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DIABETIC RETINA LOSS DETECTION USING RETINAL IMAGES

AND MACHINE LEARNING ALGORIHMS

[1]Dr. R JANARTHANAN, [2]Mr.Mohd Nawazuddin

[1]Professor, Department of CSE, Chennai Institute of Technology, Chennai.

[2]PhD Scholar, Department of CSE Chennai Institute of Technology, Chennai.

ABSTRACT: Diabetic Retinopathy (DR) is a serious consequence of diabetes that affects the eyes, resulting in vision loss and potential blindness if not addressed. Timely identification and intervention may avert permanent visual impairment. This study investigates the use of retinal imaging and machine learning methodologies for the automated diagnosis and categorisation of diabetic retinopathy. Deep learning techniques, including Convolutional Neural Networks (CNNs), Transfer Learning, and Ensemble Learning, are often used for their superior accuracy in picture categorisation. Retinal pictures undergo pre-processing to improve quality and eliminate noise, subsequently followed by feature extraction and categorisation into classifications (e.g., mild, moderate, severe, and proliferative diabetic retinopathy). Advanced methodologies such as fundus imaging, picture segmentation, and feature extraction are essential for detecting retinal anomalies. Public datasets such as DIARETDB1, EyePACS, and Messidor are crucial for model training. The results indicate that using a mix of CNN-based feature extraction, hybrid classification models, and real-time image processing may significantly enhance the accuracy of diabetic retinopathy detection systems. This paper introduces a machine learning model constructed with a variety of SNNs, comprising a sequence of layers including Dense, Gaussian Noise, Flatten, Convolution 2D, Dropout, Gaussian Dropout, Efficient Nets, and Batch Normalisation, which facilitates early diagnosis and prediction of DR likelihood. This model was evaluated using a dataset from the APTOS 2019 Blindness Detection Kaggle Competition, including retinal imaging scans obtained using fundus photography. The model surpassed

expectations and demonstrated superiority over all existing and prior methods aimed at the successful diagnosis of DR.

Keywords: Machine Learning, CNN and DR

1. INTRODUCTION

Diabetic Retinopathy is a serious ocular disorder impacting those with diabetes, with around 93 million cases reported globally each year. The condition is associated with diabetes and is projected to rise from 382 million to 592 million during the next three years. A delayed or erroneous diagnosis may result in partial or total blindness due to abrupt changes in the retinal blood vessels. In more severe instances, blood or fluids are extravasated into the retinal veins, resulting in the accumulation of exudates inside the retina. Anomalous blood vessels may also manifest in the peripheral region of the retina. The retina, a delicate layer at the back of the eye, is essential for optimal vision. In less severe instances, retinal injury may be absent; nonetheless, it may lead to microaneurysms, haemorrhaging, and exudate over time. Patients may see distorted vision or floating dots in their visual field. Diabetic Retinopathy may also result in the deterioration of macular oedema, subsequently leading to visual impairment. Diabetic Retinopathy has four stages, with Proliferative Diabetic Retinopathy being the most severe and Non-Proliferative Diabetic Retinopathy (NPDR) the least severe.

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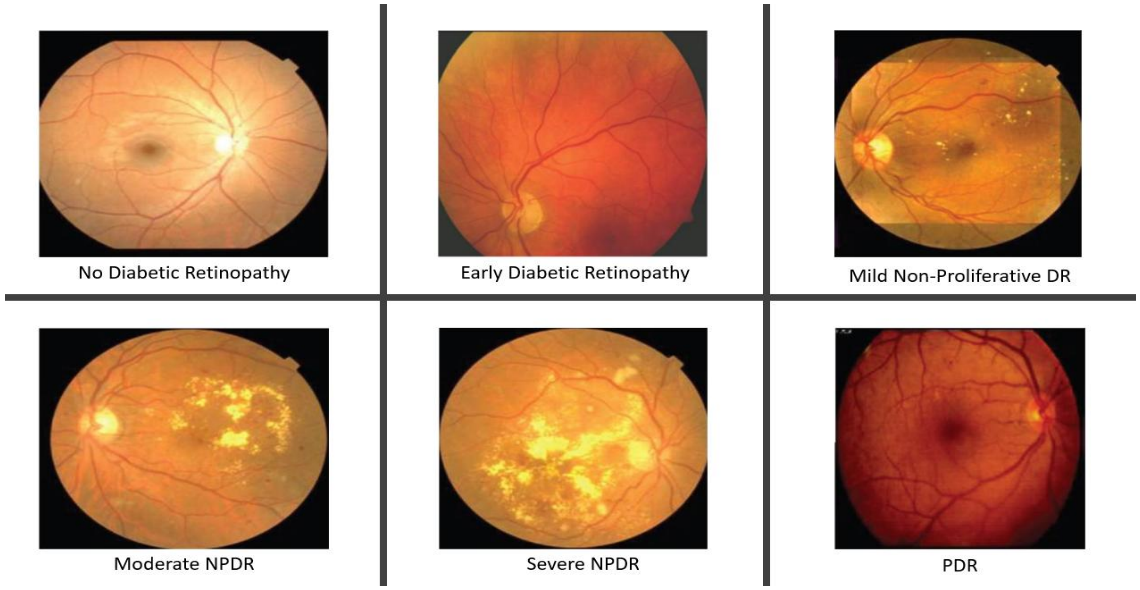

