Automated Diagnosis of Eye Fundus Images

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Abstract

Eye disease is a severe health problem. Advanced stages of the disease may lead to vision loss. Early detection may limit the development of the severity and enhance the chance of treatment. Eye disease comes from various factors such as diabetes, increasing pressure in the eye (Glaucoma), and age-related macular degeneration. Ocular fundus 2D images are one of the most common tools used to diagnose the lining of tissue eyes. Huge data availability, increasing cases, and heavy responsibility in the health sector encourage seeking new diagnosis techniques to enhance accuracy and reduce false positive and false negative diagnoses. Computer-aided diagnosis (CAD) is the state-art-technology. This paper proposes a CAD system that combines image processing techniques and artificial intelligence. The proposed method used the green channel of fundus eye images to extract the most representative features by the trained convolutional neural network to classify five eye diseases of fundus images. The build CAD system exploits deep learning and support vector machine classifier to achieve a highly accurate model of 98% for five types of eye diseases.

Keywords: Fundus images, deep learning, support vector machine.

1. Introduction

A fundus image is a 2D projection of the fundus that was made using a monocular camera, which can be acquired in a non-invasive and cost-effective manner, which makes them more suitable for large-scale screening than other eye scans including optical coherence tomography images and angiographs [1]. Clinically, the usage of fundus images for early eye disease detection is crucial. Deep learning is becoming more and more common in related applications due to its strong performance [2].

One of the available of the deep convolutional neural network called ResNet is reviewed by Esfahani et al. and used for classification of eye fundus Images into two groups of normal and diabetic images and simulation result has achieved 85% accuracy and 86% sensitivity [3]. While Raghavendra et al. trained eighteen layers of convolutional neural networks (CNNs) to extract powerful features to categorize into normal and glaucoma with accuracy of 98.13%. Burlina et al. [4] investigate the suitability of applying image features calculated from pre-trained deep neural networks on the Age-related macular generation identification which show achievement with 92% to 95% accuracy. Choi et al. [5] used fundus images and multi-categorical deep learning algorithms to automatically identify 10 categories of retinal disorders with 30.5% accuracy. In addition, the transfer learning incorporated with ensemble classifier of enhancement the multi-categorical classification performance with accuracy of 36.7%. The multi-category classifier demonstrated accuracy of 72.8% when three integrated normal, background diabetic retinopathy (BDR), and dry age-related macular degeneration (AMD) were taken into account. While using integrated normal, dry AMD, and wet AMD, achieved 77.2% accuracy, three other integrated normal, BDR, and proliferative diabetic retinopathy (PDR) demonstrated accuracy of 80.8%. Additionally, using the same model structure, 5 disease categories normal, background DR, PDR, dry AMD, and wet AMD achieved a maximal accuracy of 59.1% [6].

To have a greater knowledge of the several categories u sed to classify fundus images, Chea et al. [7] provided deep neural networks and efficient image reprocessing methods, such as shrinking the region of interest, iso-luminance plane contrast-limited adaptive histogram equalization, and data augmentation, to classify the three most prevalent eye diseases, DR, glaucoma (GLC), and AMD, which achieved peak and average accuracies of 91.16% and 85.79%, respectively.

2. Materials and Methods

The set of steps followed in this work are shown in Figure 1. The proposed methodology is divided into four main parts: 1) data augmentation, 2) Image preprocessing, 3) Convolution Neural Network (CNN), and then 4) Support Vector Machine (SVM).

