, a separation of the lining that receives light at the back of the eye, may also require surgery. Diabetic retinopathy may cause various symptoms such as the presence of spots or floaters in the vision, blurred vision, the appearance of dark or empty spots in the central vision, and difficulty seeing in low-light conditions. It is important for individuals with diabetes to undergo regular eye exams to detect any potential eye problems, even if they are not experiencing any symptoms. Early detection and timely treatment can help prevent further vision loss.

III. LITERATURE SURVEY

[1] The use of higher order spectra for the detection and classification of stages of diabetic retinopathy. To classify diabetic retinopathy (DR), both feature extraction-based classification and deep learning (DL) techniques have been employed. In one study conducted by Acharya et al., features were extracted from 300 fundus images using a support vector machine classifier (SVM) and labelled them into different classes(five) with sensitivity of 82% and specificity of 88%. Many different algorithms were created to remove Diabetic retinal abnormalities such as exudates, blood vessels and microaneurysms. For grading diabetic retinopathy, exudates were eliminated. In another study, the dataset DIABETDB1 was divided into Affirmative and negative classes based on the SVM classifier was employed to analyse the number and size of microaneurysms.

[2] Rethinking the inception architecture for computer vision. In addition to requiring specialised knowledge to identify the necessary features, feature extraction-based classification algorithms take a lot of time to choose, identify, and extract the essential features. Additionally, DL-based systems like CNNs have demonstrated superior performance. approaches that rely on feature extraction. Learning from scratch and transfer learning are the two main types of DL training for DR classification.

[3] Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. a dataset of 128,175 fundus photos were trained on the convolutional neural network (CNN). The images are categorized into two categories: the first group comprises images with severity levels 0 and 1, while the second category includes levels 2, 3, and 4. The network achieved a high sensitivity operating cut point with a sensitivity of 97.5% and a specificity of... In an evaluation cut point that prioritized high specificity. The network demonstrated a sensitivity of 90.3% and specificity of 98.1% on the EyePACS-1 dataset and 87% and 98.5% on the Messidor-2 dataset. On the Messidor-2 dataset, a sensitivity of 96.1% and specificity of 93.9% were achieved by the network.

[4] CNN for diabetic retinopathy. Pratt et al. utilized a stochastic gradient descent algorithm to train a dataset of more than 70,000 fundus images using a CNN model, classifying DR into 5 categories. Their model achieved 75% accuracy, 95% specificity, and 30% sensitivity. In another study, a deep learning model was trained on the MESSIDOR-2 dataset to detect diabetic retinopathy automatically, with a resulting sensitivity of 96.8% and a specificity of 87% achieved from scratch.

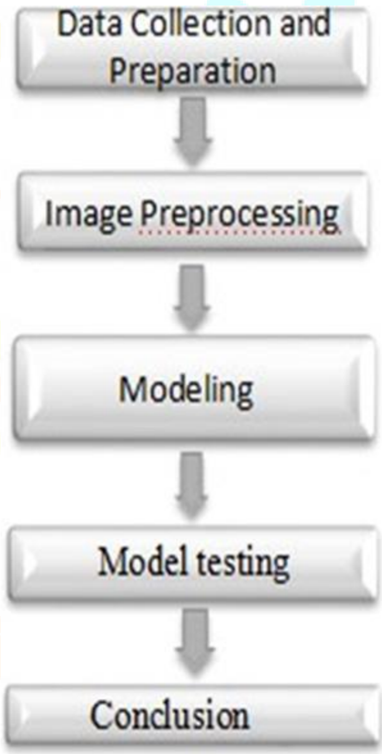
[5] A computer-aided diagnosis system for diabetic retinopathy based on deep learning techniques.. Mansour utilized the Kaggle dataset to create a system for diagnosing DR with the aid of transfer learning in a deep convolutional neural network. Meanwhile, Dutta et al. selected 2000 fundus images from the Kaggle dataset to train three models: a shallow feedforward neural network, a deep neural network, and a VggNet16 model. The shallow neural network had an accuracy of 41% on a test set of 300 images, while the deep neural network had an accuracy of 86.3% and the VggNet-16 had an accuracy of 78.3%.

[6] A study comparing fine-tuning techniques of pre-trained convolutional neural networks for screening diabetic retinopathy. Mohammadian et al. enhanced the pre-trained models of InceptionV3 and Exception to classify the Kaggle dataset into two categories, thus reducing the time and resources expended in DLThe dataset was made balanced through data augmentation techniques, and the Inception-V3 model yielded an accuracy score of 87.12%, whereas the Exception model showed an accuracy score of 74.49%.

