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Fund us OCT images captured in real time for glaucoma surveillance

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Abstract:

Glaucomatous vision loss is permanent because of damage to the optical nerve, which transmits visual information to the brain. As glaucoma progresses without warning and is ultimately irreversible, early identification is crucial. However, the generalization performance of these deep learning models has been constrained by a shortage of labelled data, in addition to their high computational cost and specific hardware requirements, making it difficult for them to be widely adopted for use in the field of glaucoma diagnosis from digital fundus images. Here, we advise making use of For early glaucoma identification in fundus pictures, we compare the performance of three distinct compact Self-Organizing Operational Neural Network OD designs (ACRIMA, RIM-ONE, and ESOGU) to that of three different traditional (deep) Convolutional Neural Networks (CNNs). The experimental findings show that OD is a practical network model for biomedical datasets, particularly in low-data settings, due to its exceptional detection efficiency and possible reduction in computing complexity.

Keywords: Glaucoma, Diabetic Retinopathy, Convolutional Neural Networks.

1. Introduction

"The silent thief of sight," glaucoma is the most common cause of irreversible optic nerve degeneration and blindness. The World Health Organization (WHO) reports that glaucoma causes more cases of permanent blindness than any other disease or condition. If glaucoma is not diagnosed and treated early, it will cause irreversible damage to the front segment of the optic nerve. Mild glaucoma may not create any noticeable symptoms like discomfort or reduced vision, making detection difficult, particularly for large-scale screening. By 2040, the number of people with glaucoma is expected to rise to an estimated 111.8 million, from an estimated 64 million in 2013. Fundoscopy, visual field testing, optical coherence tomography, and digital fundus imaging are all ways to detect glaucomatous damage to the optic nerve head. Recently, the use of digital retinal pictures for automated evaluation of the optic nerve head in a large-scale glaucoma screening environment has been suggested as a non-invasive, cost-effective, and quick technique.

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The medical literature reports several automated glaucoma diagnostic approaches. Using principal component analysis on color fundus pictures to get eigen images, Bock et al. classified the images using a support vector machine to create a Glaucoma Risk Index (GRI) with competitive Glaucoma detection performance (SVM). The glaucoma detection system described by Due et al. makes use of wavelet transform features to extract energy signatures and a number of feature ranking and feature selection methods to narrow down candidate features. Using a local dataset, they classified these characteristics using SVM and achieved 93% accuracy.

With the optic disc (OD) and cup segmentation method, Carillo et al. suggested a computational strategy for automated glaucoma diagnosis that estimates the cup-to-disc ratio (CDR) and sets a threshold. Using data received from the Glaucoma Prevention and Care Center in Bucaramanga, they were able to get an overall classification accuracy of 88.5%. Kayak et al. revealed a novel approach for identifying glaucoma that makes use of digital image processing. Automatic OD, blood vessel, and attribute recognition was achieved by pre-processing, morphological approaches, and thresholding. For validation purposes, a neural network classifier is used at India's Kasturba Medical College to differentiate between normal and glaucoma fundus images. On the test dataset, they achieved 100% sensitivity and 80% specificity with their technique. To paraphrase Singh et al., that's the general notion. Researchers analyzed their own dataset using support vector machines to describe the wavelet features of the pictures in order to develop an algorithm for recognizing blood vessels in fundus images. cut up OD picture.

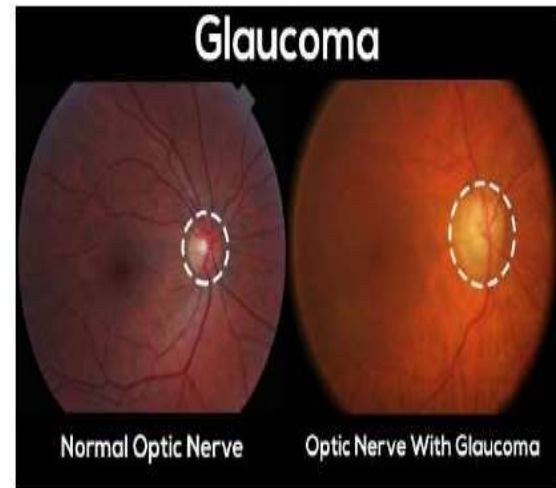


Fig1 Optic nerves in glaucoma and normal eye

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.

