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Automated Identification of Glaucoma from Fundus Images using Deep learning Techniques

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Abstract:

Glaucoma has arisen as the one of the main sources of visual impairment. A typical technique for diagnosing glaucoma is through assessment optic nerve head by an experienced ophthalmologist. This methodology is arduous and burns-through a lot of time. Despite the fact that the analysis of this infection has not yet been discovered, the period of primary identification can preserve from the glaucoma. Subsequently, customary glaucoma screening is basic and suggested. The issue can be settled by applying machine learning techniques for glaucoma detection. We present an automated glaucoma screening framework using a pre-trained Alexnet model with SVM classifier to enhance the classification accuracy . In this study, we used three publicly available dataset as HRF, Origa and Drishti_GS1 dataset. The proposed model achieved the image classification accuracy of 91.21%. This study showed that using pre-trained CNN with SVM for glaucoma detection showed greater accuracy in automatic image classification than just CNN or SVM.

Keywords: Glaucoma, Feature extraction, support vector machine, convolution neural network, AlexNet

1. Introduction

Glaucoma has arisen as the main source of visual impairment in the ongoing years. Glaucoma harms the optical nerve reason to the intraocular pressure elevated in the eye. On the off chance that the disease is undetected, at that point this may prompt the perpetual visual deficiency. Thus, there is a requirement for the detection of the

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glaucoma. The reason for glaucoma monitoring is to identify the beginning phase of the sickness, for that fundoscopy or Ocular Coherent Tomography has utilized as chosen imaging methodology [1]. The fundus photography is a strategy which catches the region of the, choroid, optical nerve and the retina utilizing the retinal camera. The pictures got through the fundus photography permits the clinical experts to break down the problems existing in the eye. Glaucoma has been announced as the main source of irreversible blindness since among the different ocular diseases [2]. Treatment of the glaucoma disease has not been originate yet, besides, the primary recognition of the disease can cure easily. The advancement of the several segmentation and deep learning algorithms has donated significantly to the clinical finding.

Accordingly, glaucoma discovery likewise has caught the notice of researchers because of the success of deep learning image classification algorithms. The glaucoma in the eye can be investigated through the computerized fundus examination. The motivation behind this work is to decide if the CNN-SVM combination can accomplish higher accuracy in automatic detection of the glaucoma disease compared to CNN or SVM alone

2. Related Works

In the field of ophthalmology, a few investigations that expect to build up a framework for determination uphold have been done. Throughout the most recent years, many emotionally supportive network using deep neural network have been under scrutiny in the ophthalmic field.

In 2018, Li et al. [3] built up a strategy based on Inception-v3 to evaluate the fullfillment of a deep learning algorithm for the glaucoma optic neuropathy (GON) monitoring. They used mini-batch gradient descent of size 32 and Adam Optimizer for training. The best outcome was touched with a learning rate equivalent to 0.002on a private data base comprising of 70,000 images. That same year, Raghavendra et al. [4] deliberate a technique with an 18-layer CNN design, which holds a max-pool layers and convolutional layer. The logarithmic soft-max activation function is utilized to perform the classification layer.

In 2019, Mamtha Juneja et al [5] presented a Deep Learning architecture scheme, which is used to segment procedure of optic cup and disc. Totally 50 fundus images are taken to

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test his model and it achieved 95.8% of an accuracy for disc and 93% an accuracy for cup segmentation.

Baida Al Bander et al [6] was developed a model which uses Convolutional Neural Network (CNN) to recognize glaucoma. Not at all like conventional techniques where the optic disc features were hand crafted, they used pre-trained Alexnet model which consists of 23 layers and SVM ideal to categorize the images into condition of either normal or irregular stage. The performance of the model was evaluated in Rim RIM-ONE database comprises 255 normal and 200 glaucomatous imageries. The proposed system has a specificity of 90.8%, sensitivity of 85% and accuracy of 88.2% correspondingly.

