Neural Network Analysis of Glaucoma Using Fundus Retinal Images

Submitted for the partial fulfilment of INSTR F266 Course

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Certificate

This is to certify that the thesis entitled, Neural Network Analysis of Glaucoma Using Fundus Images, submitted by Shrihari Viswanath, ID No. 2016A8TS0396P and Amlan Routray, ID. No. 2016A8TS0326P in partial fulfilment of BITS F421T Thesis embodies the work done by them under my supervision.

Date

Signature of the Supervisor

Name

Designation

List of Symbols and Abbreviations Used

RGC: Retinal Ganglion Cells

IOP: Intra Ocular Pressure

POAG: Primary Open Angle Glaucoma

PCAG: Primary Closed Angle Glaucoma

SVM: Support Vector Machine

CNN: Convolutional Neural Network

TPR: True Positive Rate or Sensitivity

TP: True Positives

P: Positives

FP: False Positives

TNR: True Negative Rate or Specificity

TN: True Negatives

N: Negatives

FN: False Negatives

Abstract

NEURAL NETWORK ANALYSIS OF GLAUCOMA USING FUNDUS IMAGES

By

Shrihari Viswanath

A project submitted in partial fulfilment of the requirements for the course INSTR F266 at Birla Institute of Technology and Science, Pilani

In this project, we are trying to help with the automation of the identification of glaucoma. Glaucoma diagnosis is very complex and can go wrong at multiple steps. Even seasoned ophthalmologists can make mistakes and overlook this. Glaucoma is extremely prevalent in the country, especially in the rural areas. Glaucoma is also one of the leading causes of vision loss and blindness in the world and automating the identification will help with timely diagnosis helping many people to save their vision. The analysis of the fundus images of the retina using neural network is the method chosen because fundus images are easiest to capture. Neural networks have been used in this case as they are limitless. Where conventional machine learning algorithms use features to help predict the outcome, neural networks have a mechanism where it all works internally thus leaving out features that one could not even think of. Also, CNN's are very useful for image processing algorithms as it is combining the principles of convolution, key to image processing and neural networks. We are using Keras on python to implement the CNN and Ada as the optimisation algorithm. The data used is well balanced and will not skew the accuracies while testing with an unbiased third-party data set as well. Learning about the different CNN's, their specific compatibilities and picking the right optimisation algorithm to help improve the overall accuracy was a great learning experience. Also, trying to understand the biology and clinical diagnosis of glaucoma helped us understand how important a problem this is and why it is worth solving.

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1. Introduction and Motivation

The optic nerve is the nerve that transmits all the visual data from the eyes to the brain. Glaucoma basically results in the destruction of retinal ganglion cells (RGC) which in turn lead to the erosion and damage in the optic nerve. This results in partial or complete visual impairment. The main cause of glaucoma is the increase in intra ocular pressure (IOP) due to improper draining of fluids in the eye. This increased pressure damages the cells and results in the symptoms discussed above.

Glaucoma is the second highest cause of blindness in the world and is the third highest in India. Tackling the problem of identification seems like an important fix to reducing eye fatalities in the country. India is a large country with a population of over 150 crores and even a small percentage of this number can give us a very large number. Cataract is the highest cause of blindness in the country, it can be easily treated and is the most focused upon. In contrast, glaucoma isn't commonly tackled. Epidemiological studies show us that glaucoma is estimated to affect 12 million people nationwide as of 2003. Considering the increase in population, the number of cases would have also risen. There are only about 10,000 ophthalmologists in India and under 100 glaucoma specialists in India. These numbers are clearly not enough to help identify the patients and help control the disease. India does not have the requisite infrastructure to categorize and follow-up positive results of various screening tests, let alone treat the patients with true-positive findings. This is precisely why building a platform to automate screening is important. (Ravi, Padma, & Jayaprakash, 2003)

After talking to an ophthalmologist and a scientist we came to understand the various needs that could be addressed, and the various customer bases this platform could potentially service. The first main customer category was clinicians and doctors with no OCT capability or experience with glaucoma diagnosis. The second is rural medical camp setups and other non-clinicians like testing laboratories. A value proposition chart is very useful in understanding the needs of the customers, the problems the product and solve and to help unveil all the pros and cons of any design or idea. The needs of the customer (customer jobs) are primarily accurate diagnosis, early diagnosis, the ability to classify the stage of glaucoma, track the progress of treatment and help reduce the burden on doctors thus improving their efficiency. All these needs come with gains that are received and pains that are eliminated.

