



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 1, January 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

Deep learning Based Glaucoma Detection System

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ABSTRACT: A chronic, progressive eye condition called glaucoma is characterised by damage to the optic nerve and a progressive loss of vision. In order to stop irreversible visual deterioration, early detection and prompt management are essential. Recent developments in machine learning, namely in the area of convolutional neural networks (CNNs), have demonstrated potential for automated retinal image analysis-based glaucoma identification. This paper presents a comprehensive framework for the identification of glaucoma that combines state-of-the-art CNN architectures, statistical approaches like Design of Experiments (DOE), and picture enhancing techniques like Retinex. Retinex is used to enhance fundus images in terms of quality and contrast, which in turn improves CNN- based feature extraction that follows. CNNs are optimised with DOE to achieve improved detection performance. CNNs are meant to recognise unique patterns and features suggestive of glaucoma.

KEYWORDS: Supervised learning by classification, Neural network, CNN, Glaucoma Detection, Retinex, Machine Learning, Data Analysis

I. INTRODUCTION

A common, long-term eye condition that affects millions of people of all ages and demographics, glaucoma is one of the primary causes of permanent blindness globally. Early detection and care are crucial for maintaining eyesight and improving the quality of life for those affected with glaucoma, which is characterised by progressive degeneration of the optic nerve and concomitant visual field loss. Glaucoma frequently goes undiagnosed in its early stages. Comprehensive clinical tests, such as measurements of intraocular pressure (IOP), evaluations of the optic nerve head, and visual field exams, are crucial to the traditional diagnosis of glaucoma. These techniques, however, are laborious, subjective, and might not identify glaucoma until the disease has progressed to the point where irreversible damage has already been done. The field of glaucoma detection has undergone a radical change thanks to developments in medical imaging technology, especially the use of fundus photography and optical coherence tomography (OCT). Fundus photography has become a useful diagnostic tool for the early detection of problems associated to glaucoma because it provides high- resolution images of the retina.

In order to obtain reliable and efficient automated glaucoma identification utilising fundus images, this study presents a thorough overview and analysis of glaucoma detection strategies, with a primary focus on leveraging machine learning techniques, specifically CNNs. We examine the difficulties in diagnosing glaucoma, the potential of CNNs in distinguishing characteristics related to glaucoma from fundus pictures, and the incorporation of cutting-edge methods to improve the accuracy and efficiency of automated glaucoma detection systems. We hope to offer important insights into the changing landscape of glaucoma detection by synthesising the state of the art research and developments in the field. This will help with better screening, early diagnosis, and management of this sight-threatening condition.

II. LITERATURE SURVEY

In this study, a CNN semi-supervised learning system for glaucoma detection in fundus pictures was described. The current methodology showed promising performance when compared to existing approaches by applying the self-learning strategy to expand the training samples using the unlabeled data and fine-tuning a pre-trained CNN to construct a glaucoma- specific classifier. As part of their ongoing study, the scientists are working to improve the framework's generalisation so that it can identify additional eye disorders[1].

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learning strategy to expand the training samples using the unlabeled data and fine-tuning a pre-trained CNN to construct a glaucoma-specific classifier. As part of their ongoing study, the scientists are working to improve the framework's generalisation so that it can identify additional eye disorders[2].

We provided a 3DCNN-based, totally automated glaucoma diagnosing approach. Because OD segmentation and/or data augmentation phases were not included in the suggested technique, it varies from previously described procedures. The 100% accuracy we were able to attain served as a strong indication of the results' promise, which reached levels compared to the finest research currently accessible in the associated literature. Compared to conventional designs, our volumetric analysis technique produced more favourable results; these results open up new research avenues. Last but not least, we think that our approach has value and contributes meaningfully to the medical community and, subsequently, to the computer community, particularly in the interpretation of medical pictures[3].

In this research, we present a unique Discaware Ensemble Network (DENet), which incorporates four deep streams on various layers and modules, for automated glaucoma screening. The inclusion of several levels and modules is advantageous for incorporating hierarchical representations, and the discaware constraint ensures that the optic disc region's contextual information is included for glaucoma screening. Our technique outperforms state-of-the-art glaucoma screening algorithms, according to trials on two glaucoma datasets (SCES and recently gathered SINDI datasets)[4].

In summary, this work proposed a novel AI-based method for glaucoma identification that integrates temporal (dynamic vascular) and spatial (static structural) characteristics. Our suggested strategy showed good performance in differentiating glaucoma from healthy compared with models that just used spatial information as their input while tackling the video classification issue of glaucoma[5]. In this study, a glaucoma detection model for fundus pictures is proposed. It makes use of graph-based saliency and convolutional neural network ensembles. We start by identifying the optic disc on the fundus pictures using graph-based saliency. Then, using four distinct ways, we combine the output of an ensemble of three potent CNN architectures to identify glaucoma. The results reveal that our model performs better than a comparable study from the literature that makes use of the same dataset. The results further demonstrate that they are on par with or superior to those reported by current glaucoma detection studies[6].

