Detection of Glaucoma Using Deep Learning Techniques: Literature Survey

Hari Krishna Marrapu
Assistant Professor
Dept of IT,
GMR Institute of Technology,
Rajam, Andhra Pradesh, INDIA
harikrishna.m@gmrit.edu.in

Abstract*:* Glaucoma has emerged as a major cause of vision loss. Glaucoma may be diagnosed by an expert ophthalmologist by assessing the optic nerve head. This procedure is time-consuming and demanding, and it requires a lot of effort. Glaucoma may still be avoided during this first identification stage even if this illness hasn't been well studied. As a result, routine glaucoma screening is both necessary and highly recommended. When it comes to glaucoma detection, machine learning approaches may help. With the help of an Alexnet model trained with an SVM classifier, we have developed an automated glaucoma testing framework. Three publicly accessible datasets were utilised in this study: HRF, Origa, and Drishti GS1. The suggested model was able to accurately classify images 91.21% of the time. This research found that utilising a pre-trained CNN and SVM for disease diagnosis was more accurate than using only CNN or SVM.

Keywords: Fundus, Glaucoma, SVM, CNN,AlexNet.

I.INTRODUCTION

In recent years, glaucoma has emerged as the leading cause of vision impairment. When the eye's intraocular pressure rises due to glaucoma, the optic nerve is damaged. In the event that the condition goes undiscovered, it might lead to a lifetime of vision impairments. This necessitates the need for glaucoma screenings. When it comes to diagnosing and monitoring glaucoma, fundoscopy and Ocular Coherent Tomography (OCT) have been the imaging methods of choice [1].

The retinal camera is used to capture images of the choroid, optic nerve, and retina in the fundus photography technique. Clinical professionals may analyse the images obtained from fundus photography to determine the underlying causes of the patient's vision impairment. Since among the several eye illnesses, glaucoma has been recognised as the primary cause of permanent blindness

[2]. Treatment for glaucoma has yet to be developed, however the disease's main detection is treatable. Deep learning and segmentation algorithms have made a substantial contribution to the clinical findings.

Because of the effectiveness of deep learning image categorization systems, researchers are now looking into glaucoma. A computerised fundus examination may reveal whether or not a patient has ocular glaucoma. Is it possible that the CNN-SVM combo may achieve more accuracy in automated detection than either the CNN or SVM alone?

II.RELATED WORKS

There have been a few studies in the area of ophthalmology that have attempted to develop a framework for determining uphold. Emotionally supportive networks utilising deep neural networks have been under investigation in the area of ophthalmology in recent years.

Traditional machine learning (ML) classifiers and deep learning (DL) methods have been used to predict glaucoma from fundus pictures in the past. Glaucoma categorization begins with the preprocessing and segmentation of the fundus pictures in the first category. Pretrained models or bespoke CNNs are used in the identification of glaucoma in the second group of methods. We have, however, used a DL approach to improve current glaucoma detection development methods, which has shown to be really effective in our study experiments. These are some examples of review studies. Chen et al. developed a framework of 6-layer CNN architecture for Glaucoma observation [6].

On ORIGA and SCES datasets, the AUC was 0.831 and 0.887 percent, respectively, in this experiment. Retinal Color Fundus pictures of glaucoma were studied by Ahn et al. [7] and a method employing CNN with 3 convolutional layers with max pooling performed at each layer was proposed. Using a private dataset of 1542 records, the model's performance was assessed and it showed detection performance of 87.9% and an AUC of 0.94 on the test data.

BaidaTo classify pictures into normal or glaucomatous, Al Bander et al. [13] used a pre-trained AlexNet model with 23 layers and an SVM classifier. The RIMONE database, which contains 255 normal and 200 glaucomatous pictures, was used to test the model's performance. 90.8 percent, 85 percent, and 88% were the accuracy and specificity of the suggested method.. In contrast to prior studies, this study uses four separate datasets to train and evaluate models for glaucoma detection, rather than relying on a single dataset and unique datasets. Glaucoma will be diagnosed with the use of CNN in this paper.