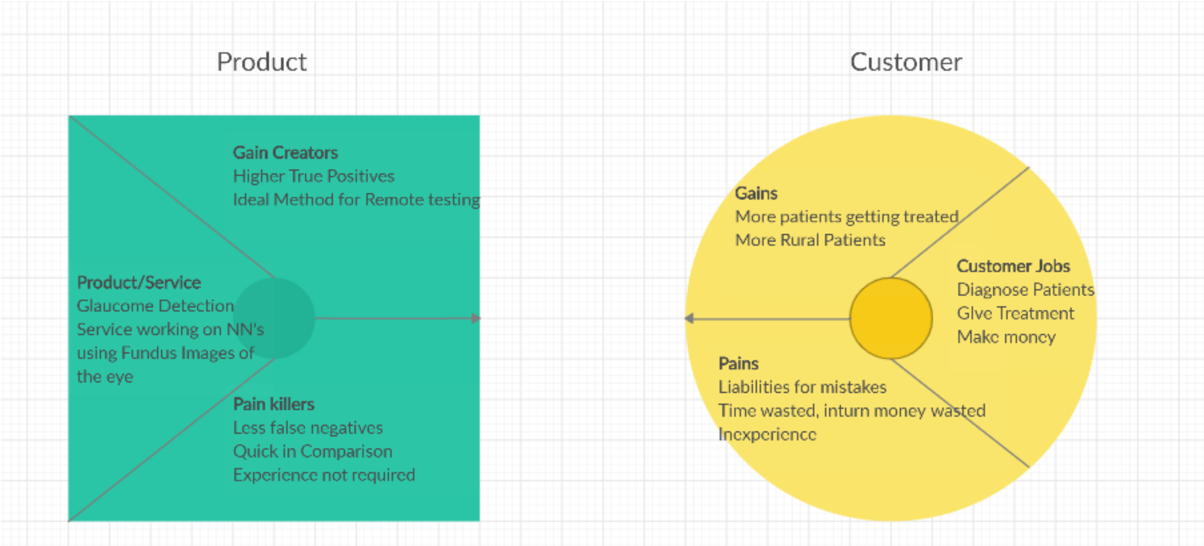

Fig. 1.1 Value Proposition Chart for Small Scale Clinicians

The best way to tackle a problem with multiple needs is to choose the most important ones and work with them. We will work on the technology that can tackle the need for accurate diagnosis, and possible categorise the stages and monitor treatment with some additional work put into it. The creation of a tool of this sort is a very lucrative idea to implement.

A study was done to help understand the burden of glaucoma in rural camp patients in tertiary care centres. The takeaway from this will be the untapped potential of glaucoma identification in rural areas and how treatment can be much more effective and easier if identified before partial loss of eyesight. Out of the 4204 people in the study, aged 40 plus, 115 people were diagnosed with glaucoma. Visual impairment was seen only in 41 eyes out of the total of 230 eyes of 115 patients. In any normal setting, only the ones with visual impairment would have the chance of being diagnosed correctly as the regular eye check-ups in rural areas never test for glaucoma, rather do not have the capability to. If we can create a tool to help automate the diagnosis, it can help identify patients with glaucoma before visual impairment will occur. This can be treated with drops and a patient does not need to bear the expenses of staying in an expensive city for treatment from a tertiary care centre under constant observation. Remote diagnosis is the key to healthcare in the future and the concept of being able to accurately diagnose glaucoma without an expert's help will greatly impact the same. (Rekha, Dhananjay, & Rachit, 2019)

2. Background Literature Review

1. Disease Background

The main site of the degenerative damage that is observed during glaucoma is the optic nerve. Cupping or general loss of tissue in the neuro retinal rim is what is used to characterize the appearance of glaucomatous optic neuropathy. Elevated IOP is by far the most important risk factor associated with glaucoma. Furthermore, the rate of degeneration of the RGC heavily depends on the magnitude of the IOP that the eye has to bear. The IOP is supposed to balance out between the fluids produced by the ciliary muscles and the drainage of the aqueous humour from the eye. When there is an imbalance in either, the increased fluid in the eye will cause the IOP to shoot up thus resulting in the damage of RGC. The trabecular meshwork is the most important cog in the outflow system. When the outflow from the trabecular meshwork is reduced, it leads to mainly open-angle glaucoma. The iris blocking the outflow of aqueous humour leads to the case of closed-angle glaucoma. These are the two major kinds of glaucoma and behave differently as well. The ranges of IOP that could be harmful to the eye varies from person to person and no absolute threshold can be observed, it is a very subjective parameter to the cause of identifying the cause of damage or glaucoma itself. In some eyes which are highly susceptible to RGC damage, glaucomatous optic neuropathy can start or develop even without elevated IOP. This kind of glaucoma is called as normal tension glaucoma which is very rarely observed. (Mantravadi & Vadhar, 2015)

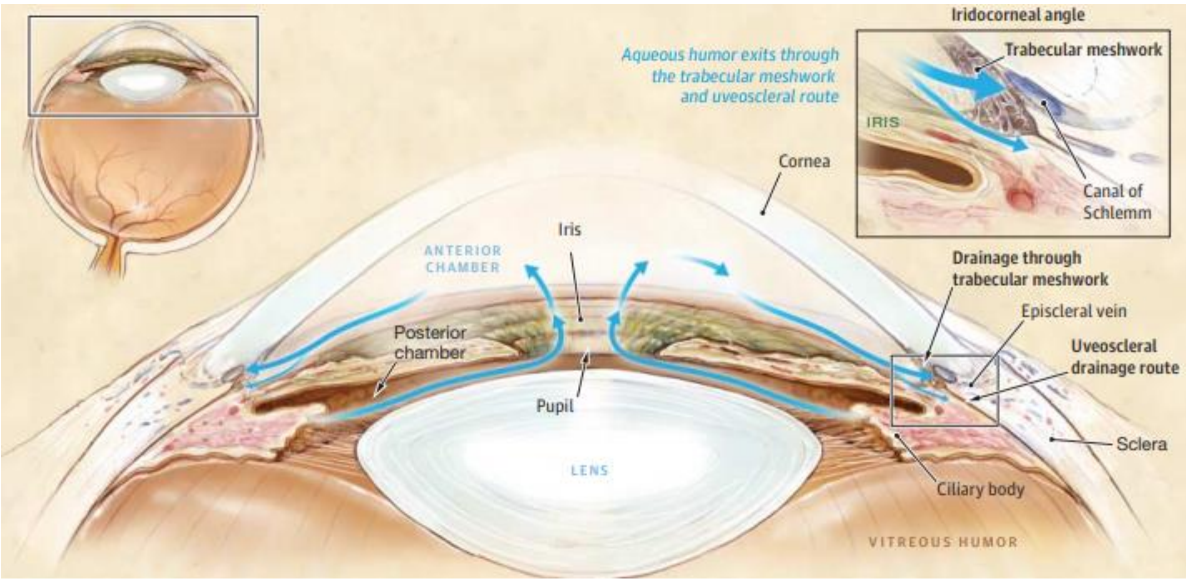

Fig. 2.1 Anatomy of Healthy Eye and Aqueous Humour Drainage Pathways, (Weinreb, Aung, & Medeiros)