[7] Diagnosis of Diabetic Retinopathy Using Deep Neural. A dataset trained of 4476 fundus images was classified into four categories by the researchers based on the detected anomalies and the necessary treatment options. The input images were then resized to 600x600 and split into images of four 300x300 before being entered into multiple pre-learned Inception-V3 models, which the researchers dubbed the Inception@4. As the accuracy results of Inception@4 outperformed those of the VggNet and ResNet models, the system was integrated into a DR classification system that is accessible via the web.

IV. PROPOSED SYSTEM

One approach to machine learning known as transfer learning involves repurposing a model that has already been trained for a specific task to perform a related task. This method can help to speed up the development process or enhance performance when building a model for the second task.



Finding the appropriate values for each filter throughout a CNN's training process is necessary for an input image to activate specific neurons in the final layer and correctly forecast the class.

Training a CNN of considerable size from the ground up for most applications can demand a significant amount of data processing and processing power and can also be a time-consuming process. As an alternative, transfer learning can be used to leverage previously learned features and improve performance or speed up the training process for a related task.

When training a deep convolutional neural network on an image dataset, filters are applied at each layer to process the images. The filter matrices are then multiplied by the image activations to determine the image belongs to which class. The best filter matrix values are determined with the help of gradient descent during the training process to accurately classify the images.

When analyzing the filters in every layer of a convolutional neural network that was trained on the ImageNet dataset, it's interesting to note that the initial layers recognize basic shapes and colors, while the following layers gradually learn to recognize more complex shapes and textures, and eventually object parts such as eyes and noses. The final layer's filters are activated by complete objects to produce the output class. A pre-learned neural network can be utilized for transfer learning, and by appending a few dense layers at the end, the extracted features from previous learning can be amalgamated to identify objects in novel datasets.

IV. METHODOLOGY

The following steps outline the methodology:

- Acquire the dataset.
- Preprocess the data.
- Split the dataset into two categories: one for training and the other for testing.
- Apply data augmentation techniques.
- Train the model using the CNN algorithm.
- Obtain the evaluation metrics.
- Generate predictions.
- Construct a classification table.

A. Dataset

The source of the dataset used in this study was the Asia Pacific Tele Ophthalmology Society's 2019 Blindness Identification [14]. The dataset consists of a large number of fundus images, captured through various imaging methods, and accompanied by detailed information. The images were assigned severity ratings for diabetic retinopathy on a scale of 0 to 4 by the attending physician. For the purpose of this analysis, the dataset was divided into two classes, class 0 comprising of images with no diabetic retinopathy, and class 1 comprising of images with various degrees of diabetic retinopathy including NPDR, PDR, and combined Mild, Moderate, and Severe images.

B. Pre-processing

The dataset is initially pre-processed using different techniques such resizing, pixel rescaling, and label encoder because it comprises picture data.

1.Resizing: Image resizing is done to a 64x64 pixel size. Figure 1 illustrates image resizing.

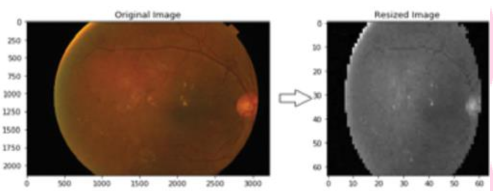


Fig 1. Image Resizing

2. Pixel Rescaling: For convenience of computation, pixel values for each image are rescaled into 0 and 1 by dividing by 255. This increases the effectiveness of the function of activation. Data between 0 and 1 work better with the Sigmoid function.

3. Label Encoding: conversion of a label into a numerical format to enable machine-readable processing

C. Dataset Splitting

The dataset is parted into two parts, where 20% of the samples are reserved for testing and 80% for training. 3,789 samples make up the training set, whereas 948 make up the validation set. samples, 583 have diabetes , 365 are stable. In order for the binary classification task to be properly completed, we make sure that the photos selected for the test are not used during training.

D. Data Augmentation

Data augmentation is a useful technique that addresses issues such as the quantity, diversity, and quality of training data, as well as problems associated with class imbalance in datasets. This technique involves applying various transformations to the original dataset, such as cropping, shifting, rotating, padding, flipping, and other methods, during the training process after the dataset has been pre-processed and split into training and validation sets. It helps to enhance the training data and improve the model's performance on various classification tasks

E. Classifier

Fig. 2 shows the CNN model's architecture, which is fundamentally broken up into multiple layers like, pooling , convolution and fully linked layers.