Using Inception-v3, Li et al. [3] developed an approach for evaluating whether a deep learning system for monitoring glaucoma optic neuropathy (GON) met its full potential in 2018. They employed Adam Optimizer and a mini-batch stochastic gradient of 32 for training. A private database of 70,000 photos yielded the greatest results, with a detection rate of 0.002. In the very same year, Raghavendra et al. [4] developed an 18-layer CNN architecture including a max-pool layer and a convolutional layer.

Using deep learning architecture, MamthaJuneja et al. [5] published a method for segmenting procedures of the optic disc and cup in 2019. Total of 50 fundus pictures were used to test his model, and the disc segmentation accuracy was found to be 95.8%, while the cup segmentation accuracy was found to be 93%.
A model created by Baida Al Bander et al [6] employs CNN to detect glaucoma in the eye. A pre-trained Alexnet model classify the pictures into normal or irregular stage conditions instead of the handcrafted optic disc characteristics employed in previous approaches. The Rim RIM-ONE database contains 255 normal and 200 glaucomatous images that were used to test the model's performance. To put it another way: the suggested approach is 90.8 percent specific, 85.2 percent sensitive, and 88% accurate.
In light of the various flaws in previous attempts to diagnose glaucoma, a new framework has been provided for glaucoma detection.

In the initial stage of glaucoma, patient does not have any symptoms. But it can lead permanent vision loss. Early diagnosis plays an important role in glaucoma. Till today no effective treatment available for glaucoma in developing countries also i.e. less than 50%. It is very dangerous disease for human life in this society. According to studies, it is expected 116 million people will be affected in this world by 2040 [11].

Chen *et al.*[12] proposed a framework. It has 6-layer CNN architecture. It is used to screening and predicting the glaucoma disease. This experimentation uses ORIGA and SCES data sets. It gives the accuracy 0.831% and 0.887%.

In examining the glaucoma, traditional methods, fluorescent dye angiography, Coherence tomography plays an important role. It is a property of dye, will be activated by shining a specific wavelength of light and being administered. Coherence tomography images are being constructed by axial scans and produces a 3-dimensional reconstruction of the retina [13].

Objective of preprocessing an image is to enhance the quality by reducing noise in the image. So there is a need to find the problems of noise, reasons for poor lighting in the image. Here contrast enhancement can be done through non-uniform illumination using adaptive histogram equalization. Here segmentation plays an important role. Segmentation divides the signal into set of components. The channel examination can be done during the signal segmentation only [14].

In Bharkad's research, he filtered the blood vessels and increased the optical depth area by using an equiripple low pass FIR filter [15].

The methodology related to Glaucoma and Retinopathy diseases have given in [16-18].

III. ARCHITECTURE OF ALEXNET

For image classification, recovery and target recognition, LeCun's CNN is an excellent neural network model [7, 8]. Because they share their weight, CNN has fewer neurons and variables, which makes it simpler to train.

In terms of delegate models, Alex-Net is the best CNN model, with greater performance, fewer training parameters, and strong resilience. We'll go through the basic structure of AlexNet in this section, as represented in Figure 1. Eight trainable layers are included, in addition to the input/output, rectified linear unit (ReLU), normalisation (normalisation), pooling (pooling), dropout (dropout), softmax (softmax), and dropout (dropout) (FC).

This layer allows photos with a resolution of up to 227 x 2273. Reduced epochs and a lower learning error rate may be achieved with the use of the ReLU layer. The generalisation and error rate reduction provided by the normalisinglayer is crucial. [10] The pooling layer dynamically shrinks the representation's spatial dimension to reduce the amount of parameters and computations in the network. It is possible to decrease overfitting issues by using both dropout layers and the Softmax layer, while the output layer categorises pictures into several categories

The last two layers of the 25 distinct layers are used to fine-tune the model. To extract features for classification, we employ the Fully Connected layers since the initial model layers can only recognize picture edges.