Different works introduced for the glaucoma recognition have numerous weaknesses, for example, in wrinkled run time, complex design, and so on, considering these, we propose a novel diagnostic framework for discrimination of glaucoma using deep transfer learning scheme based on the Alex Net with Support Vector Machine (SVM) from colour fundus images.

3. Architecture of AlexNet

Convolutional Neural Network is an exceptional neural network model suggested by LeCun, which has made an extraordinary achievement in image classification, recovery and target detection [7 and 8]. On account of their weight sharing, CNN has many less neurons and factors thus it is easier to train.

Alex-Net model is the greatest delegate model of CNN, which has superior performance, less training parameters and strong robustness [9]. In this unit we briefly explain the architecture of AlexNet depicted in Figure 1. There 2 are input and output layers, seven layers of rectified linear unit (ReLU), two normalization layers, three pooling layers, two dropout layers, one softmax layer and eight trainable weight layers consisting of five convolutional layers and three fully connected layer (FC). The input layer accepts images of dimension 227 × 227×3 pixels. The ReLU layer reduces the number of epochs and to achieve less learning error rate. The normalization layer improves generalization and reduces the error rate. The pooling layer dynamically diminish the spatial size of the representation to decrease the number of parameters and computation in the network [10]. The overfitting problem is successfully reduced by both dropout layer and the Softmax layer, while the output layer categorizes images into various categories. Fine tuning of the model is performed by tuning the last two layers from the 25 unique layers. Layers at the beginning of the model can only detect image edges, so we use the Fully Connected layers to extract features for classification.

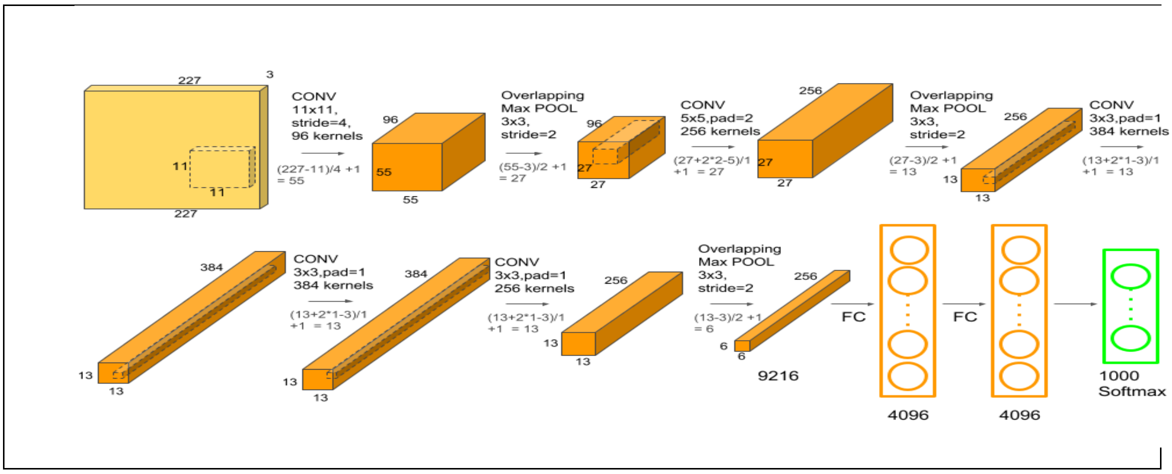

Figure 1. The AlexNet Architecture

4. Materials and Method

In this research study, we used different material and methods used to detect glaucoma automatically in earlier stage to prevent sightless issue in human. The following sub section briefly labelled the materials and methods follows as,

4.1 Materials

The proposed system for automatic glaucoma detection is implemented using two levels such as training and testing stage. In this study we used 781 fundus images from 3 publicly available HRF, Origa and Drishti_GS1 dataset.

a) High-Resolution Fundus (HRF)