Related Work

In ophthalmology, glaucoma is becoming more common. It's the leading reason why people get blind. Early detection is key to effective treatment for ocular diseases such glaucoma, cystoid macular edoema, and diabetic proliferative retinopathy. Artificial intelligence has been found to aid in the diagnosis of glaucoma. In this research, we provide

a technique for the automated analysis of fundus pictures for the detection of glaucoma. The proposed structure is as follows: First, the Bi-dimensional Empirical Mode Decomposition (BEMD) method is used to decompose the Regions of Interest (ROIs) into their component components (BIMFs + residue). Once the BEMD has been disassembled, the VGG19 CNN architecture's main purpose is to extract features from the subcomponents. Next, features from many ROIs with identical properties are combined. To reduce the dimensionality of features in such large datasets, Principal Component Analyses (PCA) are used. The resulting feature packs are then sent into a Support Vector Machine (SVM) based classifier as input parameters. In order to train our models, we have made use of the openly accessible ACRIMA and REFUGE datasets. Our models have been tested on subsets of ACRIMA and REFUGE, in addition to four other publically accessible datasets (RIM-ONE, ORIGA-light, Drishti-GS1, and sjchoi86-HRF). Accuracy on the ACRIMA dataset is 98.31%, RIM-ONE is 96.43%, ORIGA-light is 96.67%, Drishti-GS1 is 95.24%, and sjchoi86-HRF is 98.60% when using a model trained on REFUGE. Accuracy of 99.06% is achieved 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 while using the ACRIMA dataset for model training. Experimental findings acquired using different datasets demonstrate the efficacy and robustness of the proposed strategy. Ours is a significant advancement above similar recent efforts in the literature.

Glaucoma is a neurodegenerative disease of the optic nerve that causes blindness in many individuals. Early diagnosis is essential because injured nerve fibers in the visual nerve cannot be repaired. A trustworthy and mechanically performed mass screening might be useful here. Here, we show a novel automated glaucoma diagnostic method that takes use of cheap and easily accessible digital color fundus photos. After some glaucoma-specific preprocessing, numerous different kinds of features are compressed using an appearance-based dimension reduction approach. The innovative Glaucoma Risk Index (GRI) is then derived using a probabilistic two-stage classification approach, and the results demonstrate our ability to accurately detect glaucoma. In a 5-fold cross-validation setup, we were able to obtain 80% classification accuracy on a dataset of 575 fundus pictures. A prior topography-based glaucoma likelihood score based on scanning laser tomography (AUC = 87%) has been surpassed by the GRI, which has an AUC of 88%. The proposed color fundus image-based GRI uses statistical analysis of full pictures of the optic nerve head to provide competitive and accurate detection performance on a cost-effective modality.

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)

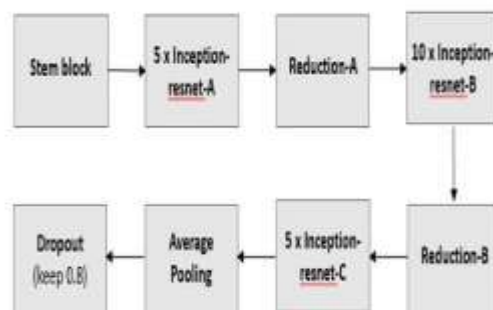
design that employs shorter connections between layers to train deep learning networks more efficiently while allowing them to grow deeper. DenseNet is a convolutional neural network with fully-connected layers, meaning that the first layer communicates with the second, third, fourth, and so on in the 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. Instead of summing up features, like ResNets 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.



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.