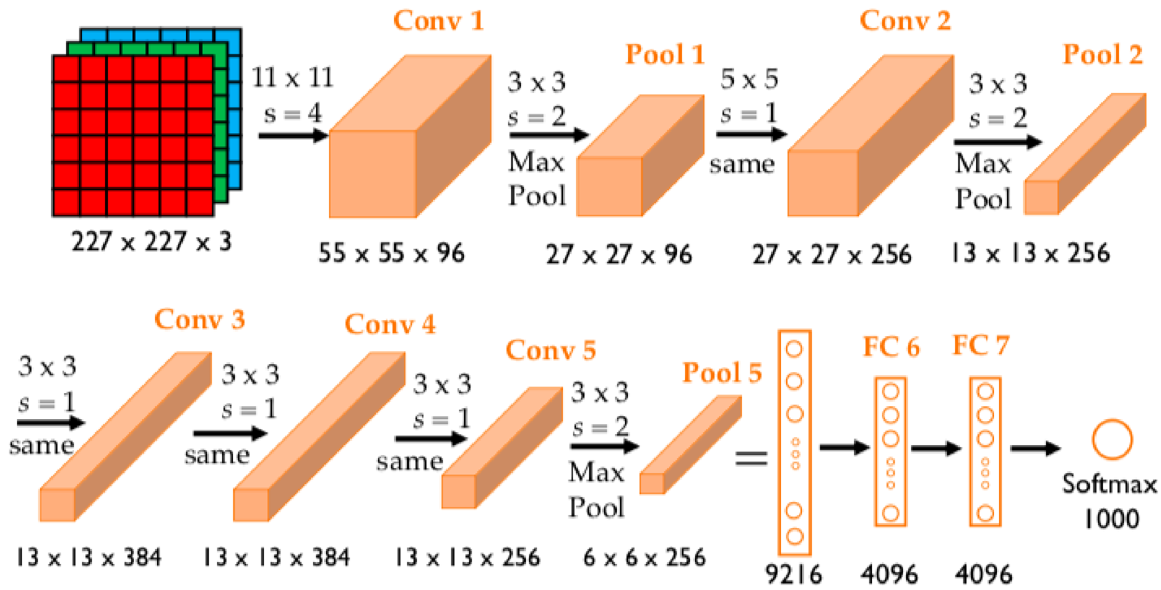

Fig 1: The AlexNet Architecture

IV. Materials and Method

We employed a variety of materials and procedures in this work to diagnose glaucoma in humans at an early stage and avoid sight loss. Materials and procedures are referred to in the following subsections.

Materials

Training and testing are used to construct the suggested method for the automated identification of glaucoma. Data from the HRF, Origa, and Drishti GS1 datasets were utilised in this investigation.

High-Resolution Fundus (HRF)

It has a total of 30 HRF Retinal Images, 15 of which are healthy and 15 of which are glaucoma-related. An f/4.5 Canon CR-1 fundus camera with a 3504x2336 pixel resolution and a 45-degree field of view captured the robbers. Every picture has a binary best practice level vascular segmentation image created by doctors.

ORIGA

There are 650 retinal pictures in ORIGA-light that have been marked by professionals (Z. Zhang et al. 2010). It had 168 glaucomatous photos and 482 non-glaucomatous images with a 3072x2048 pixel resolution. This record is often used as a standard for glaucoma classification techniques that are based on gut feelings. Nimte's database may be accessed at http://imed-origa-652 english.htm

DRISHTI_GS1

The retinal fundus of 101 images is included in this collection for the purpose of segmenting the optic disc. Aravind Vision Clinic in Madurai provided the backdrop for all of the photographs. Clinical professionals were able to identify glaucoma patients based on their findings during an evaluation. Indians in their 40s to 80s provided the retinal images used in this study. An optical disc was utilised to create pictures with a resolution of 2996 by 1944 pixels. The following is a description of three different datasets that may be found in Table 1.