The HRF Image Database includes of totally 30 HRF Retinal Images which contains 15 images are denoted as Healthy and 15 pictures are marked as Glaucomatous. They were caught by a Canon CR-1 fundus camera with a field of view of 45^{o} with a resolution of 3504x2336 pixel. Binary gold standard level vessel segmentation image produced by clinicians are accessible for every image. The dataset accessible from the link of

https://www5.cs.fau.de/research/ fundus- images/

b) ORIGA

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ORIGA-light comprises 650 retinal images marked by experts from Singapore eye Institute (Z. Zhang et al. 2010). It composed glaucomatous images of 168 and normal images of 482 with a resolution of 3072x2048 pixels. This record is generally utilized as a benchmark for instinctive glaucoma categorization strategies. Database accessible at http://imed.nimte. ac.cn/en-imed-origa-650.html

c) DRISHTI_GS1

This dataset includes retinal fundus of 101 imageries for optic disc segmentation. Every images were composed from Aravind Eye Clinic in Madurai. Glaucoma having persons determination was selected by clinical specialists on the basis of discoveries during assessment. The retinal imageries originate from Indians of 40-80 years of age. The images were reserved with the eyes widened, focused on the optic disc, with an arena of vision of 30^{o} and of resolution 2996x1944 pixels. In table 1 labeled that the description of three given dataset as follows,

Table 1 Data set description

Database	Glaucoma	Normal	Resolution	Total
Drishti-GS1 (Sivasway et. al 2014)	70	31	2996x1944,PNG	101
HRF (Kohler et. al 2013)	15	18	3504x2336,PNG	30
ORIGA-light (Z. Zhang et al.2010)	168	482	3072x2048,JPG	650

4.2 Methods

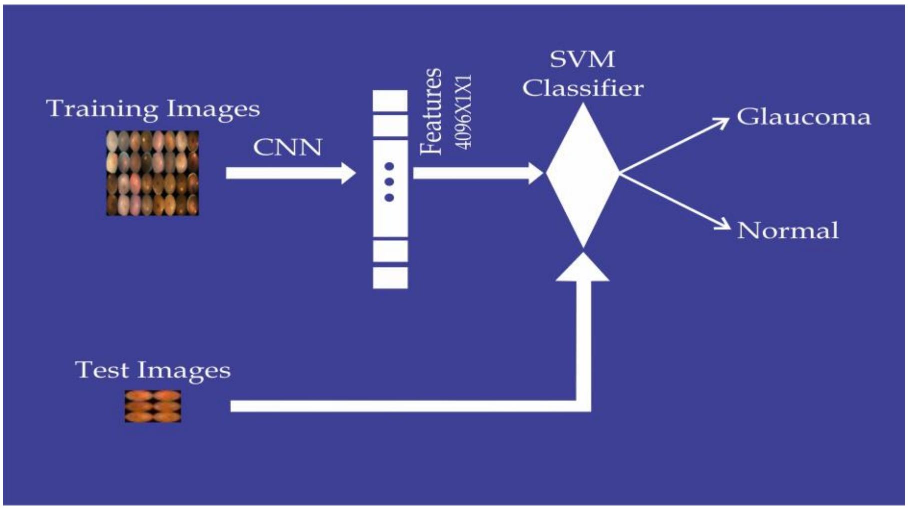

Figure 2. Frame work of Glaucoma detection

In this research study, we suggested a deep transfer learning technique to familiarize our classification task by fine tuning the pre trained AlexNet on the ImageNet data set. First, we categorized images into two categories: glaucomatous and normal images and labeled consequently. The images in the dataset are taken from variety imaging conditions, we preprocessed all the images. In this phase, all the input images were re-sized, normalized and cropped the optical disc part from each image. Figure 2 shows the classification scheme. According to the computational requirement of AlexNet, we have to make a uniform size of 227×227×3 for all cropped images and the output of CNN is the 4096×1×1 feature map. SVM classifier is used for training and classification the test images by with help of feature map. We then split the datasets into training and test images; Training images were used to bring out and learn attributes, and test images were used to calculate the accuracy of the method. We downloaded a pretrained CNN that was trained from over a million images and tuned the last two convolutional layers. Based on the last fully connected layer data, we measured the performance of CNN-based training and test images. The class tags were then extracted from a set of training and test images.