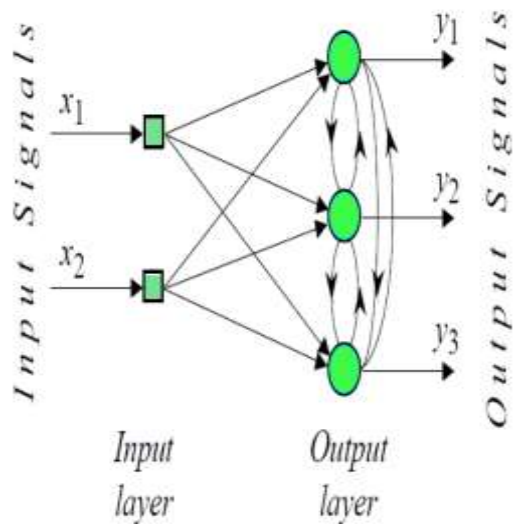


Fig No: Self Organized ONN

2. Results



Glaucoma Detection

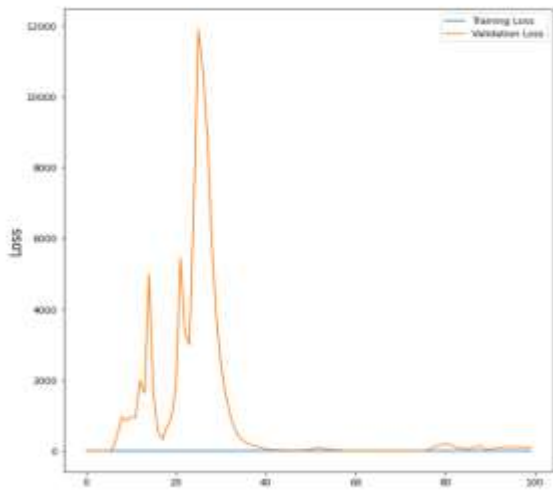
Inception ResNet V2

Diabetic Retinopathy

Glaucoma Detection using Transfer Learning

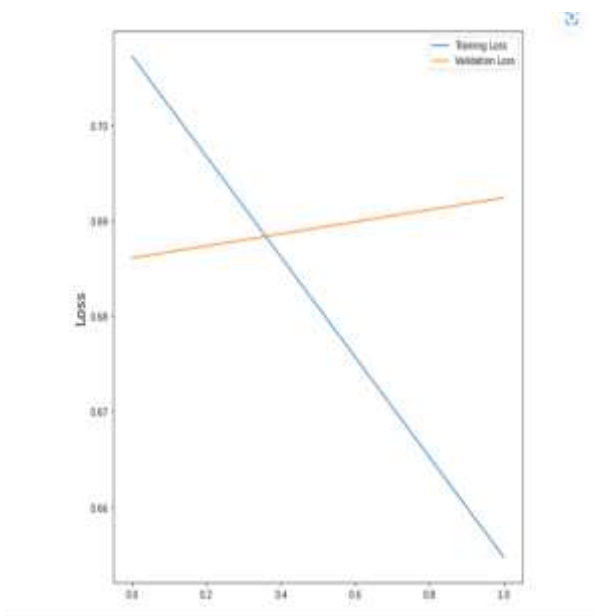


Diabetic Retinopathy

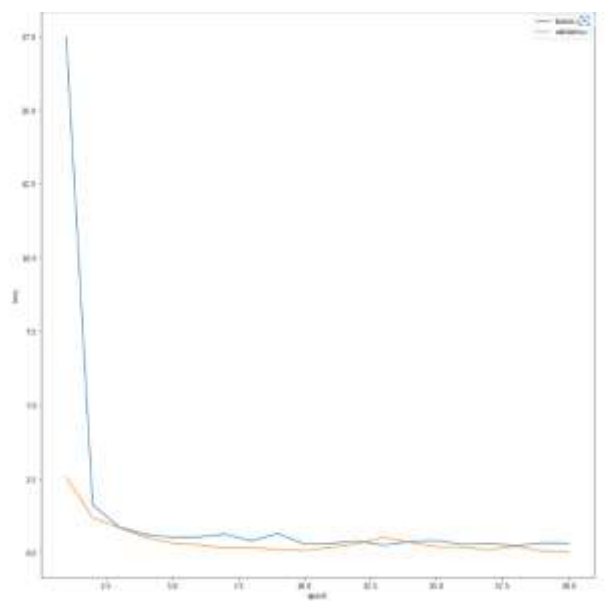


Inception ResNet v2

ONN with Generative Attention



ONN with Generative Attention



Self Organized ONN

ACCURACYRATE

Self Organized ONN

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

Table No:6.2.2 Accuracy Rate

3. 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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