TABLE 1: FIELDS IN DATA SET

Database	**Glaucoma**	**Normal**	**Resolution**	**Total**
Drishti-GS1	70	31	2996x1944, PNG	101
HRF	15	18	3504x2336, PNG	30
ORIGA-light	168	482	3072x2048, JPG	650

Methods

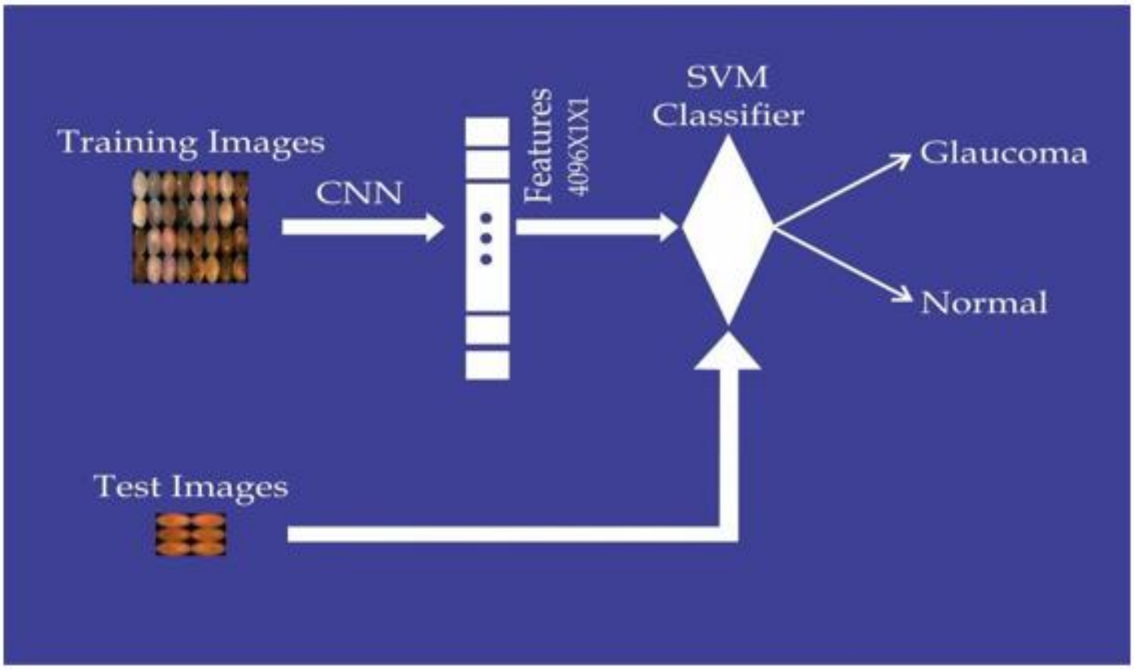

Fig 2 : Detection of Glaucoma - Framework

By fine-tuning AlexNet just on ImageNet dataset, we were able to acquaint ourselves with our classification job in this research study. Initially, we divided the photos into two groups: glaucomatous and non-glaucomatous. We preprocessed all of the photos in the dataset, which includes photographs obtained under a wide range of imaging settings. The optical disc portion of each picture was cropped and resized from each of the input images at this stage. The categorization system may be shown in Figure 2. All cropped photos must have a consistent size of 2272273, and the output of CNN is a 409611 feature map, as per AlexNet's computing requirements.

The test photos are trained and classified using an SVM classifier and a feature map. Training and test photos were then divided into two sets: one for learning properties, and the other for determining the method's correctness. To fine-tune the last two convolutional layers, we used a pre-trained CNN built from more than a million photos. We evaluated the performance of CNN-based training and testing pictures using the most recent fully connected layer data. A set of training and test photos were then tagged with the appropriate class labels.

Classifiers are optimised using a grid search technique. The efficacy of the SVM classifier was then assessed, and the classes of the new photos were evaluated based on the skillful categorization of the test images.

