Fund us OCT images captured in real time for glaucoma surveillance

PRIYABRATA NAYAK
ASSISTANT PROFESSOR, Mtech,
Department of CSE
Gandhi Institute for Technology,Bhubaneswar.

Abstract:

Damage to the optical nerve, which carries visual signals to the brain, is the direct cause of the irreversible vision loss that results from glaucoma. Since glaucoma advances without warning and cannot be reversed in its later stages, early detection is essential. Although several deep learning models have been addressed to the problem of diagnosing glaucoma from digital fundus pictures, their generalisation performance has been limited by a lack of labelled data, in addition to their high computational cost and unique hardware requirements. Here, we suggest using We test the efficacy of three different compact Self-Organizing Operational Neural Network OD architectures for early glaucoma detection in fundus images vs more conventional (deep) Convolutional Neural Networks (CNNs) (ACRIMA, RIM-ONE, and ESOGU). The results of the experiments demonstrate that OD is a viable network model for biomedical datasets, especially in scenarios with little data, since it not only provides outstanding detection performance but also has the potential to significantly reduce the computational complexity.

Keywords: Glaucoma, Diabetic Retinopathy, Convolutional Neural Networks.

1. Introduction

Glaucoma, sometimes known as "the silent thief of sight," is a leading cause of permanent optic nerve degeneration and, ultimately, blindness. According to the World Health Organization's (WHO) statistics, glaucoma is the leading cause of irreversible visual loss worldwide. Early diagnosis and treatment of glaucoma is crucial because it causes permanent damage to the optic nerve's front portion if left untreated. However, identification is challenging, especially for large-scale screening, since mild glaucoma may not cause any visible symptoms like pain or decreased vision. There will be an estimated 111.8 million individuals living with glaucoma by the year 2040, up from an estimated 64 million in 2013. Diagnostic methods for the optic nerve head damage caused by glaucoma include fundoscopy, visual field testing, optical coherence tomography, and digital fundus imaging. Digital retinal images have recently been proposed as a non-invasive, cost-effective, and rapid method of using signal processing and machine learning methods for the automated assessment of the optic nerve head in a large-scale glaucoma screening setting.

Many methods for automated glaucoma diagnosis have been reported in the medical literature. Bock et al. performed principal component analysis on color fundus photographs to get eigen images, and then they used a support vector machine to classify the images in order to develop a Glaucoma Risk Index (GRI) with competitive Glaucoma detection performance (SVM). Energy signatures were extracted using wavelet transform features in Due et a proposed.'s glaucoma detection system, which also made use of several feature ranking and feature selection techniques. They used SVM to classify these features using a local dataset and got an accuracy of 93%.

Carillo et al. proposed a computational approach for automatic glaucoma diagnosis that uses the optic disc (OD) and cup segmentation technique to estimate the cup-to-disc ratio (CDR) and establish a threshold. From a collection of images obtained from the Center for the Prevention and Care of Glaucoma in Bucaramanga, they were able to achieve an overall classification accuracy of 88.5%. Using digital image processing, Kayak et al. presented a new method for detecting glaucoma. Pre-processing, morphological methods, and thresholding were employed to automatically recognize the OD, blood vessels, and compute attributes. Kasturba Medical College in India uses a neural network classifier to distinguish between normal and glaucoma fundus pictures to validate the characteristics. Their method was shown to be one hundred percent sensitive and eighty percent specific across the test dataset. That's the idea, anyhow, to quote Singh et al. In order to construct an algorithm for detecting blood vessels in fundus images, the researchers analysed their own dataset and used support vector machines to characterize the wavelet properties of the images. segmented OD image.