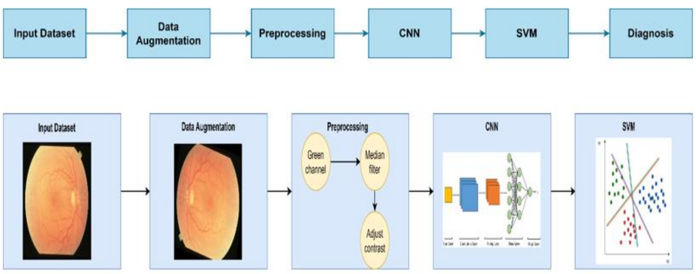

Figure 1: The proposed method architecture

2.1. *Image Database*

This paper utilizes full raw images from the STARE database (structured analysis of retina) project, which is carried out in 1975 in California [8]. Almost 400 images are acquired and diagnosed for 13 types of eye diseases. Only five types of classes are selected to build an automated diagnosis system in this paper. The aim behind this selection is the intended system aims to diagnose a single kind of disease per image, not multi diseases, while some cases are diagnosed for multiclass. The classes are normal, Central Retinal Vein Occlusion (CRVO), Background Diabetic Retinopathy (BDR), Proliferative Diabetic Retinopathy (PDR), and Choroidal Neovascularization (CNS). One sample for each class is illustrated in Figure 2 (a), (b), (c) (d), and (e), respectively.

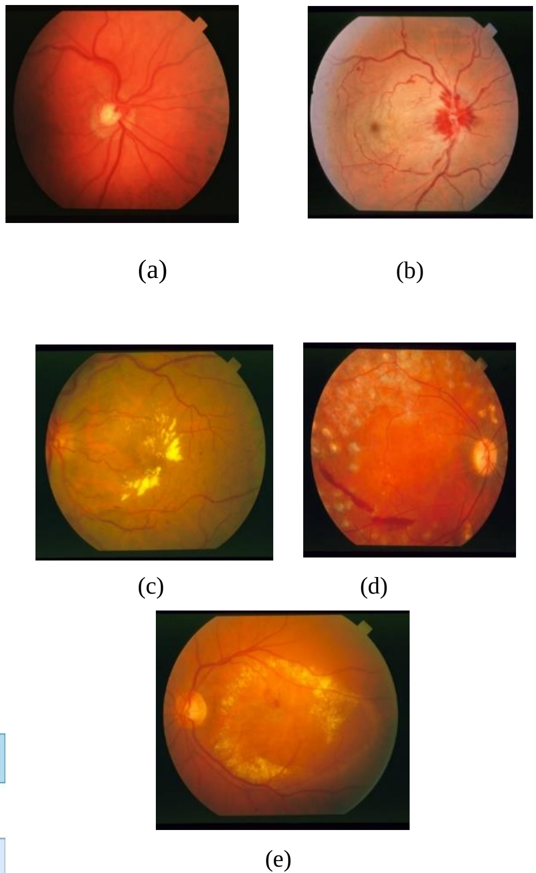

Figure 2: Samples of eye fundus images (a) Normal, (b) CRVO, (c) BDR, (d) PDR, and (e) CNS [8].

Table 2(1?). The planning and control components.

Class	Name	Number of images
Class00	Normal	39
Class05	Central Retinal Vein Occlusion (CRVO)	25
Class07	Background Diabetic Retinopathy (BDR)	69
Class08	Proliferative Diabetic Retinopathy (PDR)	23
Class13	Choroidal Neovascularization (CNS)	61

2.2. *Image Augmentation*

Over-fitting may occur when a classifier model is overly complicated in relation to the quantity of training examples. The deep learning community has proposed numerous regularization and data augmentation techniques to overcome this issue, including various data augmentation techniques as cropping, flipping, and translating [9]. The need for large data volume in deep learning helped in using data augmentation to increase the number of samples for the training set. In this paper all classes are augmented to 100 images for each class. The total images for five classes are 500.

2.3. *Image Preprocessing*

Medical images are affected by noise during the image collection process, so medical image analysis requires an image pre-processing stage. At first, the green channel was used in RGB path which gives better results compared to other channels. In order to remove input noise from the image while preserving edges, especially salt and pepper noise, a median filter was used [10]. After that, image adjustment was utilized to enhance the contrast and brightness of the image.