Grid search method is applied to optimize the SVM classifier. We then evaluated the effectiveness of the SVM classification and, based on the skilled classification of the test images, evaluated the classes of the new images.

The freshly modified network was trained on a single NVIDIA Tesla K40c GPU. We Applied Adam Optimizer to train layers in batches of 32 images per step with a learning rate of 0.001. After 50 epochs, the training was stationary since together accuracy and loss would not be further better.

5. Result and Discussions

After the network converges, we evaluate the performance of our system on the test data which contains 91 images. To analyze the performance of the trained ideal, we plotted the confusion matrix of the model on test set is illustrated in Figure 3. From the confusion matrix 35 images correctly classified as glaucomatous from the 40 glaucomatous images and 48 images were properly classified as normal from the 51 normal images. The proposed system obtained overall accuracy of 91.21%. Model accuracy and model loss is depicted in figure 4.

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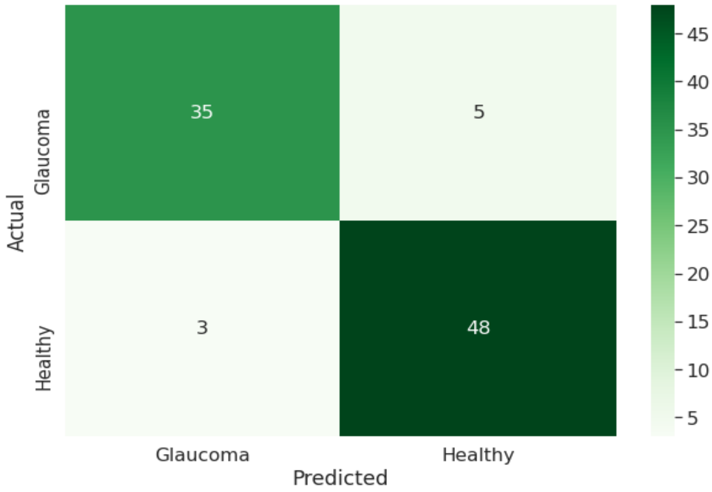

Figure 3. Confusion matrix

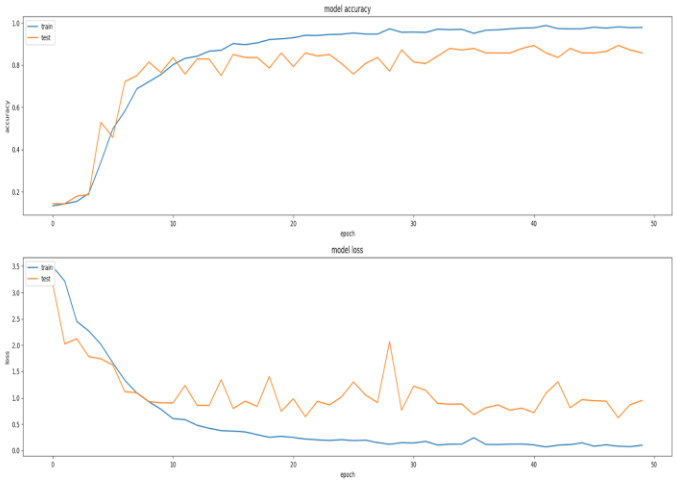

Figure 4. Model Accuracy and Model loss

Figure 5 shows the comparison of prediction accuracy of CNN, SVM and Combination of CNN - SVM.

CNN-SVM has higher accuracy than other methods. Figure 6 shows the accuracy and loss of model with and without transfer learning.

