CNN model Channel Separation for glaucoma Color Spectral Detection

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Abstract:

Glaucoma is a leading type of eye disease that affects the optic nerve causing permanent vision loss. As this optic nerve is important for good vision safety, glaucoma can be prevented only if detected earlier. Optic disc to cup ratio is one of the key factors for glaucoma diagnosis with abnormally high eye pressure. A descriptive analysis of glaucoma diagnosis using Convolutional Neural Network (CNN) for spectral color detection of the eye is presented in this study. Initially, the color components are separated as red, green, and blue. Then, the region of Interest (ROI) is obtained from the green channel of the fundus image for the feature extraction. The Green channel is used for the fundus image analysis and detection because it is the only sensitive and high contrast color that the other two components for humans. Finally, the proposed system's glaucoma color spectral diagnosis and its performance are analyzed using CNN with accuracy.

Keywords: Glaucoma diagnosis, Color spectral detection, Color channel Separation, Convolutional neural network, accuracy.

Introduction:

Retinal images-based glaucoma detection is discussed in [1]. First, the distance transformation is used to localize the optic disc. Then Principal Component Analysis (PCA) is aided for glaucoma detection. Support Vector Machine (SVM)-based glaucoma diagnosis is described in [2]. From the input retinal image, the ROI, optic cup region, and disk are also detected. Then optic cup boundary is smoothed. Finally, the disk height, level set based ellipse fitting with a cup to disc ratio is detected.

Glaucoma diagnosis based on focal edge detection is discussed in [3]. First, the input angle image is determined by quadrant. Then the focal edges are detected. Finally, grading is made. Glaucoma classification using retina images using the Independent Component Analysis (ICA) is discussed [4]. The ICA and K-Nearest Neighbor (KNN) for feature extraction and classification.

Neural network-based glaucoma classification is described in [5]. First, the texture features are used for feature extraction then PCA and statistical analysis methods are used. Next, a neural network classifier makes the prediction using the Haralick texture feature-based glaucoma diagnosis is described in [6]. Then, a gray-level co-occurrence matrix pre-processes the retinal image. Finally, a prediction is made by KNN.

Glaucoma detection-based color and texture features are described in [7]. The input the features like mean, standard deviation, skewness, variance, energy, and entropy features are also extracted the texture features are extracted. Prediction is made by SVM and artificial neural networks. Texture feature extraction-based glaucoma detection is discussed in [8]. The input images are pre-processed by extraction of red and contrast adjustments with the ROI area removed by utilizing Hough change, morphological activity, and k-implies grouping procedure.

The highlights are extracted by dim level co-event framework and Markov arbitrary field least gauges. At long last, the forecast is performed using the SVM [9].

A descriptive CNN analysis for glaucoma color spectral detection is presented in this study. The remaining part of the paper is coordinated as follows: The strategies and materials of glaucoma recognition are depicted in area 2. In segment three, the exploratory outcomes and conversation are depicted. The last area closes the glaucoma shading phantom location framework.

Methods and Materials:

Initially, in the fundus input images, green color components are separated. Then separated color components are classified by using CNN. Figure 1 shows the glaucoma color spectral detection using CNN.

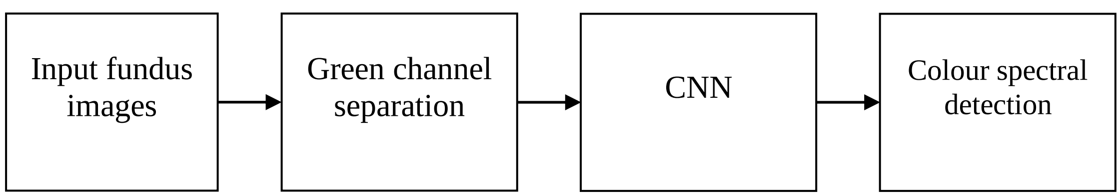

Figure 1 Glaucoma color spectral detection using CNN

Green channel separation

The RGB shading model is an added substance shading plan with a wide assortment of tones joined with red, green, and blue light [10]. The first names of the example are the three essential added substance tones, red, green, and blue. The principle point of the RGB shading design, regularly utilized in customary photography [11], is detecting, addressing, and seeing pictures in electronic gadgets, like TVs and PCs. The RGB shading model had effectively had a strong behind it hypothesis before the electronic time because of human shading insight [12]. RGB is a standard dependent on the item tone, while the shading component and reaction to every one of the R, G, and B levels change from makers to fabricators, even on a similar item. RGB is the shading model for various gadgets. Hence, with no sort of control, RGB esteem doesn't address similar shading across gadgets.

ANN-Artificial Neural Network:

The ANN inspires the natural human neural network. Actually, in humans, one end of a neuron is fired when a stimulus is triggered; the neural signals are then sent down to the axon of that neuron to the dendrites of the next neuron with the help of a synapse. The firing of the new neuron causes the stimulus to fire another neuron, which is repeated in the whole system.

