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Retinal Diseases Detection and Diagnosis of Using Machine Learning

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Abstract:
These are common retinal diseases will damage the retina. Every person needs to take care of their eyes based on the conditions. Suppose the retina got damaged and identified in the later stages. In that case, the patient may lose eyesight gradually, leading to permanent eye loss if the patient does not take any prevention methods. Detecting and diagnosing retinal diseases becomes complex for traditional machine learning (ML) algorithms This paper discusses the comparative performance of various ML algorithms and analyzes the performance in terms of disease detection rate. The ML models applied to two benchmark datasets from Kaggle and UCI repositories.

Keywords: Retinal Diseases, Machine Learning.

Introduction

The eyes are the main organs in the human body. In human life, vision and healthy eyes play a significant role in daily activities. The retina is one of the essential parts of the human eye. If the retina gets damaged, immediate medication required for the patient. Early detection of retinal diseases is a challenging task. Diseases like Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), DRUSEN, and NORMAL class in Optical Coherence Tomography (OCT) images. The eyes are a significant part of the human body, providing the vision to do daily activities. Retinal diseases show a substantial impact on human life, which causes permanent vision loss if the disorders don't detect in the early stages. Based on several factors, the causes of retinal diseases include age, gender, daily activities, job or business, etc. Some environmental conditions also affect the human retina based on dust, temperature, daylight, and various factors [1]. Retinal diseases such as CNV, DME, DRUSEN, and regular are some illnesses that affect people vision [2-6]. Figure 1 shows the types of retinal diseases that can show the abnormalities in the given OCT images.

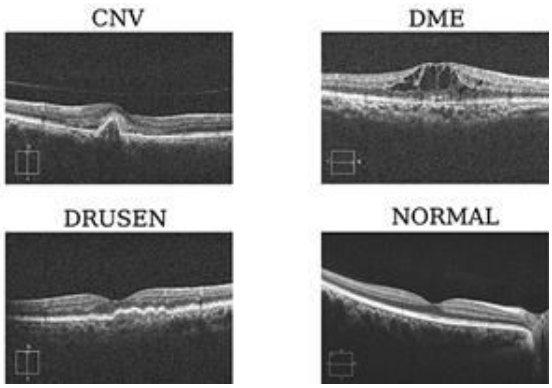

Figure 1: Showing Retinal Diseases

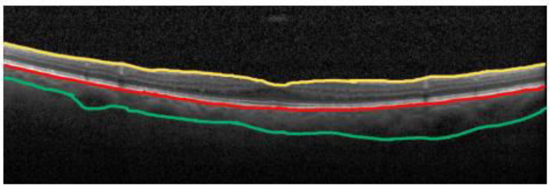

Figure 2 Layers present in the Retinal OCT Image (Sample)

There are 9 layers present in OCT retinal images. In figure 2 shows the types of layers present in OCT retinal images. Diabetic Macular Edema (DME) [7] is an eye disease that can occur with diabetic retinopathy that causes the lack of fluid in the retina's center. Several artificial intelligence (AL) and Machine Learning (ML) algorithms are used to diagnose and detect retinal diseases. In the retina, the macula is a significant part that shows the nearest objects and helps to identify the faces and text. Based on the retinal issues, the macula significantly impacts vision if mishandled. Sometimes it takes work to find or diagnose AMD early because of its asymptomatic nature. Over the days, this may cause vision loss in both eyes. Generally, the loss of central vision may not cause complete vision loss, but this may impact the daily activities of human life. DME mainly affects older people more than 60+ years. Drusen is an eye disease that forms small yellow deposits. These deposits may destroy central vision if it is not detected in the early stages. This paper describes various deep-learning algorithms that classify retinal diseases using OCT images.

Literature Review

P. Seebock et al. [1] proposed an unsupervised method that finds anomalies in the retinal OCT images. The dry and wet AMD OCT samples used for evaluation results. The auto-encoder is applied on typical, dry AMD, and wet AMD OCT images to train the OCT images. The proposed approach acquired an accuracy of 81.4%, and the ROC curve is 0.94. W. A. Al et al. [2] proposed a policy-based redesigned model to solve various issues in localization based on optimal policy. The performance of the proposed approach increased by combining the reinforcement learning that needs to show the optimal behavior.

X. Li et al. [3] proposed an automated diagnosis approach that finds retinal diseases using fundus images. The proposed approach combined with a feature-based softmax layer increases the disease detection rate. The proposed approach has been applied to two publicly available OCT images.

Z. Yan et al. [4] proposed the automated segmented approach that segments the retinal images using eye-based diseases. The automated model combined with various segmented approaches significantly impacts finding the overall vessel depth. The automated approach is applied to three datasets and gives better vessel segmentation.

Gokhan Altan [5] proposed the lightweight CNN approach that classifies retinal diseases based on macular edema (ME). The automated models find the tiny pathologies on OCT images using DL algorithms. The proposed CNN model called DeepOCT uses the feature learning and classification phases.