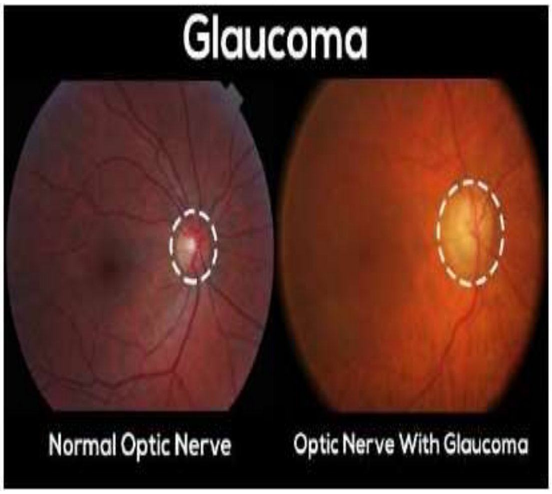


Fig1 Optic nerves in glaucoma and normal eye

The second primary culprit for visual impairment is the common but permanent eye disease glaucoma. It becomes recognisable and vigilant only in the latter stages of glaucoma due to the absence of a professional early screening framework. As of 2015, there were 64.3 million people worldwide who have glaucoma; by 2020, that number is expected to rise to 76.0 million. Preventing visual loss from glaucoma requires prompt diagnosis and treatment. Taking a look at your retinal fundus photos often might help you spot glaucoma early on. The back of the eye, the retina, the optic disc, the fovea, and the macula are all entangled in a fundus photograph of the eye. The best method for monitoring retinal changes is by the use of retinal fundus photographs. Fundus image inspection is the most visual among the several techniques used for confirming glaucoma in the clinic. A new glaucoma framework is proposed in this paper. zone, which will have consequences for CDR imaging of the fundus. The area of the retina known as the optic disc (OD) or optic nerve head is where axons from the retinal cells that will eventually become the optic nerve exit the eye. The suggested method begins with dividing the optical plate using CNN.

2. Related Work

The prevalence of glaucoma is rising in the field of ophthalmology. It is a primary cause of blindness. Glaucoma, cystoid macular edoema, and diabetic proliferative retinopathy are all treatable, but only if caught early. The use of artificial intelligence has been shown to be helpful in glaucoma diagnosis. In this study, we provide a method for automatically diagnosing glaucoma using fundus photographs. Here's how the suggested framework is built up: first, the Regions of Interest (ROIs) are broken down into their constituent parts (BIMFs + residue) using the Bi-dimensional Empirical Mode Decomposition (BEMD) technique. Extracting features from the BEMD subcomponents once they have been deconstructed is the primary function of the VGG19 CNN architecture. The characteristics of the same ROI are then merged into a single set of features. Principal Component Analyses (PCA) are used to minimise the dimensionality of features in these lengthy datasets. The obtained feature packs are used as input parameters in the deployed Support Vector Machine based classifier (SVM). We have utilised the publicly available ACRIMA and REFUGE datasets to train our models. Parts of ACRIMA and REFUGE, as well as four additional publicly available datasets (RIM-ONE, ORIGA-light, Drishti-GS1, and sjchoi86-HRF), have been utilised to evaluate the performance of our models. Using a model trained on REFUGE, we get an average accuracy of 98.31% on the ACRIMA dataset, 96.43% on RIM-ONE, 96.67% on ORIGA-light, 95.24% on the Drishti-GS1, and 98.60% on the sjchoi86-HRF dataset. Using the ACRIMA dataset to train a model, we get an accuracy of 99.06% on the REFUGE dataset, 98.27% on the RIM-ONE dataset, 97.10% on the ORIGA-light dataset, 96.36% on the Drishti-GS1 dataset, and 96.36% on the sjchoi86-HRF dataset. The effectiveness and resilience of the suggested method are shown by experimental results obtained using various datasets. When compared to other more recent works in the literature, ours has been found to be a major improvement.

One of the most frequent reasons people become blind is glaucoma, which is a neurodegenerative disease of the optic nerve. Since it is not possible to restore the function of damaged nerve fibres in the visual nerve, early diagnosis is crucial. A reliable and automatic mass-screening may help with this. Here, we present a unique automated glaucoma diagnosis approach that utilises digital colour fundus pictures, which are widely available and very affordable to collect. After some initial processing tailored to glaucoma, several Next, a dimension reduction technique based on appearance is used to compact the many feature types that are general. After that, we use a probabilistic two-stage classification technique to derive the novel Glaucoma Risk Index (GRI), and the results show that we can reliably identify glaucoma. On a dataset of 575 fundus images, 80% classification accuracy was achieved in a 5-fold cross-validation configuration. The GRI has a higher area under the curve (AUC) of 88% than a previously reported topography-based glaucoma probability score based on scanning laser tomography (AUC = 87%). To achieve competitive and accurate detection performance on a cost-effective modality, the proposed color fundus image-based GRI employs statistical analysis of whole images of the optic nerve head.

3. Methodology

An unusual effect on our daily life is the result of the glaucoma disclosure model. The reality is to create a self-ruling application for devices and to make it easy for glaucoma patients in developing nations to access their data stored in the cloud with just a fast internet connection. There will be no need to set aside separate areas for gatherings because to this program's ability to boost an organization's overall development.