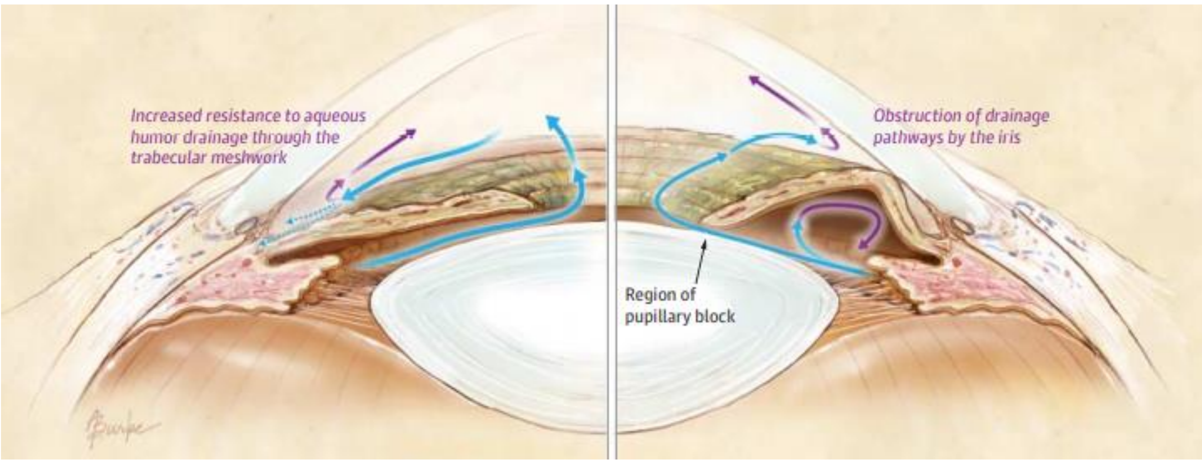

Fig. 2.2 Aqueous Humour Drainage Pathways in POAG (left) and PCAG (right), (Weinreb, Aung, & Medeiros)

Treatment of glaucoma mainly aims to slow down the degeneration rate and preserve the quality of life of the patient undergoing the treatment. Reduction in IOP is the only proven methodology to treat glaucoma. There are several classes of drugs that can be used to treat glaucoma. Look at the table below to understand more:

Class of Medication	Example	Usual Dosages	Mechanism of Action	Local Adverse Effects	Systemic Adverse Effects
Prostaglandin analogues (prostamide)	Latanoprost, travoprost, tafluprost, unoprostone, bimatoprost	1/d At night	Increase in uveoscleral outflow of aqueous humor	Conjunctival hyperemia, lengthening and darkening of eyelashes, brown discoloration of the iris, uveitis, macular edema	Minimal systemic adverse effects; may be related to headaches
β-Adrenergic blockers	Timolol, levobunolol, carteolol, metipranolol, betaxolol	1/d In the morning	Reduction of aqueous humor production	Ocular irritation and dry eyes	Contraindicated in patients with asthma, chronic pulmonary obstructive disease, and bradycardia
α-Adrenergic agonists	Brimonidine, apraclonidine	3/d (Sometimes 2/d)	Initial reduction of aqueous humor production with subsequent effect of increase in outflow	Ocular irritation, dry eyes, allergic reaction is relatively common	Central nervous system effects and respiratory arrest in young children; caution in patients with cerebral or coronary insufficiency, postural hypotension, and renal or hepatic failure
Carbonic anhydrase inhibitors	Dorzolamide, brinzolamide, acetazolamide (oral)	3/d (Sometimes 2/d)	Reduction of aqueous humor production	Ocular irritation, dry eyes, burning sensation with topical agents	Topical form has minimal systemic adverse effects; oral form may be associated with paresthesia, nausea, diarrhea, loss of appetite and taste, lassitude, or renal stones
Cholinergic agonists	Pilocarpine, carbachol	Usually 4/d, but may vary	Increase in aqueous humor outflow	Ocular irritation, induced myopia and decreased vision due to ciliary spasm	Ciliary spasm leading to headaches in young patients

Table 2.1 Classes of Medicine to Lower IOP, (Weinreb, Aung, & Medeiros)

The problem with these drugs is that there is a very good chance of relapse back into the disease as they do not cause a considerable large reduction in IOP. These drugs could have adverse side effects to many at times. When medicinal treatments don’t achieve the required results, the patient is referred to laser or incisional surgeries. Laser trabeculoplasty is the most common form of surgical treatment where the trabecular meshwork is altered to better the aqueous outflow from the eye. Trabeculectomy is the incisional alternative to this. It also has a very high success rate when compared to the less frequently used alternatives like sclerectomy, viscocanalostomy or canaloplasty. (Weinreb, Aung, & Medeiros)