A single NVIDIA Tesla K40c GPU was used to train the new network. With a learning rate of 0.001, we used De Algorithm to train levels in batches of 32 photos each step. After 50 eras, the training was at a standstill since accuracy and loss could not be improved further.

V.RESULT COMPARISON

Following network convergence, we analyse our system's performance using 91 photos from the test set. For the purpose of evaluating our trained ideal, we projected the model's confusion matrix on a test set in Figure 3. 35 of the 40 glaucomatous photos in the confusion matrix were accurately labelled as glaucomatous, whereas 48 of the 51 normal images were correctly classified as normal. 91.21 percent accuracy was achieved by the suggested approach.

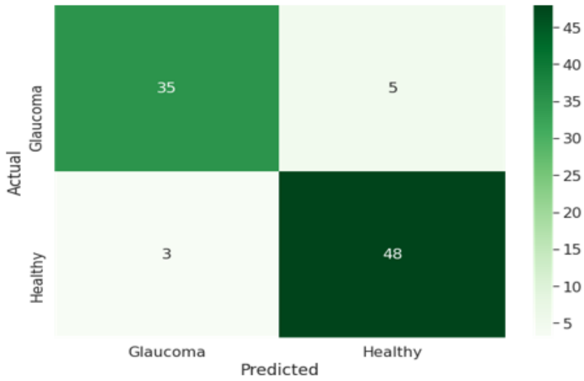

Fig 3: Confusion Matrix

The comparative results of with TL and without TL is shown in Table-2;

TABLE-2: WITH TL VS WITHOUT TL

Model Type	Accuracy(%)	Loss(%)
with Transfer Learning	90	18
without Transfer Learning	60	35

Using and not using transfer learning may be shown in Figure 6, which depicts model accuracy and loss.

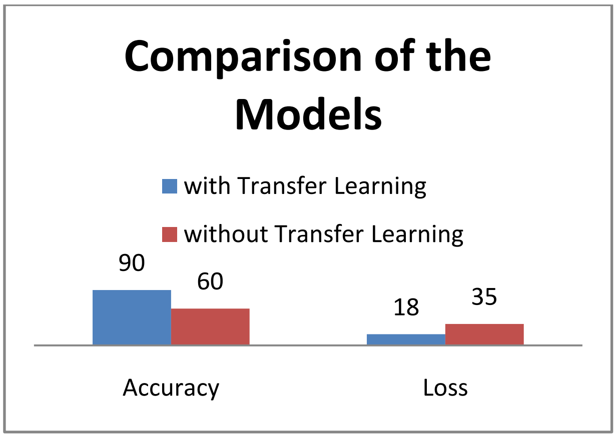

Fig 6: Model accurary and mode loss with and without TL

This research found that combining a pre-trained CNN with SVM improved automated picture categorization accuracy over using either CNN or SVM alone. An advantage of our pipeline technique is that we were able to eliminate a large number of features from the prior CNN model

(Alexnet) and instead use SVM to train the features for long-term stability (4096 features in each picture). This comparison shows that our strategy is more accurate than earlier work using CNN and SVM models. This shows that our approach is accurate in identifying glaucoma images.

VI.CONCLUSION

To diagnose glaucoma in fundus pictures, a pre-trained CNN-based architecture is suggested that uses transfer learning. To increase classification accuracy, a pre-trained Alexnet model is employed in the proposed system to extract features from fund photos via transfer learning. Finally, the suggested model's classification accuracy is compared to that of the CNN and SVM models independently. Using CNN and SVM to classify pictures produced an image classification accuracy of 91.21%, outperforming prior approaches that just employed SVM or CNN. SVM classification is more accurate when CNN extracts additional functionality from pictures, which is why CNN is more accurate than low-performance extraction approaches. To discover more eye illnesses in the future, the suggested framework might be adapted.

REFERENCE

[1]. Nawaldgi S, Review of automated glaucomadetection techniques, IEEE InternationalConference WirelessCommunications, SignalProcessing andNetworking, IEEE, Piscataway,New Jersey, UnitedStates, pp. 1435-1438, 2016.