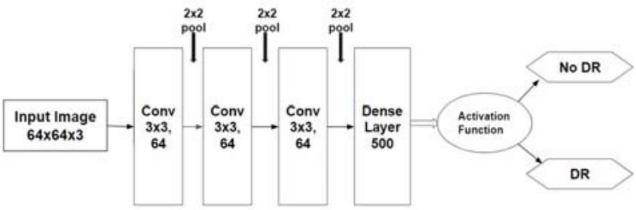


Fig. 2. CNN Architecture

1. Convolutional Layer: The initial layer, also called as the input layer, is responsible for performing intensive computations that facilitate additional tasks. This layer serves as the entry point for the neural network, with the image's input size specified as 64x64x3.

2. Max pooling Layer: The 3x3 matrix preceding this layer is processed to extract the most significant feature, resulting in a smaller matrix. This is achieved by converting the matrix into a 2x2 matrix that retains only the highest weighted feature from the original matrix.

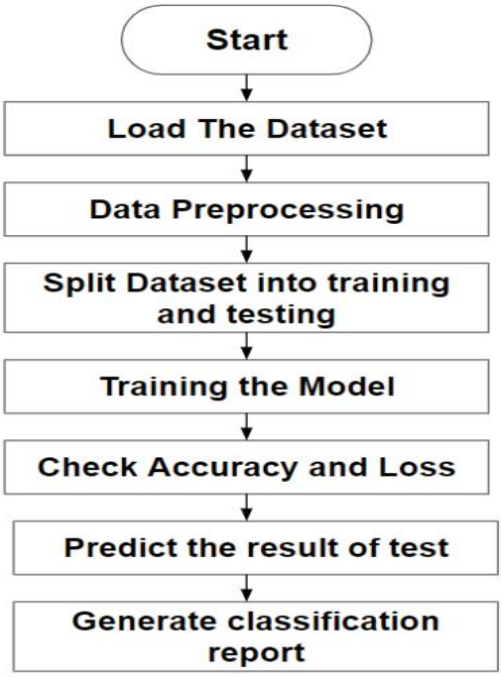
3. Flatten Layer: The inputs for the dense layer are provided by the flatten layer, which lowers the picture to a one dimensional matrix.

4. Dropout Layer: The greater and more effective operation carried out by the dropout layer greatly improves the network's capacity for normalisation. This approach Throughout training, employs random removal and may recover neurons by using probability specified by a hyperparameter termed dropout rate.

5. Dense Layer: The properties that the previous convolutional layer eliminated are input into these layers, which are the last ones in a deep neural classifier.

6. Output LayerThe output of the final layer of the network, which can be either the Softmax layer or the sigmoid neuron, determines the classification type, which can be either binary or multiclass.

The flowchart for creating an algorithm is shown in Figure 3. We performed classification based on four criteria after creating the algorithms: Fl-score, accuracy, recall, and precision.



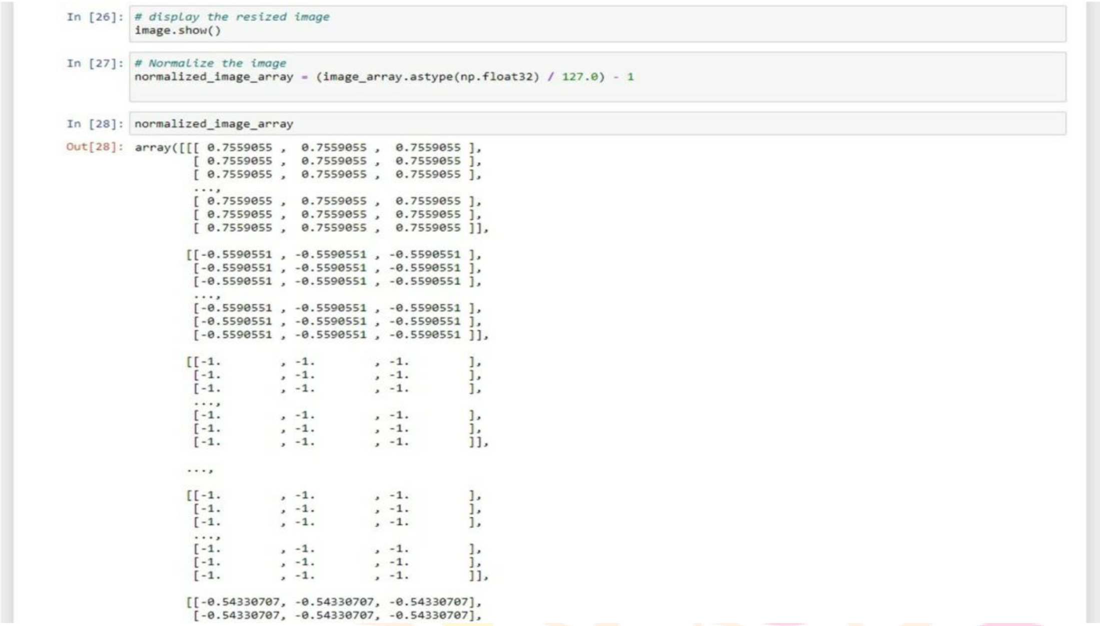
Optimizers play a crucial role in deep learning. In this particular case, the RMS prop optimizer is utilized, This distinguishes between the learning rate and the exponential decay of the average square gradient. The number of epochs is set to 50, the batch size is set to 128.