2. Conventional Diagnostics

The diagnosis of glaucoma is generally done clinically and requires a complete eye exam, including observation under the slit lamp, flattening tonometry, gonioscopy, and dilated stereoscopic evaluation of the optic disc and retina. Automated perimetry is obtained if glaucoma is suspected. This establishes the presence of functional damage and provides a baseline for monitoring. Imaging techniques are not essential for diagnosis, but they can play a role in monitoring. It is recommended to get a complete eye exam for each patient in the clinic to screen for all life-threatening diseases, including glaucoma. The standard comprehensive eye exam is recommended as a routine for all ophthalmic patients. The complete eye examination helps detect not only glaucoma but also other potentially blinding eye pathology. Such a comprehensive eye exam includes visual acuity and refraction, external examination and evaluation of eye motility, examination of the pupil with special attention to the presence of a relative afferent pupillary defect, slit lamp microscopy, IOP measurement, Gonioscopy to examine the angle of the eye, dilated examination of the optic disc and retina and visual fields: If glaucoma is suspected, automated perimetry is performed to detect functional defects in the visual field. A standard clinical diagnosis of glaucoma involves IOP measurements, Gonioscopy, optic disc and visual field examination. The IOP measurements are generally done using a standard tonometer attached to the slit lamp. The IOP has a general range of safety but on this basis alone glaucoma cannot be diagnosed, some people might inherently have high pressures. Gonioscopy is a method to identify specifically open angle glaucoma, rather differentiate between the two types. It is generally done using a four mirror gonioscope, no dilation or anything of the sort is needed. The eye is examined under the gonioscope and the trabecular meshwork is observed. Depending on the angle at which it is seen it is used to identify type of glaucoma. The optic disc is examined under a slit lamp by the doctor and various features such as rim colour, cup to disc ratio and all are looked at to observe abnormalities. The visual field test is very subjective as it depends heavily on the response of the person being observed, but it gives the best understanding of how far the disease has progressed hence is key to the process of diagnosis. All these put together and the doctor can give a definitive judgement. (Thomas, Loibl, & Parikh, 2011)

3. Imaging

Colour retina photography uses a fundus camera to record colour images of the condition of the inner surface of the eye to document the presence of disorders and monitor their change over time. A fundus camera or retinal camera is a specialized low-power microscope with an attached camera designed to photograph the inner surface of the eye, including the retina, retinal vasculature, optic disc, macula, and posterior pole (i.e. the fundus of the eye). Your eyes will dilate before the procedure. The widening (dilation) of a patient's pupil increases the angle of observation. This allows technicians to image a much larger area and have a clearer view of the back of the eye. (Department of Ophthalmology & Visual Sciences, 2020)

Fig. 2.3 Fundus Photography Equipment, *(https://www.zeiss.com)*

Fundus photography is primarily digital which has various advantages in today’s day and age. These images are readily available, high resolution and can easily be enhanced and modified digitally. Standard fundus photography provides us 30 to 50-degree images. In many cases multiple fundus images are stacked in such a way to provide a higher field of view. Fundus images have a major disadvantage as to stereoscopic imaging, that is the depth of field which cant be observed. This is very important in the case of glaucoma identification or diagnosis. Ultra-wide field imaging can be used to obtain over 200-degrees of field of vision thus enabling us to view over 80 percent of the retina. This has also become extremely common while capturing fundus images today. Trying for a larger field of view in fundus imaging has a few disadvantages like, eyelash artifacts and false colour representation which might give us the wrong idea. Red free fundus images are key to observing the retinal neuro fibre layer degeneration which is an important aspect to consider while diagnosing for glaucoma. Image post processing will not give us the necessary details of a red free image and a red filter must be used while capturing the image. (Baumal, 2017)

4. Analysis of Fundus Images Using Machine Learning

The standard machine learning process that can be used in the case of glaucoma identification would involve some pre processing of the image and then extracting the necessary features which will help the algorithm decide if the subject has glaucoma or not. In the image below the pre processing involves sample, extracting the region of interest, channel selection and then segmenting the image based on the features one wants to extract.

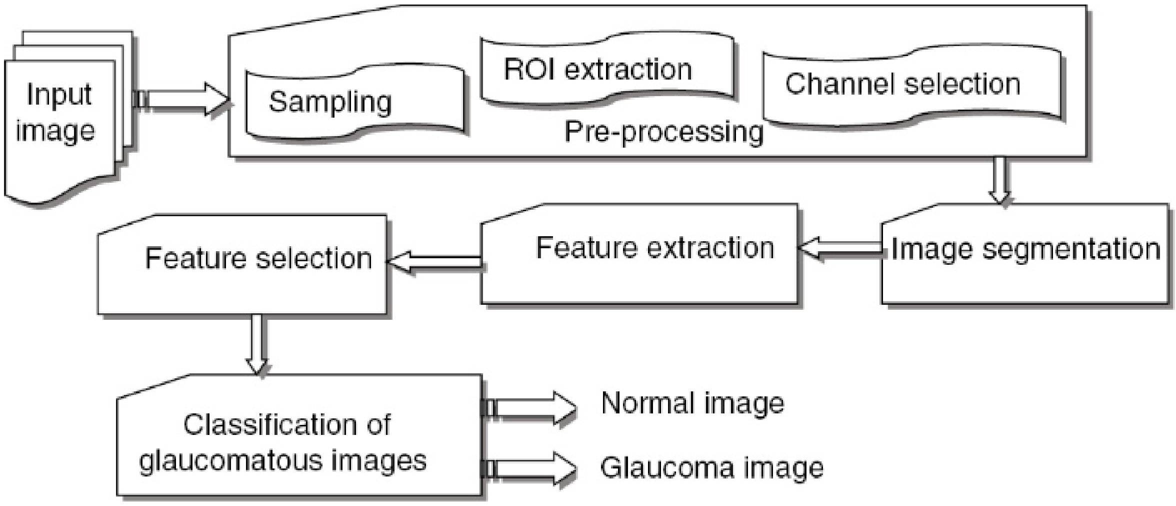

Fig. 2.4 Architecture of Glaucoma Detection, (Kanse & Yadav, 2017)