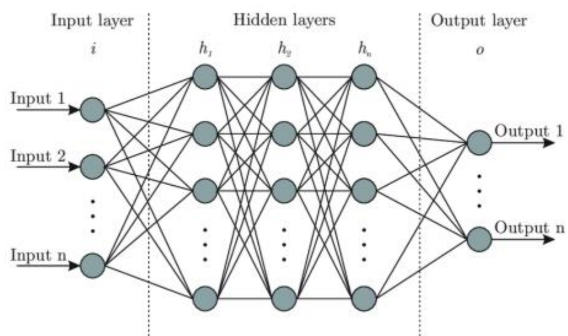

Figure 4: ANN architecture (ANN –n level with input, hidden, and output layer).

It has layers with units or nodes; each unit of a single layer is individually connected to the other layer nodes, as shown in Figure 4.

CNN Classification:

CNN is a deep neural learning class. The image recognition of CNN architecture is represented in Figure 2 as a significant advancement. They are most used to analyze visual images and often work in image classification behind the scenes. It uses 2-Dimensional (2D) convolution layers, and CNN learned characteristics with input data. So, this type of network is ideal for 2D image processing [13]. In addition, CNN uses very little pre-processing compared to other image classification algorithms meaning that the filters made by hand in other algorithms can be learned. Thus, CNN's are available for tons of applications, from recognizing images and videos, the classification of images and recommending systems for natural language, and the analysis of medical images [14].

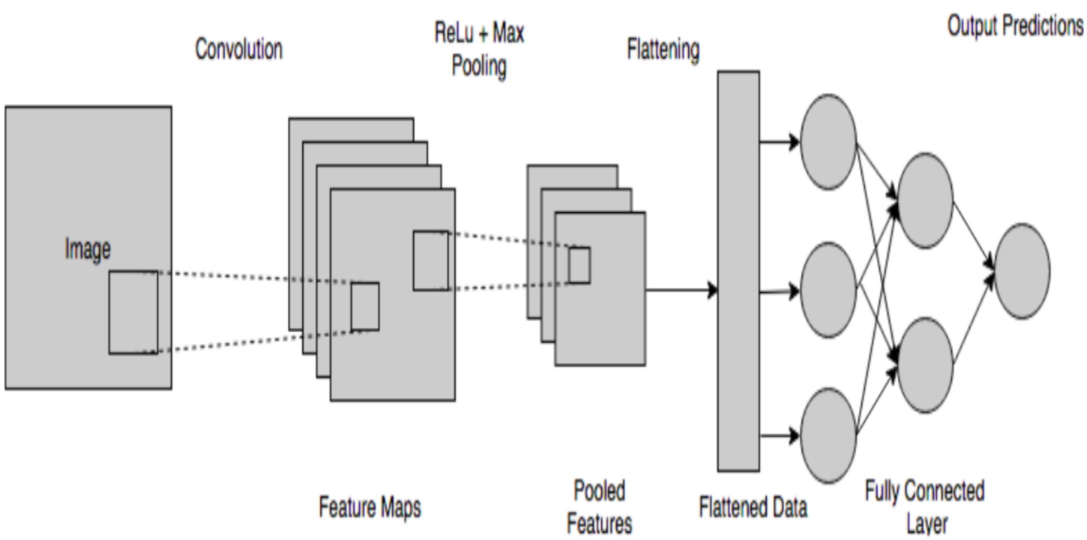

Figure 2 CNN architecture

Results and Discussion:

At first, the fundus input images, the red, green, and blue color components are separated. The green channel is used for performance because it is sensitive to the human eye [15]. Then, the separated color components are classified by using CNN. Figure 3 shows the sample fundus image in the dataset.

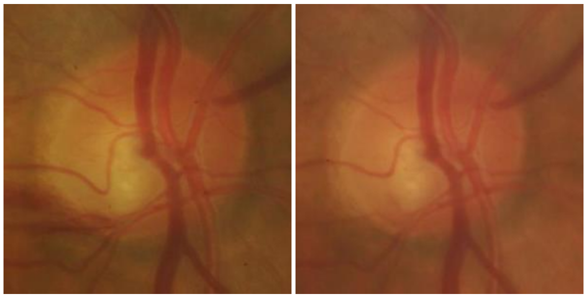

Figure 3 Sample images in the database

The input fungus image is converted into red, green, and blue color components separated using the color space method. The CNN is used for prediction. The Green color component performs the classification because the green color is highly sensitive for the human eye. Figure 4 shows the original image and green color component images.