Figure 1: Fundus eye images [14]

The current diagnostic approach is time-consuming, involving scheduling an appointment, undergoing imaging, and having the results evaluated by a professional ophthalmologist. Confidentiality rules prevent sharing findings without the patient's presence. The patient then arranges a follow-up appointment to review the tests and formulate a treatment plan, which often takes over 14 days. This method is laborious and often results in wasted time on therapy.

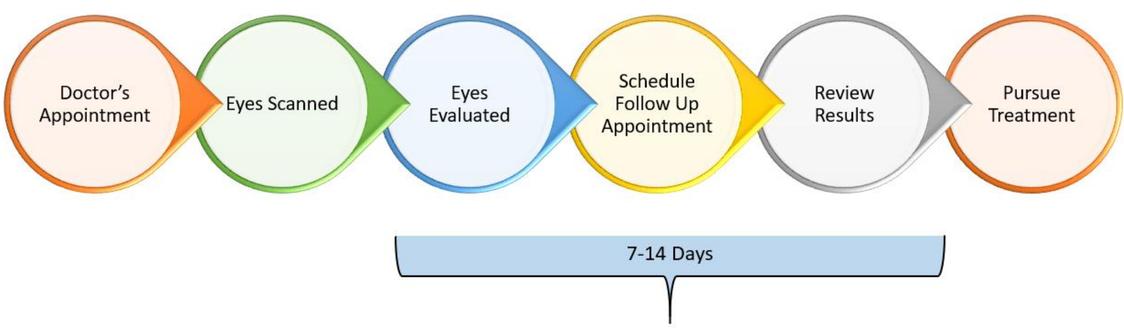

Figure 2: Present Diagnostic Procedure

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This research presents a machine learning system designed to detect issues at an early stage and assess the likelihood of Diabetic Retinopathy. The model may be used during a vision assessment by an ophthalmologist, enabling them to ascertain the probability of diabetic retinopathy on the same day. The model is essential for the early detection of Diabetic Retinopathy and is used in the Kaggle competition known as APTOS 2019 Blindness Detection.

2. RELATED WORK

Early identification of Diabetic Retinopathy is crucial to prevent ocular damage and vision loss, which affects approximately 33% of individuals with diabetes. This project aims to identify Diabetic Retinopathy in its early stages, facilitating timely diagnosis and treatment to avoid irreversible retinal damage. Various methods have been used to identify Diabetic Retinopathy, including constrained datasets, neural networks, SVM implementation, preprocessing and augmentation techniques, automated methods, CNN frameworks, cross-disease attention networks, hand-crafted models, Kaggle datasets, denoising mean, and multi-class categorisation. Recent initiatives can be categorized into binary classification, which determines if a patient is afflicted by Diabetic Retinopathy, and multi-class categorisation, which addresses the issue of categorizing photos into stages or levels. Artificial Intelligence and Machine Learning are rapidly growing fields that aim to close the gap between human and computer intelligence. Computer Vision domain is one such area that aims to allow computers to know the world as thoroughly as humans, using data from Image Recognition, Video Recognition, Natural Language Preprocessing, Image Analysis, and Image Classification. Developments in Computer Vision and Deep Learning have been constructed and evolved over time, with the goal of enabling computers to know the world as thoroughly as humans.

3. Convolutional-Neural-Network (CNN)

The Convolutional-Neural-Network, sometimes “ConvNet”, is a group of neural networking in deep learning which are utilized to analyze grid-like data structures such as images. This model uses images as source and notes weights and biaseo various aspects or objects in the photo and helps in classifying the images. In contrast to other classification models, CNN

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demands limited preprocessing which is beneficial as CNN trains itself to optimize the kernel. In other algorithms, kernels are almost always hang-engineered. More benefits of CNN include autonomy from previous learning and human intervention in component extraction.