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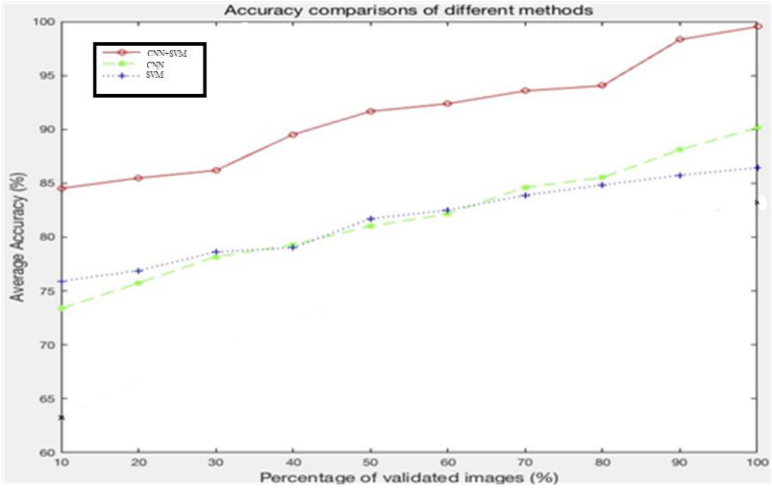

Figure 5. Accuracy comparison

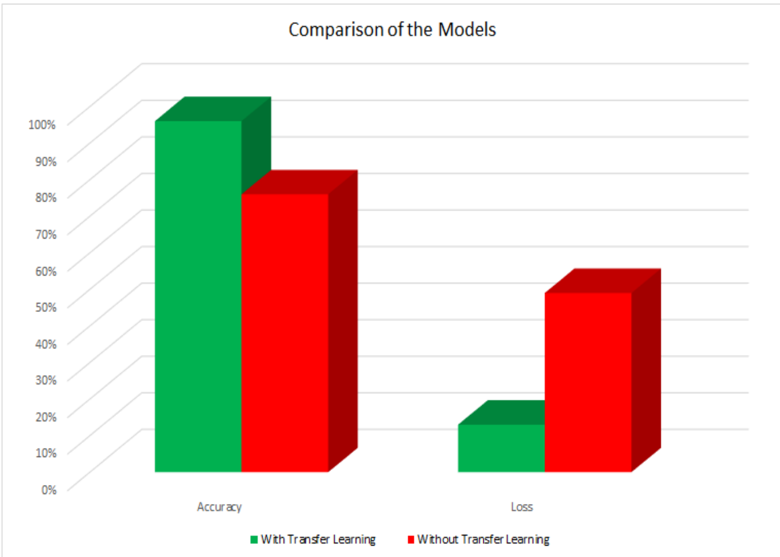

Figure 6. Model Accuracy and Mode loss with and without TL

This study showed that using pre-trained CNN with SVM for image classification showed greater accuracy in automatic image classification than just CNN or SVM. A key benefit of our pipeline approach is that we removed many features (4096 features in each image with details on each image) from the previous CNN (Alexnet) model and used SVM to train the features for the sake of persistence. Compared to previous work with CNN and SVM model, our method offers more accuracy by this comparison. This indicates that our method is reliable for correct Glaucoma image identification.

6 Conclusion

In this study, a pre-trained CNN-based framework is proposed to detect glaucoma in fundus images using transfer learning. In the proposed framework, a pre-trained Alexnet model is used to extract features from funds images based on transfer learning to improve classification accuracy. Finally, the classification accuracy of the proposed model is compared separately with the CNN and SVM models. The results showed that classifying the combined images of CNN and SVM into images resulted in image classification with 91.21% accuracy, an improvement over previous methods that used only SVM or CNN. CNN extracts more functionality from images, which can better inform SVM classification, resulting in greater accuracy than low-performance extraction methods. In future works, the proposed structure may be modified to identify other eye diseases.

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