There are several classification techniques that can be used. SVM is the first to be discussed. SVM basically divides a space into two or more sections using a surface, this is done based on clustering the outcomes and splitting the sample up into the necessary spaces. Most commonly the rim to disc and cup to disc ratios have been used as the necessary features. Firstly, the SM classifier with the best compatibility must be chosen with respect to the problem and the features being used. The kernel function could be linear, polynomial or even a radial basis function. Thresholding is another method commonly used. Thresholding basically helps you segregate a cumulative sum of multiple values into a few stark important ones. Thresholding can be very useful to identifying haemorrhages, corroded or damages blood vessels, laminar dot signs and other occurrences that could suggest glaucoma. Image transformation coupled with thresholding at the correct values will give us a lot of information to segregate between the diseased and a healthy eye. Thresholding and edge detection is used to automate the calculation of the disc and cup diameters as well as they help identify the boundaries. Naïve Bayes classifiers are not used as often but it is one of the few probabilistic algorithms discussed. When feature extraction is extremely specific so as to accommodate this method, it can yield good results. Radon transforms and higher order statistic cumulants are some such examples that have yielded high accuracy classifiers in the past. Neural network classifiers, which is the one being used in this project will be discussed in the following section. (Kanse & Yadav, 2017)

The pre-processing involved could take a very different approach> The following approach uses a non-stationary signal processing approach to classifying glaucoma. It uses a decomposition technique known as variational mode decomposition and uses various entropies and fractals as the features that are then ranked using the ReliefF algorithm. Then based on their importance and the grouping, an SVM algorithm is used to classify the features. Variational mode decomposition is extremely efficient as it prevents any unnecessary loss of information during the decomposition. Since it works in the frequency domain, a lot more can be ascertained while pre-processing. This is an example of how conventional machine learning algorithms can be used efficiently. (Maheshwari, Pachori, Kanhangad, Bhandary, & Acharya)

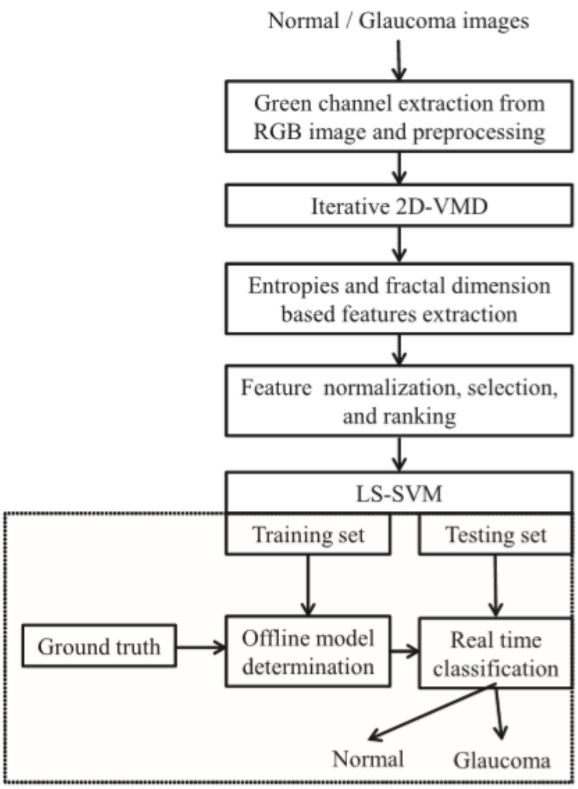

Fig. 2.5 Glaucoma detection system with VMD, (Maheshwari, Pachori, Kanhangad, Bhandary, & Acharya)

5. Convolutional Neural Networks Based Methods

Deep learning methods are being used more commonly today for the purpose of image classification. It streamlines the entire process and integrates both the feature extraction and the classification. Using complex networks and large data sets these methods can come up with much better results as there is no limitation applied by introducing only select features but the images themselves are used. Convolutional neural network is a deep learning model, in effect comes under the umbrella of deep learning. CNN's consist of several layers and depending on the size and detail of the image the number of layers can be varied. The deeper the network the more it learns. This is a backbox techniques it learns on its own and organises itself without any manual intervention of any sort. But increasing the number of layers increases the load on the system and computing time, hence a right balance must be struck to obtain an optimally functioning CNN for classification. It doesn't need extensive pre-processing or any specific feature extraction as well. The features are extracted internally in a hierarchical method by mapping the raw pixels of the input image and further it is classified using fully connected layers. The network parameters are optimally tuned to obtain the best performance. There are various types of layers in a CNN and a few of the key ones are discussed here. The image input layer is always the first layer in any image-based CNN. Next comes the convolutional layer which basically performs convolution on the image using specified windows ad generates feature maps used in the following layers. The pooling layers help reduce the unnecessary information obtained from the features and keep only what's needed. In a fully connected layer, each output neuron of the previous layer is connected to each and every neuron of this layer. Sometime a soft-max layer is used to remove all outliers. (U, et al., 2017)