CNN infrastructure is indicative of the assortment of neurons in our brains. It takes inspiration from the arrangement of the visual cortex in animals. Our brains can process information at the very moment the eyes are exposed to the image. When the receptive field of several neurons partially overlap, a visual field is captured. These neurons are internally connected, and every single neuron works in its exclusive receptive field as shown in Figure 4 below.

Convolutional Neural Network Architecture

Three layers make up a CNN, namely, input layer, output layer and hidden layer. The hidden layer sits in the center as it masks all inputs and outputs by making use of activation functions such as ReLU, pooling, final convolution, fully connected and normalization. Hidden layers also perform convolution.

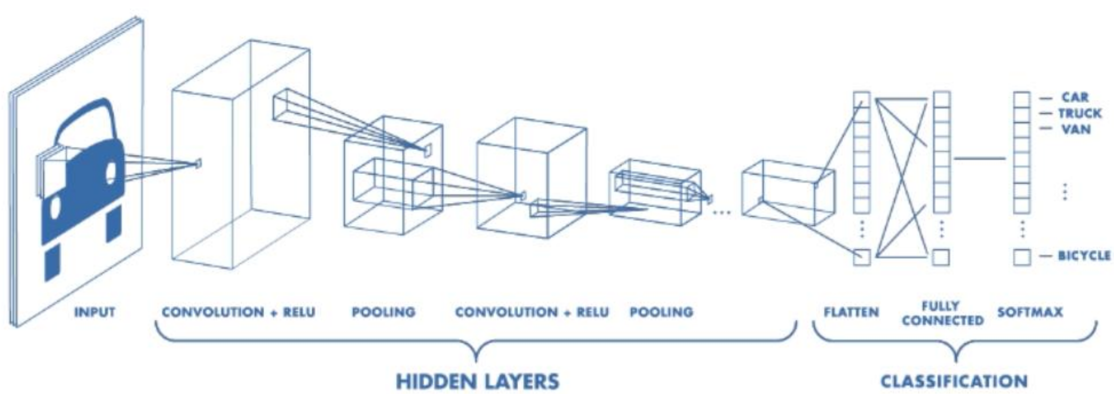

Figure 3: CNN Architecture [16]

The convolution layer being the core of CNN has carried a significant branch of the network's computational work. Dot products of the receptive field matrix as well as the kernel matrix are calculated in this layer. Images could also be recognized progressively by training the CNNs. Its primary objectives to predict even precisely can be accomplished without missing out on any elements even when images are diminished into a simpler structure for processing.

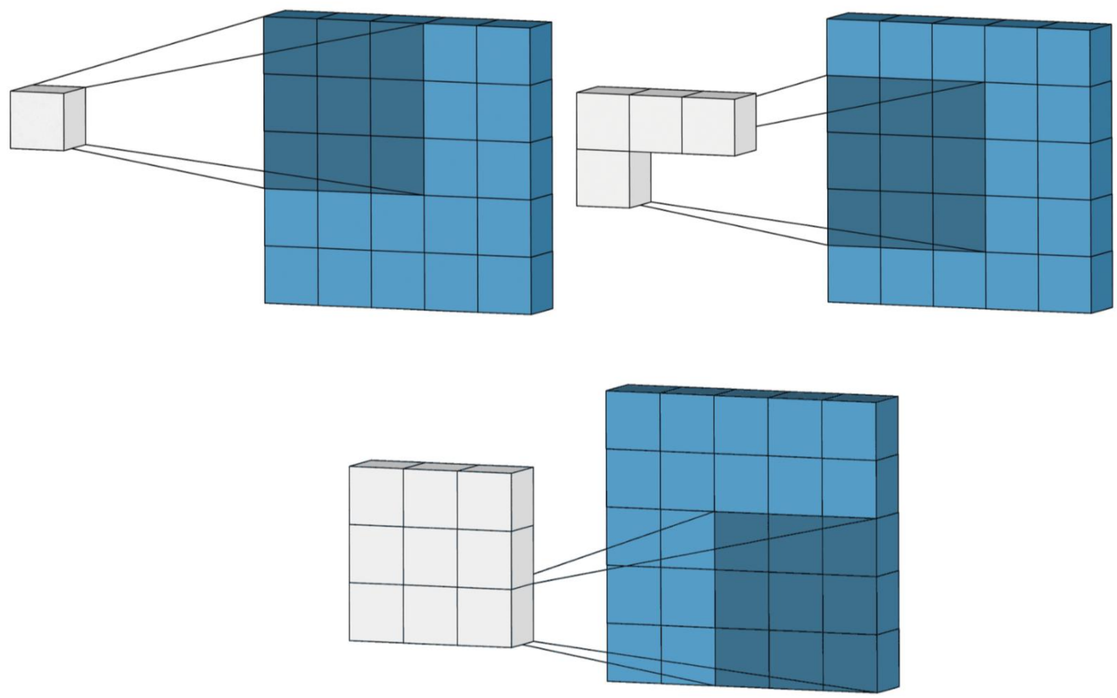

Figure 4: Representation of Convolution Operation [11]