You won't have any trouble using this programme because of its simple layout. Fast Internet connections provide instantaneous communication between all of the clients. The director has a high degree of autonomy over the streams that are stream grouped and likely for record streams. It's also the most astute strategy, since detecting glaucoma doesn't need any special hardware or software. This method may be used for the express goal of scientific enquiry. The cup-to-disc ratio is presently the most widely used indicator of optic disc abnormalities (cdr). Although the majority of publications rely on cup intensity, some have proposed using other parameters, such as vessel kink integration, super pixels, and pixel-level segmentation. These methods are more reliable than intensity-based methods, but they still only estimate cdr to identify od-s exhibiting a single symptom of glaucoma. many ophthalmologists don't rely only on cdr when making diagnoses of problems, and even among human experts there is substantial variability in calculating cdr. The suggested method uses dynamic data mining to discover discriminative OD characteristics in an effort to overcome the aforementioned drawbacks. Methodology We employ an incremental development approach, breaking the project down into smaller sub-projects. The actual requirements implementation is comprised of these subsystems, which have been further broken down into smaller manageable subsystems. Motives for using this paradigm include: Throughout the iterative process, testing and fixing bugs is simple. Since user needs tend to evolve over time, it's better to roll out updates to software in stages rather than all at once. Database of Diabetic Retinopathy Patients with DR may be placed into one of five severity categories using terminology established by the National Eye Institute (which are the classes that our classifier predicts). Non-proliferative DR (NPDR) is the first three categories, whereas proliferative DR is the fourth (PDR). Each of the severity scales has four levels, as follows: Micro-aneurysm lesions, or tiny balloon-like enlargements in the retinal blood vessels, characterise mild no proliferative diabetic retinopathy. Vascular dilation and swelling, many microaneurysms, widespread retinal haemorrhage, and firm exudates are all signs of moderate NPDR. In severe cases of NPDR, numerous blood vessels are clogged, leading to the aberrant release of growth factors. Other symptoms include massive blot haemorrhages, cotton wool patches, and a variety of abnormalities. Retinal detachment may be caused by scar tissue that forms as new blood vessels grow under the retina's surface in response to growth stimuli.

Fig 3.1 Glaucoma in eye

3.1 ALGORITHMS

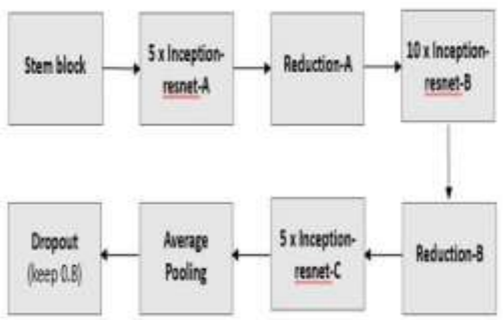
DenseNet (Dense Convolutional Network)

design that employs shorter connections between layers to train deep learning networks more efficiently while allowing them to grow deeper. DenseNet is a convolutional neural network with fully-connected layers, meaning that the first layer communicates with the second, third, fourth, and so on in the network, and so on for each successive layer. This is carried out so that there is optimal communication between the various levels of the network. In order to keep the feed-forward structure intact, each layer pulls data from the layers above it and sends its own feature maps to the layers below it. In instead of summing up features, like Resents do, they join them together using a concatenation method. Therefore, feature maps of all its previous convolutional blocks make up the 'it' layer, which has I inputs. It communicates its own feature maps to all subsequent 'I-i' layers. This adds a new kind of link to the network, denoted by the notation (I(I+1))/2, rather than the more common 'I' connection used in conventional deep learning designs. Since it doesn't have to train any superfluous feature maps, it can function with fewer parameters than regular convolutional neural networks.

3.2 The Inception Revised Convolutional Neural Network

More than a million photos from the ImageNet collection were used to train the convolutional neural network known as Inception-ResNet-v2. This 164-layer network can sort pictures into a thousand different categories, including things like animals, plants, and various types of furniture. That's why the network can now handle a broad variety of pictures with the same level of sophistication: it's learnt to represent them all with detailed features. The network accepts 299x299 pixel images as input and produces a probability distribution across classes as output.

It is constructed using a hybrid of the Inception model and the Residual link. Convolutional filters of varying sizes are merged with residual connections in the Inception-Resnet building component. By using residual connections, not only is the degradation issue brought on by deep structures sidestepped, but also the training time is cut down considerably. The diagram depicts the fundamental network layout of Inception-Resnet-v2



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The basic architecture of Inception-Resnet-v2.