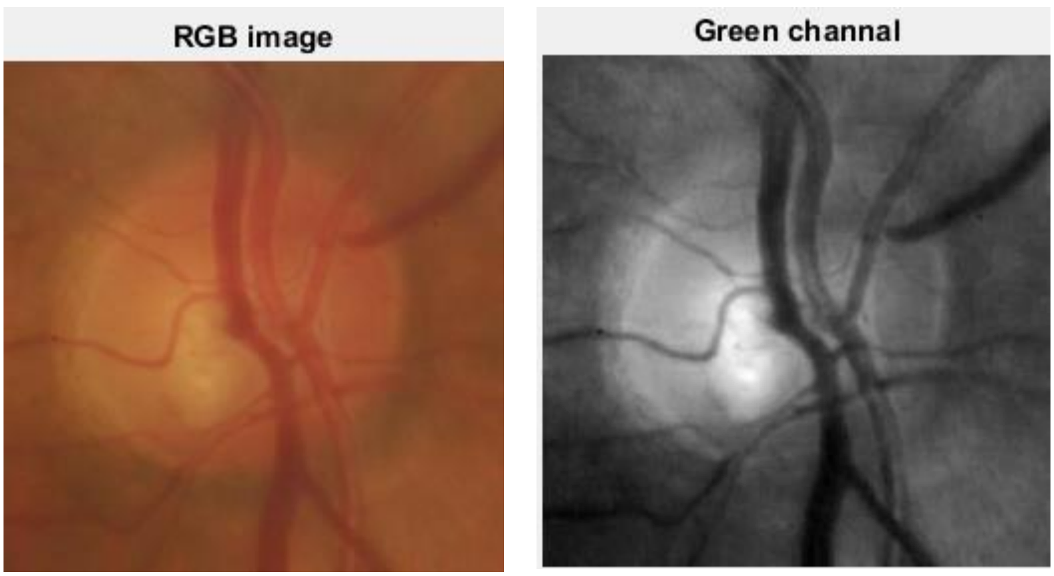

Figure 4 Original image and green color component

The red, green, and blue color sample features are separated from the original images. The CNN model is used for prediction. The performance chart of the CNN model is shown in figure 5.

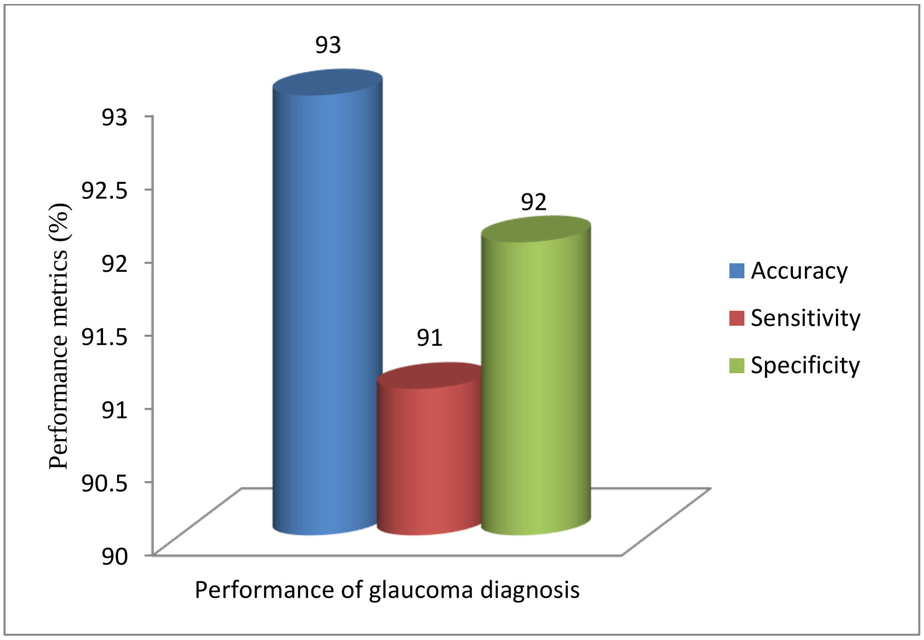

Figure 5 Performance of CNN

Figure 5 depicts that the system performs the classification with an accuracy of 93% and its sensitivity and specificity are 90% and 91%, respectively, using the color channel separation and CNN classifier.

Conclusion

As the glaucoma disease caused in the optic nerve is important for good vision, it can be prevented only detected earlier. Hence, the descriptive CNN model network analysis for glaucoma color spectral analysis and detection of the fundus images using the ROI region is determined. Initially, the red, green, and blue color channels are separated from the input fundus images. Then the extracted green channel features are given to the CNN classifier model to identify and classify glaucoma fundus image or normal fundus image for the prediction. The performance of this CNN-based classification system is demonstrated, and the system yields the classification accuracy of 93%, with its sensitivity and specificity is 91% and 92%, respectively. The result shows that the proposed classification system accuracy obtained is better using color space spectral analysis with a color channel separation of the fundus image and the CNN classifier model.

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