[2] Roodhooft J, Leading causes of blindness worldwide, Bull Soc Belge Ophtalmol283:19-25, 2002

[3] Li Z, He Y, Keel S, Meng W, Chang RT, He M. Efficacy of a deep learning system for detecting glaucomatous optic neuropathy based on color fundus photographs. Ophthalmology. 2018;125(8):1199–206.

[4] Raghavendra U, Fujita H, Bhandary SV, Gudigar A, Tan JH, Acharya UR. Deep convolution neural network for accurate diagnosis of glaucoma using digital fundus images. Inf Sci. 2018;441:41–9.

[5] Juneja, M., Singh, S., Agarwal, N. et al. Automated detection of Glaucoma using deep learning convolution network (G-Net). Multimed Tools Appl 79, 15531–15553 (2020).https://doi.org/10.1007/s11042-019-7460-4

[6] Baidaa Al-Bander, Bryan M. Williams, Majid A. Al-Taee, Waleed Al-Nuaimy, Yalin Zheng, "A Novel Choroid Segmentation Method for Retinal Diagnosis Using Deep Learning", Developments in eSystems Engineering (DeSE) 2017 10th International Conference on, pp. 182-187, 2017.

[7] Alex Krizhevshy, Ilya Sutskever, Geoffrey Hinton. ImageNet Classification with Deep Convolutional Neural Network. In NIPS, 2012.

[8] Girshick R, Donahue J, Darrell T, et al. Rich feature hierachies for accurate object detection and semantic segmentation[J]. IEEE Conference on Computer Vision and Pattern Recegnition, Columbus, USA, 2014.

[9] Abbas Q. Glaucoma-deep: detection of glaucoma eye disease on retinal fundus images using deep learning. Int J Adv Comput Sci Appl. 2017 Jun 1;8(6):41-5.

[10] Raghavendra U, Fujita H, Bhandary SV, Gudigar A, Tan JH, Acharya UR. Deep convolution neural network for accurate diagnosis of glaucoma using digital fundus images. Information Sciences. 2018 May 1;441:41-9.

[11] World report on vision. [Last accessed on 2021 Jan 09]. Available from: https://www.who.int/publications-detail-redirect/world-report-on-vision

[12] Haloi M. Improved microaneurysm detection using deep neural networks. ArXiv150504424 Cs. 2016. [Last accessed on 2021 Jan 09]. Available from: http://arxiv.org/abs/1505.04424

[13] F. Guo, W. Li, J. Tang, B. Zou, and Z. Fan, “Automated glaucoma screening method based on image segmentation and feature extraction,” Medical, & Biological Engineering & Computing, vol. 10, 2020.

[14] F. Abdullah, R. Imtiaz, H. A. Madni et al., “A review on glaucoma disease detection using computerized techniques,” IEEE Access, vol. 9, pp. 37311–37333, 2021.

[15] S. D. Bharkad, “Frequency domain analysis of grey level intensities for extraction of optic disc in retinal images,” International Journal of Medical Engineering and Informatics, vol. 13, no. 4, pp. 297–307, 2021.

[16] Veerraju Gampala, Balajee Maram, S. Vigneshwari, R. Cristin, "Glaucoma detection using hybrid architecture based on optimal deep neuro fuzzy network", International Journal of Intelligent Systems, Wiley Online Library, First published: 13 March 2022

[17] V Srinadh, Balajee Maram, Veerraju Gampala, “Prediction of Retinopathy in Diabetic Affected Persons using Deep Learning algorithms”, 6th International Conference on Trends in Electronics and Informatics ICOEI 2022, 28-30, April 2022, Tirunelveli, India.

[18] Balajee Maram , Jitendra Sahukari, Tandra Lokesh, “A Framework for Glaucoma Diagnosis Prediction Using Retinal Thickness using Machine Learning”, 1st International Conference On Smart Technologies for Power and Green Energy (STPGE-2022), 12th and 13th February 2022