This study offers an automated primary glaucoma screening based on quantitative analysis of fundus pictures to help ophthalmologists identify glaucoma illness more quickly and affordably. Two primary processing phases make up the suggested technique. Five different deep semantic algorithms are employed to experiment with OD segmentation, and the characteristics recovered from the clipped OD region are then utilised to train a classifier to predict the existence of glaucoma in the test pictures[7].

Existing Open Issues

The goal of integrating CNN, DOE, and Retinex enhancement is to improve the robustness and accuracy of glaucoma identification using fundus pictures. While CNN collects pertinent characteristics and DOE optimises the model for greater performance, the Retinex method enhances image quality. On the other hand, I suggest reading the most recent ophthalmology and computer vision research papers, publications, or journals for comprehensive and current information on this particular framework.

III. METHODOLOGY

We are going to describe various algorithms, libraries and types of neural networks used for Image Processing.

Types of Neural Networks

For image compression, here, we have used two types of Neural Networks, namely:-

1. Convolutional Neural Networks (CNNs)
2. Generative Adversarial Networks (GANs)

Convolutional Neural Network (CNN) Basically, this network is designed to process the data with a greed like topology such as image classification.

There are basically 3 types of Layers in CNN:-

1. Convolutional Layer.
2. Pooling Layer.
3. Fully Connected Layer.



Convolutional Layer:- It learns to detect the specific features in the data and extract the data. This layer is also known as the core building block of CNN. In this layer **Filter** element is used for conducting operation in Convolutional Layer. The filter or also known as the kernel makes horizontal and vertical shifts according to the given stride rate until the whole image is traversed.

Pooling Layer:- It reduces the spatial dimension of the data which is also known as dimensionality reduction. It helps in reducing the Computational Power required for processing. We have two types of Pooling:-

1. Max Pooling:- It returns the Maximum Value from the area covered by the kernel, i.e, max value from matrix (normally 2x2).
2. Avg Pooling:- It returns the Average Value of all the parts covered by the kernel ,i.e, average value from matrix (normally 2x2).

Fully Connected Layer:- It is operated on flattened input where each every input is connected to all the neurons present in the Architecture. The FC Layer or Flatten is always present at the end of CNN Architecture CNN is mainly used for extracting features using its different layers as mentioned above.

Generative Adversarial Network (GAN) These Networks are used for generative Modelling. It is having two parts:-

1. Generator:- It generates new data sample.
2. Discriminator:- It is able to distinguish between the real data and the generated data.

GAN models use an unsupervised learning approach.

Further, Generator is not allowed to see the real image which results poor performance in starting phase while at the other end Discriminator allowed to look all real images but they are jumbled with fake ones which are produced by Generator but the Discriminator have the ability to Bifurcate them.

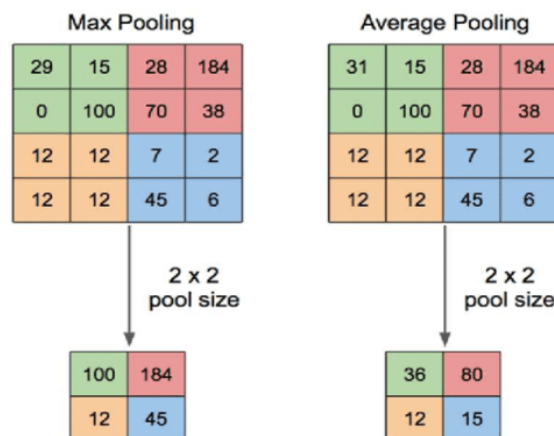
When the Discriminator makes predictions, with the help of it the Generator tries to improve itself.

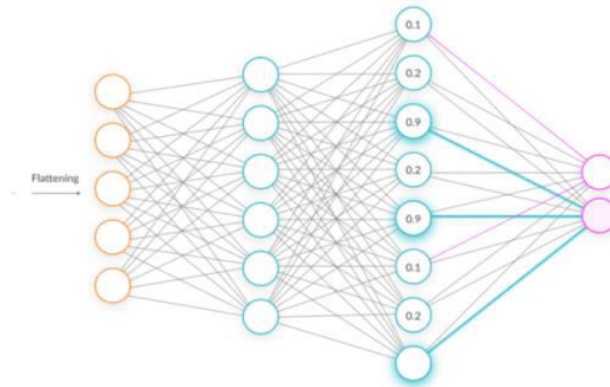
Discriminator also improves its performance as it is provided with more and more realistic images at each time by the Generator.

One point of time comes where the Generator produces such kind of Images which are more harder to distinguish so now it is easy for user to get satisfied result.

Some of the popular GANs are listed below:-

1. Deep Convolutional GANs (DCGANs)
2. Conditional GANs (CGANs)





IV. CONCLUSION

Automating the diagnosis of glaucoma, a prevalent eye illness that can cause vision loss if left untreated, has shown encouraging results when it comes to machine learning, especially deep learning algorithms like Convolutional Neural Networks (CNNs). The field of machine learning, particularly CNN- based methods, has enormous potential for the diagnosis of glaucoma. By improving early diagnostic speed and accuracy, these strategies may help improve glaucoma care and therapy, thereby protecting affected persons' vision. But the effective integration of these developments into clinical practise will require ongoing research, strong validation on a variety of datasets, and cooperation with medical experts.

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