2.4. *Convolution Neural Network*

Convolution Neural Network (CNN) is developed based on multi-layer neural networks, which are a type of deep learning model created specifically for image classification and recognition. For high accuracy, CNN uses automatic feature extraction. It employs specific convolution layers, pooling techniques, and parameter sharing [11]. Modified CNN was devised in this study [12]. The structure started from an input layer of green channel image, while the classification layer terminated the proposed network. The goal of using the modified CNN is to extract the features for use in the SVM part. Figure 3 shows the layout of its layers with distinct mass convolutional layers.

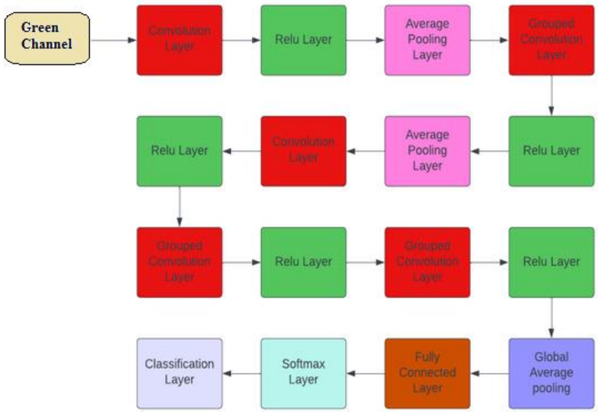

Figure 3: The modified CNN structure [12]

2.5. *Support Vector Machine*

Supportive Vector Machine (SVM) is an educational technique used to classify data entered two supervised classes. The SVM algorithm creates a model that predicts the new instance class using specific training data. Finding the ideal cut-off hyperplane for a data set - which optimizes the distance between the nearest data point and the cut-off hyperplane - is the goal of SVM [13]. In this work, a classification layer of modified CNN output was used as the property input data for an SVM classifier, to achieve the output objective of classifying the five classes of fundus images. The complete input data set was divided as: 70% subsets were used as training data, and the remaining subset was used to test a prediction model.

3. Results and Discussion

The green chancel of each image is selected and passed to the modified CNN. The first scenario is deep learning classification. Figure 4 shows the output of the modified CNN model after transfer learning to be compatible with five classes.

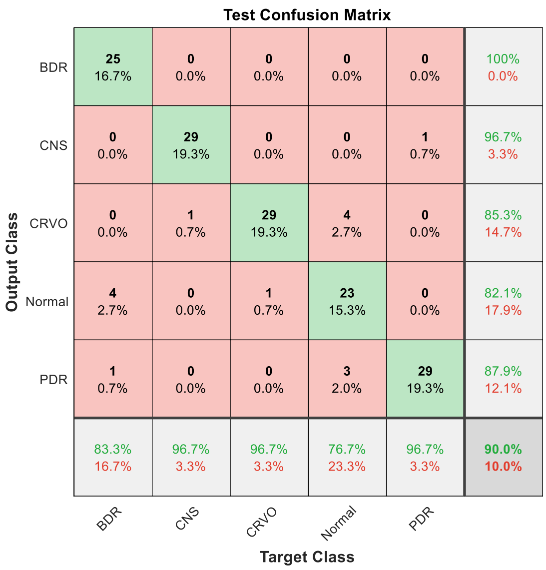

Figure 4: Confusion matrix using deep learning approach

As clear in Figure 4 twenty-five occurrences are correctly classified for BDR class with a sensitivity of 83.3% and a misclassification rate of 16.7%, besides a precision of 100%. Meanwhile, the CNS has equal results in both recall and positive predictive value with 96.7%. On the other hand, the CRVO obtain 96.7% sensitivity and 85.3 % of precision. The Normal class has the lowest results in terms of sensitivity and precision at 76.7% and 82.1%, respectively. The fifth class is PDR, where 29 cases are classified correctly among 30 test cases with a recall of 96.7% and a precision of 87. 9%. The overall accuracy does not exceed 90% for all classes.