V. RESULTS AND DISCUSSION.

- Real time image is fed from internet,image is first obtained.
- Real time image is resized.
- 224*224 is the size choosen.
- ANTIALIAS Filters are used to remove crowding.
- Image is fit using ImageOps()function.

- Real time image is converted into array, Arrays are created.
- Arrays are normalized, Each matrix element is divided by 2^7.

- Subtracted by 1, We get prediction output as 2D array.
- Result is predicted telling if the patient has DR or not with its probability Array.



```
In [26]: # display the resized image
         image.show()

In [27]: # Normalize the image
         normalized_image_array = (image_array.astype(np.float32) / 127.0) - 1

In [28]: normalized_image_array

Out[28]: array([[[ 0.7559055 ,  0.7559055 ,  0.7559055 ],
                 [ 0.7559055 ,  0.7559055 ,  0.7559055 ],
                 [ 0.7559055 ,  0.7559055 ,  0.7559055 ],
                 ...,
                 [ 0.7559055 ,  0.7559055 ,  0.7559055 ],
                 [ 0.7559055 ,  0.7559055 ,  0.7559055 ],
                 [ 0.7559055 ,  0.7559055 ,  0.7559055 ]],

                [[-0.5590551 , -0.5590551 , -0.5590551 ],
                 [-0.5590551 , -0.5590551 , -0.5590551 ],
                 [-0.5590551 , -0.5590551 , -0.5590551 ],
                 ...,
                 [-0.5590551 , -0.5590551 , -0.5590551 ],
                 [-0.5590551 , -0.5590551 , -0.5590551 ],
                 [-0.5590551 , -0.5590551 , -0.5590551 ]],

                [[-1.        , -1.        , -1.        ],
                 [-1.        , -1.        , -1.        ],
                 [-1.        , -1.        , -1.        ],
                 ...,
                 [-1.        , -1.        , -1.        ],
                 [-1.        , -1.        , -1.        ],
                 [-1.        , -1.        , -1.        ]],

                ...,

                [[-1.        , -1.        , -1.        ],
                 [-1.        , -1.        , -1.        ],
                 [-1.        , -1.        , -1.        ],
                 ...,
                 [-1.        , -1.        , -1.        ],
                 [-1.        , -1.        , -1.        ],
                 [-1.        , -1.        , -1.        ]],

                [[-0.54330707, -0.54330707, -0.54330707],
                 [-0.54330707, -0.54330707, -0.54330707],
```

VI. CONCLUSION

For this study, a training dataset of 3500 records was collected, which was categorized into four classes based on treatment requirements and anomalies. The Asia Pacific Tele-Ophthalmology Society (APTOS) dataset was used to obtain all of the fundus images. The fundus images in this dataset were labeled as 0, 1, 2, 3, and 4 for Normal, Mild DR, Moderate DR, Severe DR, and Proliferate, respectively, based on the severity of diabetic retinopathy. The dataset consisted of a total of 4700 fundus images, out of which 3500 were used for model training, and the remaining 1200 images used for model testing .In the upcoming research, the images will be pre-processed, converted into arrays, and manipulated using image matrices. A retina prediction model will be developed and verified using CNN, followed by validation and testing using live images.

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