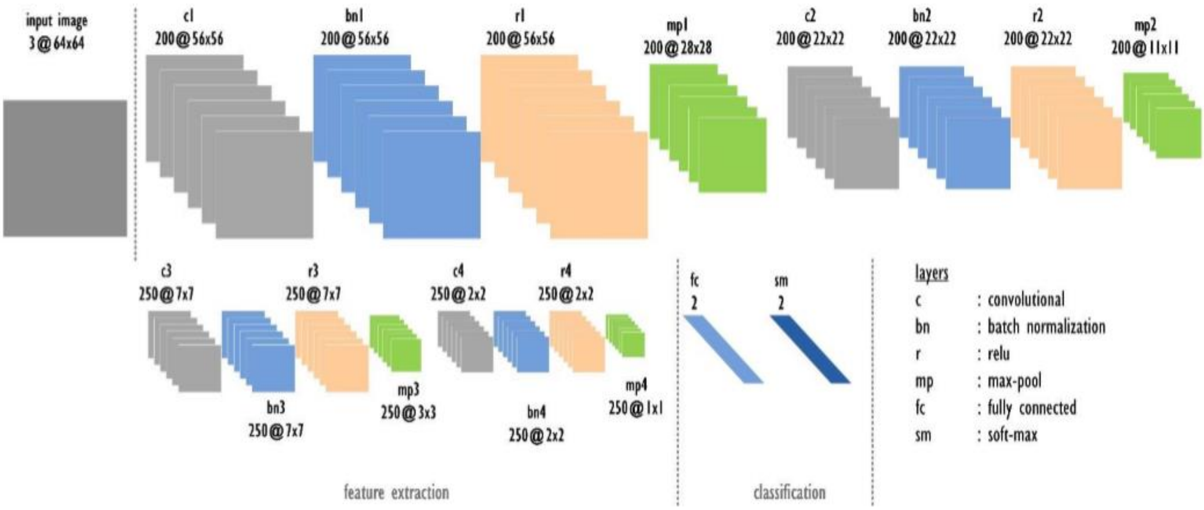

Fig. 2.7 Layers in a CNN Implementation, (U, et al., 2017)

The image below describes one of the processes used to identify glaucoma using CNN's.

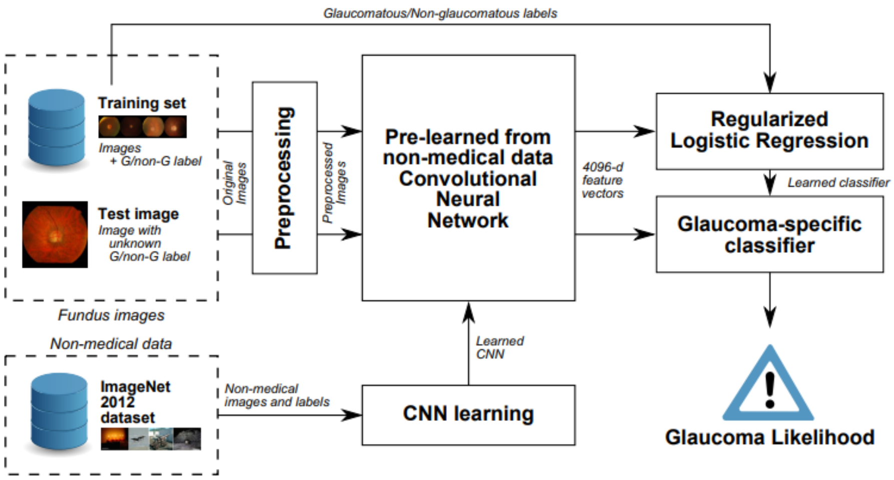

Fig. 2.7 Schematic for CNN Application, (José, Elena, Mariana, & Matthew, 2017)

Optimisation algorithms are used to train CNN's by basically optimising the progress it itself accomplished during training. Stochastic gradient descent, momentum and AdaGrad are some of the more commonly used training optimisation algorithms and the required learning rate and the number of epochs in the particular problem will help decide on the algorithm of choice.

One of the unique approaches taken to training is the Contextualised CNN. In this, the output of one trained CNN model is taken as the contextual input to a fully connected layer of another CNN. This in turn helps to optimise the learning process of the second CNN thus behaving as an optimisation algorithm to train the CNN. The study also reveals that this method far outperforms other common algorithms used for training. But, the study itself says that the potential for this method is truly useful for the detection of multiple ocular diseases and that it will have a much larger impact on the performance then. For our purposes, using an optimisation algorithm will be easier and economical in terms of the power required to run a contextualised model. (Xiangyu, et al., 2015)

3. Data and Methods

1. Image Database

In the study we have used the online available public database from the website of the Medical Image Analysis Group from the Universidad de La Laguna. These can be accessed and used by anyone without the requirement of any special permission from the creators. The database consists of 255 fundus images of eyes free of glaucoma and 200 images of glaucoma ridden eyes. This database was carefully curated with accurate gold standards of optical nerve head testing by various experts. The size of the original image is 490*490 pixels, but the inbuilt pre-processing of the neural network used condenses this image into a 224*244 size image for easier and faster operation. In the image, the parts of the fundus image that aren't relevant have been cropped out, the disc and some area surrounding it, which has the most number of features to help identify glaucoma have been cropped, this is very helpful as the model will train with only relevant data making the model more suited for our use. We haven't used algorithms like histogram equalisation to balance out irregularities in the illumination as this is a black box technique and we don't really need to think about optimising feature extraction for the same.

2. Neural Net Implementation

The images obtained from the public dataset contain the part of the fundus images which are essential for determining whether they are affected by glaucoma or not. As our model is required to perform a binary classification, the proposed network uses basic convolutional 2D layers, max pool layers, dense layers for flattening the features and a finally a sigmoid function for classification.