3.3 Self Organized ONN

An unsupervised learning model in ANN, SONNs are also known as Self-Organizing Feature Maps or Kohonen Maps. During the model training process, a two-dimensional discretized representation of the input space, known as feature maps, is produced (based on competitive learning). The parallels to biological systems are striking. Multidimensional sensory input spaces (such as auditory, motor, tactile, visual, somatosensory, etc.) are represented as two-dimensional maps in the human brain. Topology preserving projection is a concept used to describe a method of projecting higher level inputs onto lower dimensional maps. Self-organizing networks are capable of performing this topology-preserving mapping. Why is SONN Necessary? Lower-dimensional representations of higher-dimensional data may be categorised and seen with the help of these Self-Organizing Maps.

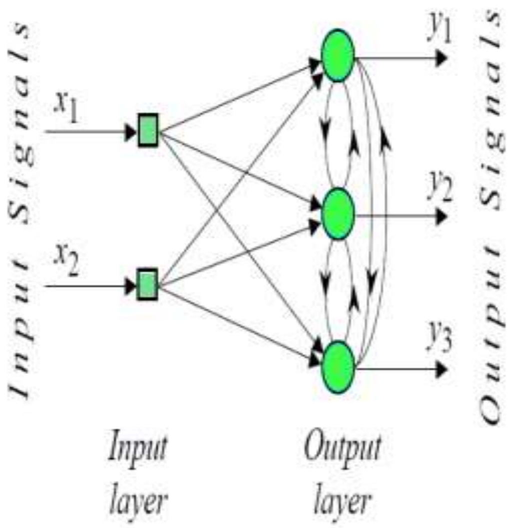

Fig No: Self Organized ONN

4. Results

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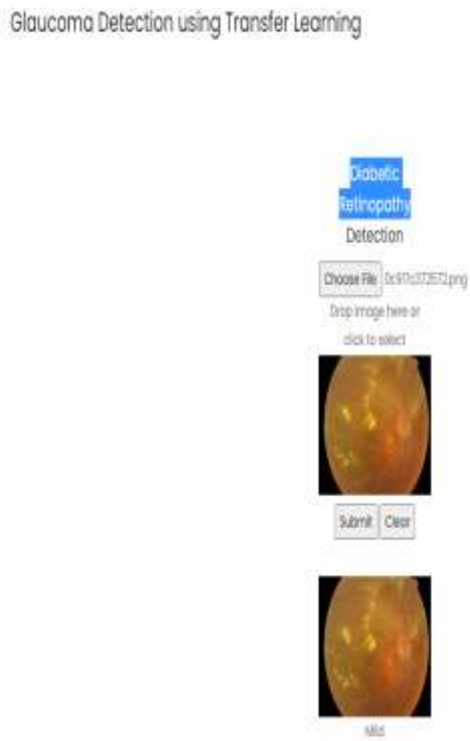
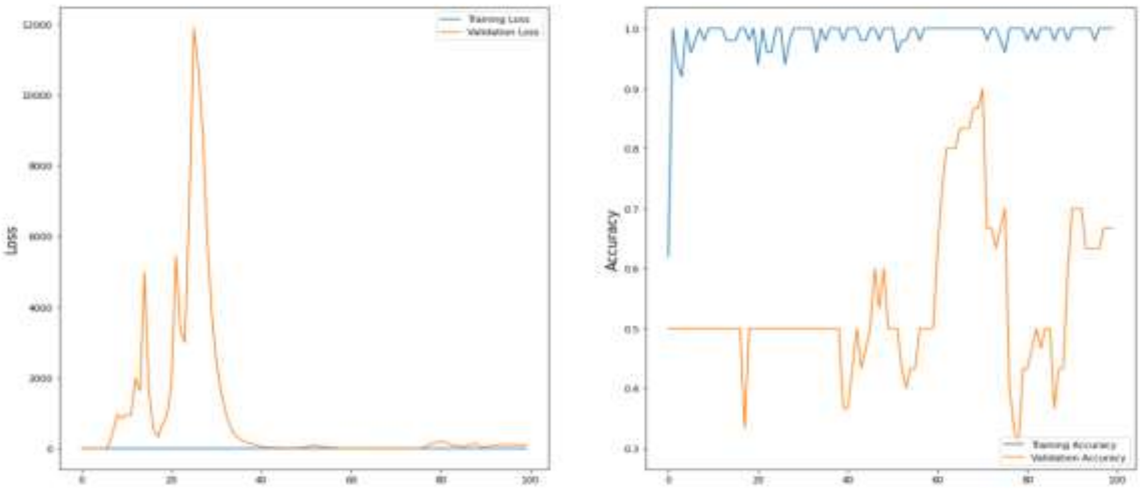
Glaucoma Detection