Figure 4 has the kernel comparatively small in contrast to the image however it is deep relatively. If the image consists of RGB channels, its width and height will be comparatively smaller as depicted in the picture, however the depth will be extended to all three red, green and blue channels. The movable side of the kernel is stride. This is expressed mathematically as follows, here D represents output layers count, W represents input layers count, P tells us the convolution padding size, K represents the Convolution kernel size and S tells us size of stride.

$$D = \frac{[W + 2P - K]}{S} + 1$$

Formula for Convolution Layer

4. DESCRIPTION OF DATASET

Aravind Eye Hospital used a dataset from the 2019 Kaggle competition to identify diabetic retinopathy. The collection included 5,590 high-resolution photos, of which 3,662 were

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classified according to their first detection. The approach is essential for averting diabetic retinopathy in those who have challenges with medical screening. Professionals evaluated the photos for the severity of diabetic retinopathy, guaranteeing precise diagnosis and treatment.

Diabetic Retinopathy Stage	# of Examples
Normal(0)	1805
Mild(1)	999
Moderate(2)	370
Severe(3)	295
Proliferative DR(4)	193

Table 2: Dataset Allocation

5. RESULTS AND DISCUSSION

In the past, developers used various Convolutional-Neural-Networks (CNNs) like Inception and Seresnet Resent for diagnosis, while some used EfficientNets to improve their code. In this experiment, both CNN and EfficientNetB5 are used to assess the possibility of Diabetic Retinopathy. Data pre-processing is crucial for model enhancement, aiming to remove irregularities and improve image quality. The data was obtained from various sources and subjected to various lighting conditions, resulting in some images being tainted and blurry. Some images also have a black background, which can be problematic. The experiment aims to improve the accuracy of the model.

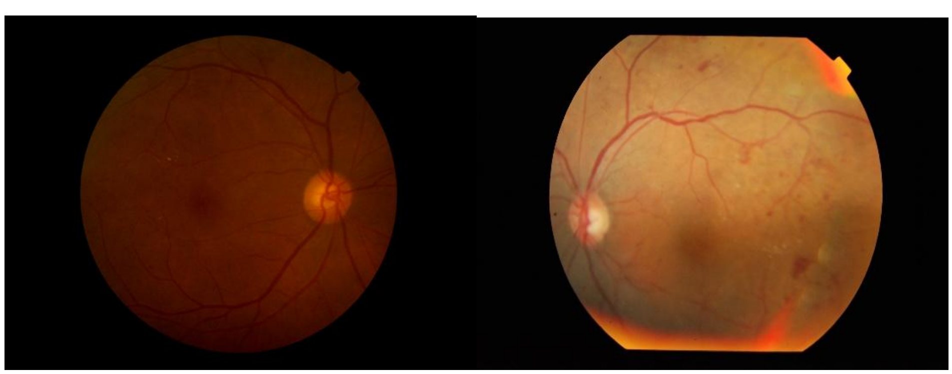

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Figure 8: Extra black background of the Fundus images

The black background was removed during preprocessing and resized to 96x96x96x3 before training. Gray-scaling images are not recommended as it doesn't improve the project's score. ImageDataGenerator Augment was used to enhance model performance and generalization, and to increase training data volume. The table explains the process for sorted data.

Transformation Type	Description
Rescaling	Scale factor = 1./255
Shearing	0.2, angle = 20º
Validation Split	0.2
Zoom range	Zoom in/out by 20%
Flipping	Horizontal Flip = True

Table 3: Image Data Generator (transformation kind)

Implementation of Convolutional Neural Networks

The model uses Support Vector Machines (SNNs) with layers such as Dense, Gaussian Noise, Flatten, Bath Normalization, Convolution 2D, Dropout, and Gaussian Dropout. These layers consist of pooling operations and alternating convolution. The convolution 2D layer converts 2D input into a 2D matrix of attributes. Dense is a collection of fully connected layers in a network

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layer that can set batch size, input shape, timestamps, and size with dimensions. Dropout is an approach to reduce model overfitting by ignoring a subset of nodes during training. Dropout nodes are not involved in data prediction, allowing the model to better summarize and prevent aggressive co-adjusting. Each node is assigned a fixed probability P, which can be set to 0.5 for a broad range of networks. The network type determines the dropout method, which can be Pooling Dropout, Standard Dropout, or Gaussian Dropout. The flatten function transforms the pooled feature into a single column, passing to the fully connected layer before passing to the neural network. Batch normalization maintains the estimates mean output to 0 and standard deviation at 1.