The original size of the images is 490 X 490, which is considered to be much larger than what is needed to feed a neural network, so the network is fed with a particular target size of 224 x 224. The network has been grouped into three parts consisting of two, two and three convolutional layers separated by max pool layers between them. The number of filters used for the groups are 64, 128 and 256 respectively. The features obtained after the seventh convolutional layer has been flattened and densed into a 1000-dimensional layer. So, when an input image of 490 X 490 X 3 is fed into the network, the dimension of the feature vectors in the three groups are 224 X 224 X 64, 112 X 112 X 128 and 56 X 56 X 256 respectively. After flattening this we get a feature vector of (802816,1) which is further densed into a smaller (1000,1) feature vector and is used by the sigmoid function for the binary classification.

The convolution 2d layers used has various parameters, namely - number of filters, strides, padding and activation function.

The number of filters has been doubled in every subsequent layer as the network grows deeper, this helps to retain the important features after every layer. The number of strides has been set to two with keeping the padding value as 'same', so as to prevent loss in features because of convolution operation. Relu activation function has been used for non-linearization of the feature vector and helps in faster learning as it can easily back propagate the errors and have a constant gradient. It is defined as R(x) = max(0;x)

Max pooling layers have been used to reduce the spatial size of the feature vector. In doing so the max pooling layers reduce the number of parameters and reduce the computational time and space of the following layers.

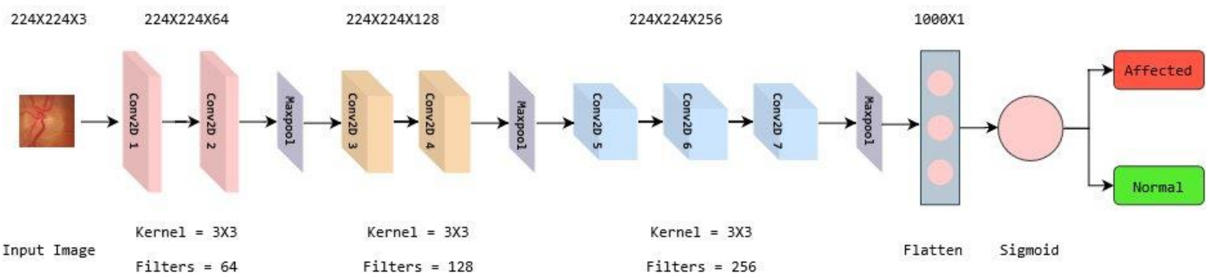

Fig. 3.1 Schematic for the Neural Net Architecture Implemented

The model has been trained using the Binary cross entropy loss function. It is defined as:

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

It is a good cost function for the binary classification because it minimizes the distance between two probability distributions in every iteration. It helps to set the parameters such as the difference between predicted value and true value decreases with iterations.

4. Results

The model has been trained on a total of 410 images out of which 180 are images of glaucoma ridden eyes and 230 are glaucoma free. Then, the model was tested on 45 images. The model was evaluated on the basis of accuracy, specificity and the sensitivity on the test images. Sensitivity is also called as the true positive rate and it measures the proportion of positives that have been correctly identified.

$$TPR = \frac{TP}{P} = \frac{TP}{TP + FN}$$

Specificity, also known as the true negative rate, measure the proportion of true negatives that have been correctly identified.

$$TNR = \frac{TN}{N} = \frac{TN}{TN + FP}$$

For obtaining best results the model was trained while fixing the sensitivity at 0.75, 0.8, 0.85, 0.9 and 0.93. To understand the algorithm better we kept track of various parameters while using the above-mentioned sensitivity values. The graph below shows us how the training accuracy changes over the epochs for various sensitivities.

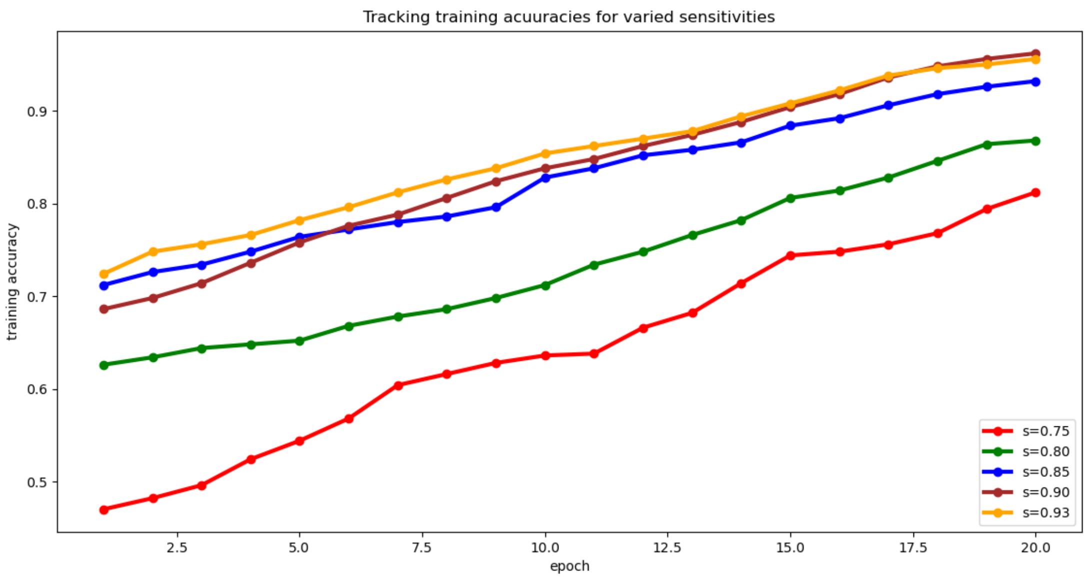

Fig. 4.1 Training accuracies over epochs for varied sensitivities

Out of the 45 images in the testing set, 25 are normal and 20 are affected. The models trained by fixing the sensitivities were tested over this testing set and the results have been tabulated below.