Diabetic Retinopathy



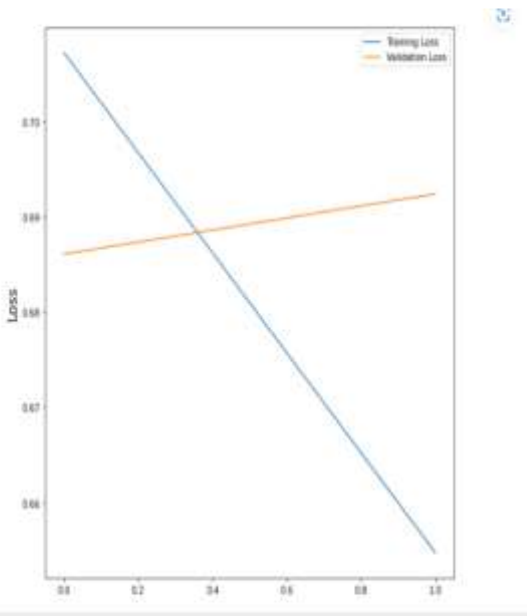
Diabetic Retinopathy

Inception ResNet V2



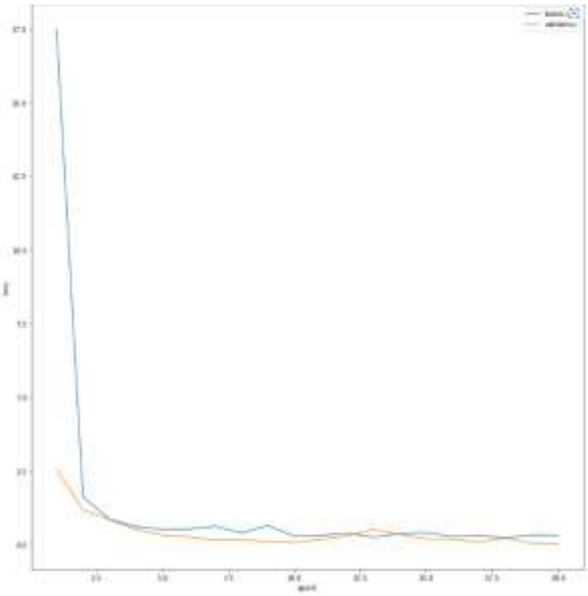
Inception ResNet v2

ONN with Generative Attention



ONN with Generative Attention

Self Organized ONN



Self Organized ONN

ACCURACYRATE

Algorithms	Accuracy Rate
Self Organized ONN	93%
Inception ResNet V2	89.5%
DenseNet121	81%

Table No:6.2.2 Accuracy Rate

5. CONCLUSIONS

To combat the high computational complexity and particular hardware requirements of deep CNNs, this research proposes using OD to diagnose glaucoma illness from acquired fundus pictures. Here, we suggest a new framework for the glaucoma zone that will affect how we take fundus pictures using CDR. The area of the retina known as the optic disc (OD) or optic nerve head is where axons from retinal pigment epithelium (RPE) cells exit the eye to form the optic nerve. The suggested method begins with dividing the optical plate using CNN. Focal wretchedness exists on the optic plate, which is not addressed by the suggested method. A focal wretchedness, devoid of material tissue, may be found in the optic plate. Expansion of this circular zone is an early sign of glaucoma, which is shown by the death of nerve tissue and often appears in inconvenient and deficient areas first. Fuzzy C advises using ROI in addition, for this morphological task of segmenting an optic glass. To diagnose glaucoma, the Cup-to-Disk Extent metric is calculated. Specific Identification of the Issue.

1. FUTURE WORK

As the topic of interest and the findings of this research turned out to be rich and wide, there are numerous approaches to expand it. Future avenues of research into this work are described below.

1. Design a database associated with the programme to store the patient's fundus photographs and medical reports.

2. Design a full, integrated, automated approach to categorise all distinct forms of glaucoma namely: Primary Open-Angle Glaucoma, Normal Tension Glaucoma, Angle Closure Glaucoma, Acute Glaucoma, Exfoliation Syndrome and Trauma-Related Glaucoma.

Third, finish the system so that it can calculate the progression of the illness by comparing several images of the same patient for follow-up purposes, rather than only diagnose glaucoma. Create a holder that converts a smartphone into a portable, low-cost fundus camera.

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