The improvement is obtained by combining deep learning as an automated features extractor and machine learning as classifiers. This method has been widely used in the literature [14]. Therefore, the modified CNN extracts five features. Each one represents its corresponding class. These features pass to multi-class SVM. However, only 70%of them train SVM model and the rest evaluates the model generalization. Figure 5 explains the results of the hybrid model.

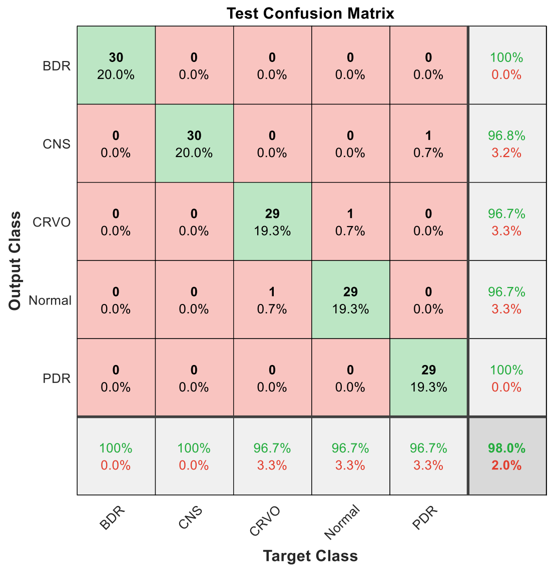

Figure 5: Confusion matrix using hybrid (machine learning and deep learning)

As clear in Figure 5 the performance is improved where all cases in BDR and CNS classes are distinguished correctly with a sensitivity of 100%. One case from the PDR class is misclassified as CNS. Therefore, the precision of the CNS class is reduced to 96.8%. For CRVO cases, one occurrence is misclassified as normal. Therefore, the sensitivity is 96.7% and one case from normal is classified as CRVO. The precision is reduced to 96.7%. The sensitivity for normal and PDR is 100%, but the positive predictive value for normal is 96.7%. The overall results are better than deep learning classification scenario. The overall accuracy is 98%. Figure 6 illustrates the comparison between the two scenarios.

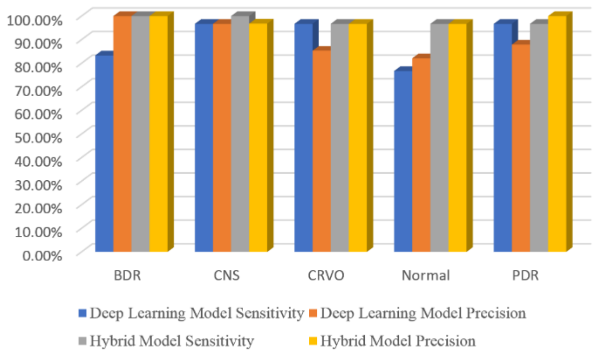

Figure 6: Comparison two approaches in terms sensitivity and precision

As clear from Figure 6 the combination between deep learning and machine learning classifiers yields high performance results in distinguishing five fundus classes. When the proposed approach results are compared with literature, it indicates to prominent computer aided diagnosis for eye diseases.

4. Conclusion

This paper presents a new CAD system for eye fundus images diagnoses for five classes: Normal, Central Retinal Vein Occlusion (CRVO), Background Diabetic Retinopathy (BDR), Proliferative Diabetic Retinopathy (PDR), and Choroidal Neovascularization (CNS) using extraction features from modified pre-trained CNN. The representative features passed for multi-class SVM. The system obtains high accuracy reaching 98% for all five classes and a sensitivity of 100 for BDR, CNS, and normal. Whereas the precision is 100% for BDR, CRVO, Normal, and PDR. The system can be dependable software for eye diagnosis by utilizing a large dataset to be used in rural areas and poor countries.

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