Training Sensitivity	Sensitivity	Specificity	Accuracy
0.75	0.75	0.56	0.644
0.80	0.75	0.72	0.733
0.85	0.8	0.8	0.8
0.90	0.85	0.84	0.844
0.93	0.9	0.8	0.844

Table 4.1 Parameters Observed While Testing

5. Analysis

In any diagnosis problem, the sensitivity and specificity must be taken into consideration. In a disease like glaucoma which is one of the leading causes of glaucoma, early and large-scale detection of positive cases is more important than correctly identifying healthy eyes. If a person with a healthy eye is given eye drops for treatment, he/she will only lose money on the drops but an affected person who isn't diagnosed positively will have to spend much more on surgery. This is why in our problem, the sensitivity should be in focus and should be as high as possible. Initially, the model trained without constraining/setting the sensitivity or specificity parameters gave us an accuracy of 71% on the testing set. The model was trained by fixing the sensitivity at different values as we wanted to observe how the trained model would differently on the testing set. On changing the values, we observed that we were able to increase the overall accuracy on the testing set by increasing the sensitivity values up to a particular limit, this is corroborated by the data in the table above (Table 4.1). As evident from the graph (Fig. 4.1), the training accuracy after 20 epochs also increased with increasing initial sensitivity value.

Of all the various trained models, as shown in the results table, the models which were trained with sensitivities of 0.9 and 0.93, both had the highest accuracy of 84%. Since we must pick the most optimal model for our scenario, the sensitivity and specificity of the models come into play. As the model trained with 0.93 sensitivity had a testing sensitivity of 0.9 which is higher than that of the model trained with 0.9 sensitivity, it is the model that would best suit our purpose of diagnosing glaucoma.

6. Conclusion

Epidemiological studies show us that glaucoma is estimated to affect 12 million people nationwide as of 2003. There are only about 10,000 ophthalmologists in India and under 100 glaucoma specialists in India. Accurate glaucoma diagnosis can be very complex and deceiving at times and multiple tests have to be done for confirmation. Hence, a large chunk of the population cannot afford regular checks, creating a preliminary diagnostic tool to lift the burden off of the ophthalmologists in India and help identify it at an early stage will benefit both the parties

We obtained 455 images from a public database and split it into training and test set in a 90:10 proportion. The image consists of the portion of the fundus images that are relevant to glaucoma diagnosis, thus reducing the need for further cropping or object identification. The images were fed into a neural network consisting of seven convolutional layers and a final sigmoid layer. The model was trained with various fixed values of sensitivities and the accuracies were observed. The most optimal model had an accuracy of 84% with a sensitivity of 0.9 and specificity of 0.8.

In terms of the future scope, use of larger datasets coupled with data augmentation will help make the process of training the large number of parameters much more efficient and accurate. This can also help make our network deeper with better learned weights giving us a better result overall. Turning this into a product will also be economically viable, thus creating a platform where doctors could upload fundus images and get results of preliminary diagnosis will definitely be the way to go to turn this research into something with real world application.

List of Images

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Bibliography

Baumal, C. (2017). Imaging in Diabetic Retinopathy. In C. Baumal, & D. Jay, *Current Management of Diabetic Retinopathy* (p. 192). Boston: Elsevier.

Department of Ophthalmology & Visual Sciences, U. (2020, 05 04). *University of British Columbia*. Retrieved from Faculty of Medicine, Department of Ophthalmology & Visual Sciences: https://ophthalmology.med.ubc.ca/patient-care/ophthalmic-photography/color-fundus-photography/

José, I. O., Elena, P., Mariana, d. F., & Matthew, B. B. (2017). Convolutional neural network transfer for automated glaucoma identification. *International Symposium on Medical Information Processing and Analysis.* Tandil.

Kanse, S., & Yadav, D. (2017). Retinal Fundus Image for Glaucoma Detection: A Review and Study. *Journal of Intelligent Systems*.

Maheshwari, S., Pachori, R., Kanhangad, V., Bhandary, S., & Acharya, U. (n.d.). Iterative variational mode decomposition based automated detection of glaucoma using fundus images. *Computers in Biology and Medicine*.

Mantravadi, A., & Vadhar, N. (2015). Glaucoma. *Primary Care: Clinics in Office Practice*.

Ravi, T., Padma, P., & Jayaprakash, M. (2003). Glaucoma in India. *Journal of Glaucoma*.

Rekha, R. K., Dhananjay, R., & Rachit, R. K. (2019). Clinical profile and burden of primary glaucoma in rural camp patients attending a tertiary care center in India. *Journal of Clinical Opthalmology and Research*.

Thomas, R., Loibl, K., & Parikh, R. (2011). Evaluation of a glaucoma patient. *Indian Journal of Ophthalmology*.

U, R., Hamido, F., Sulatha, V. B., Anjan, G., Jen, H. T., & U, R. A. (2017). Deep Convolution Neural Network for Accurate Diagnosis of. *Information Sciences*.

Weinreb, R. N., Aung, T., & Medeiros, F. A. (n.d.). The Pathophysiology and Treatment of Glaucoma. *The Journal of the American Medical Association*.

Xiangyu, C., Yanwu, X., Shuicheng, Y., Damon, W. K., Tien, Y. W., & Liu, J. (2015). Automatic Feature Learning for Glaucoma Detection Based on Deep Learning.

International Conference on Medical Image Computing and Computer-Assisted Intervention. Munich.