To reduce the time consumed by computation convolutional layers make use of pooling layers.

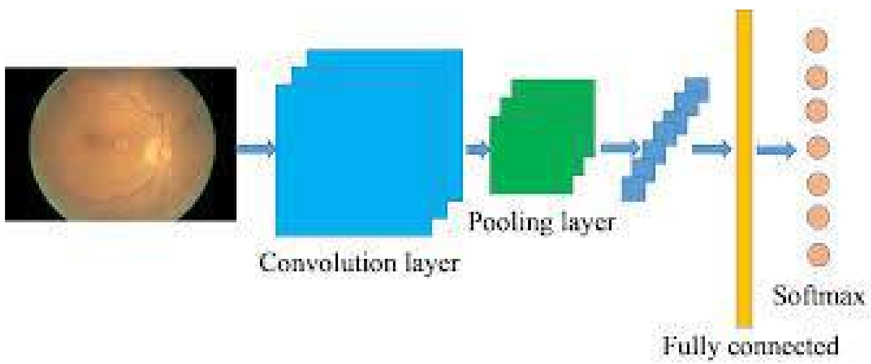

Figure 9: Convolutional Neural Network

Convolutional layers are square blocks of neurons used in each convolutional layer, with each layer utilizing a grid of neurons from the prior layer. The pooling layer also sources from these layers. The results of multiple convolution layers and max pooling layers create a flattened, connected one-dimensional layer. The model is initialized and augmented, containing the diagnosis.

CNN Architecture Description

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Input 96 x 96 x 3
3 x 3 convolution 2D, 15 filter
GaussianDropout
5 x 5 convolution 2D, 30 filter
2 x 2 max-pooling 2D
3 x 3 convolution 2D, 30 filter
2 x 2 max-pooling 2D
5 x 5 convolution 2D, 50 filter
7 x 7 convolution 2D, 50 filter
Dropout
Flattened and Fully connected
Dense layers
Classification Softmax

Table 4: Design of the proposed CNN architecture

Implementation of EfficientNetB5

EfficientNet, a cutting-edge technique launched by Google's AI team in June 2019, is used for picture categorisation. This project employs the EfficientNet B5 model, which is compatible with the Keras and TensorFlow Keras frameworks. Out of 3662 pre-labeled photos, only 1928 were used for training and testing purposes. A neural network with an integrated layer of EfficientNet B5 was developed using Keras, facilitating straightforward layer substitution. The transfer learning technique facilitates optimisation on any picture dataset. Abhishek [17] presents an enhanced iteration of the OptimizedRounder() algorithm, and a regression model is developed for categorisation purposes.

Regression Value	Class
<0.5	0
0.5 – 1.5	1
1.5 – 2.5	2
2.3 – 3.5	3
>3.5	4

Table 5: Classifications from OptimizedRounder()

The table indicates that the coefficients are [0.5, 1.5, 2.5, and 3.5]. These coefficients may not consistently be ideal. To get superior coefficients and boost the overall evaluation, an optimiser (OptimizedRounder()) is used to round thresholds, hence improving Quadratic Weighted Kappa scores.The number of epochs is vary, since the model may be optimised, underfitted, or overfitted. This may result in resource depletion. This project employs callbacks (EarlyStopping, ModelCheckpoint) to determine the optimal amount of epochs, hence conserving computational resources. It autonomously preserves the most efficient version of the model. The neural network is preserved and trained for future use or consultation. This advanced model is used to infer diagnostic findings from images.

7. CONCLUSION

Diabetes is an escalating medical condition impacting approximately 1 in 10 individuals, with 1 in 3 diabetics susceptible to diabetic retinopathy. Timely diagnosis is essential to avert blurred vision and irreversible blindness. Manual diagnosis via fundus images is laborious and costly, particularly for patients lacking access to expensive diagnostic methods. EfficientNetB5 is a model capable of predicting diabetic retinopathy utilising publicly available datasets. As advancements occur, enhancements can be implemented to fortify this model, including real-

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time classification and the acquisition of superior datasets reflective of actual screening environments. This will augment the model's overall efficiency, particularly in the early stages of diabetic retinopathy. Furthermore, developing distinct mini-models for each stage can enhance the model's accuracy, thereby aiding healthcare professionals in more effectively predicting the likelihood of diabetic retinopathy.

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