Image Segmentation Models for Retinal Diseases

The proposed model divides the text from a background in images. V. Badrinarayanan et al. [20] proposed a novel and fully developed CNN that can be used for semantic pixel-based segmentation using SegNet. The proposed model contains an encoder and decoder combined with a pixel-based classification model. The proposed network consists of 13 conv_layers in the VGG-16 network. Thus, the SegNet provides high performance in terms of processing time and the most efficiency. Y. Yuan et al. [21] proposed the automated segmentation model applied to dermoscopic images. The automated model was developed with a 19-layer deep CNN that efficiently processes the testing and training data. A loss function is developed based on Jaccard distance to remove the re-weighting for the segmentation of images to remove the foreground and background pixels. J. Fu et al. [22] proposed the Stacked Deconvolutional Network (SDN) segmentation approach that processes any image. SDN contains several shallow deconvolutional networks called SDN units, mainly used to recover the localization data. Noh et al. [23] proposed the typical segmentation approach for de-convolution. DeConvNet contains two components; an encoder convolutional layer obtained from VGG 16 and proposed network input the feature vector and creates a map of pixel accurate class estimations. Thus the remaining layers, such as de-convolution and unpooling layers used to find the pixel-wise class labels and estimate segmentation masks.

Convolutional Neural Network (CNN)

CNN shows the massive performance in classifying retinal diseases based on the given OCT input samples. CNN focused on designing the Multilayer Perceptrons

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(MLPs) to process the 2D retinal images. CNN model mainly combines the retinal OCT images as a network and develops the deep neural network (DNN) [24]. Based on the convolution layer, the algorithm processes the dataset. The CNN contains various convolutions, activation, pooling, and flattening layers. Figure 2 shows the layers present in CNN and classify the retinal diseases by using several layers.

$$\text{Convolution function, } C(a,b) = (I * K)(a,b) = \sum_x \sum_y \times I(x,y)K(a-x,b-y) \quad (1)$$

$$\text{Activation Layer, Sigmoid } S(a) = \frac{1}{1+e^{-a}} \quad (2)$$

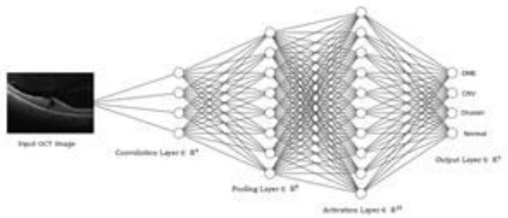

Figure : CNN Architecture

Dataset Description

The benchmark dataset-1 is obtained freely from Kaggle online source consists of 84495 grayscale images labeled with 4 classes such as NORMAL, CNV, DME, and DRUSEN [13]. The dataset consists of 10000 training images, 2500 images for one disease and testing set consists of 74495 OCT images. Another dataset used for experimental analysis is also OCT images data contains 110,657 training images and 10k testing images. This dataset is collected from UCI repository.

Table 1: Dataset Description

Class	Training Set	Testing Set
CNV	21,212	2500
DME	23,878	2500
Drusen	13,876	2500
Normal	15,529	2500

Table 2: Dataset Description

Class	Training Set	Testing Set
CNV	38,987	2500
DME	31,345	2500
Drusen	17,967	2500
Normal	22,358	2500

Experimental Analysis

This section focused on finding the model performance which was applied on two benchmark datasets. Confusion matrix is applied to analyze the performance of DL algorithms.

Accuracy: Accuracy shows the total number of prediction that is correct. Actual and predicted values are correct. It is represented with below formula.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

Precision (P): Precision or the positive predictive value, is the fraction of positive values out of the total predicted positive instances. In other words, precision is the proportion of positive values that were correctly identified:

$$P = \frac{TP}{TP + FP}$$

Sensitivity (Sn): Sensitivity, recall, or the TP rate (TPR) is the fraction of positive values out of the total actual positive instances (i.e., the proportion of actual positive cases that are correctly identified):

$$S_n = \frac{TP}{TP + FN}$$

Specificity (Sp): Specificity gives the fraction of negative values out of the total actual negative instances. In other words, it is the proportion of actual negative cases that are correctly identified. The FP rate is given by (1 − specificity):

$$S_p = \frac{TN}{TN + FP}$$

Conclusion

This paper mainly focused on classification of retinal diseases based on the detection and diagnosis of OCT images. Retinal Optical Coherence Tomography (OCT) images are used to find the diseases based on the features of every disease. In this paper, several novel approaches are discussed and identified the various issues in detecting the retinal diseases such as age-related macular degeneration (AMD), diabetic macular edema (DME), Drusen, choroidal neovascularization (CNV) and other types of retinal diseases that shows the impact on human eyes. Also this paper focused on applying several deep learning (DL) algorithms on various OCT images and retinal datasets gives the performance of various algorithms.

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