Automated Diagnosis of Glaucoma using Deep Learning Architecture

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Iqra Memon[1], Ahsan Ahmed Ursani[1], Muhammad Ali Bohyo[2], Rabia Chandio[1]
[1] *Department of Biomedical Engineering, Mehran University of Engineering and Technology, Jamshoro, Pakistan*
[2] *Institute of Biomedical Engineering and Technology, Liaquat University of Medical and Health Sciences, Jamshoro, Pakistan*

Abstract: Glaucoma is an eye disease that affects the optic nerve head and, if not treated, may cause full or partial loss of vision. Since damage caused by glaucoma is irreversible, early diagnosis caries a paramount importance. Lately, automatic methods of glaucoma detection are getting popular, and the recent literature reports a continual increment in their accuracy and performance. In this paper, we opt deep learning based on a convolutional neural network for automatic feature extraction and classification in one go. The proposed system uses five convolutional layers for feature extraction and two fully connected layers for classification. A bigger dataset is formed by combining all three releases of RIM-ONE datasets. Dataset is further augmented using affine transform of the original dataset for the purpose of training and a dropout layer is also added to avoid overfitting. The results with five-fold experiments on binary classification are presented. The average results show the overall classification accuracy of 0.85, sensitivity of 0.80 and specificity of 0.88 with an equal error rate of 0.15.

Keywords: *Glaucoma, Deep Learning, Convolutional Neural Network, RIM-ONE.*

1. Introduction

Glaucoma is world's second-largest prevalent cause of blindness [1] [2]. By the year 2020, about 80 million people will be affected by the glaucoma worldwide. Pakistan's population is projected to be 213 million in 2020, out of which almost 0.2 million people will be affected with glaucoma [3]. It is a neurodegenerative disease that damages the retinal neurons and nerve fiber layer. The single major cause of glaucoma is increased intraocular pressure (IOP) that harms optic nerve responsible for transmitting the object to the brain [4]. The IOP rises due to blockage in out flow of aqueous humor. It is a liquid that flows through the surface of eye and drains out through trabecular meshwork [2]. If not detected in an early stage, glaucoma may lead to permanent loss of vision. At initial stage, it shows no pain and no vision changes. Although damage caused by glaucoma is irreversible, it can be slowed down if diagnosed at an early stage [5].

The classical methods of automatic detection of glaucoma involve two steps, i.e. feature extraction and classification. Table.1 is the summary of the related work, stating the feature extraction methods and classifiers used.

Table.1: The detail summary of two-step process feature extraction and classification

Authors	Method/ Features	Classifier	Performance measure
[6]	HOS and wavelet features	SVM	Accuracy --95% Sensitivity -- 93.33% Specificity -- 96.67%
[7]	HOS cumulants	Naïve Bayesian	Accuracy -- 92.65% Sensitivity -- 100% Specificity – 92%
[8]	Gabor transform	SVM	Accuracy --93.10% Sensitivity --89.75% Specificity --96.20%
[9]	Variational mode decomposition (VMD)	least squares support vector machine (LS-SVM)	Accuracy --94.79%
[2]	bit-plane slicing (BPS) and local binary pattern (LBP)	SVM	Accuracy-- 99.30% Sensitivity--98.84% Specificity-- 99.64%
[10]	CDR	__	Accuracy--98% Sensitivity--100 % Specificity-- 94.4 %

However, lately, deep learning methods have become popular among machine learning community. Recent publications report promising results in several problems. Likewise in Biometrics: Iris recognition [11], face recognition [12], finger print recognition [13], voice recognition [14], speech recognition [15]. Apart from these examples, CNN-based deep learning has also been used for the automatic detection of glaucoma. The examples include [16], [17], [18], [19], and [20]. Table 2 summarizes their methods, datasets, and results.

Corresponding author Email address*: ahsan.ursani@faculty.muet.edu.pk*

Table.2 The detail of related work and proposed method

Authors	Method	Performance	Explanation	Dataset (No. of images)
[16]	CNN	AUCROC values ORIGA - 0.831 and SCES - 0.887	Experimental setup was not clearly mentioned, AUCROC calculation method is not clearly defined, therefore results cannot be reproducible	ORIGA (650) and SCES (1676) Now publically un-available
[17]	Alexnet	Acc 0.88 Sn 0.87 Sp 0.85	overfitting of model occurs	RIM-ONE r2 (455)
[18]	CNN1 with RGB CNN2 with Binary using Multimodal data	Acc 0.95 Acc 0.96	Same subset of RIM-ONE dataset used for training and testing, therefore accuracy is high Model validation is missing	RIM-ONE r2 (455)
[19]	CNN	Acc=0.98 Sn =0.98 Sp =0.98	Model validation is missing	Private-Kastbura Medical College (1426)
[20]	Multi-branch neural network model	Acc=0.91 Sn=0.92 Sp=0.90	Image and non-image features are required	Private-Tongren hospital (Not-reported)
Proposed Method	CNN	Acc=0.85 Sn=0.80 Sp=0.88 ERR=0.15	5 -fold cross validation done Best classification accuracy in K-fold Acc=0.88 Sn=0.85 Sp=0.92	RIM-ONE r1, r2, r3 (930)

Acc*=Accuracy; Sn*=Sensitivity; Sp*=Specificity

In this paper we present results on automated glaucoma diagnosis on fundus images from RIM-ONE datasets using CNN-based deep learning explained in the following paragraphs.

2. Methods and Materials

Deep learning is a machine learning technique that utilizes a vast amount of data and neural networks comprising multiple layers in order to learn the patterns within a dataset. In this work we design a Convolution Neural network (CNN) to classify a dataset of fundus images into two classes, namely normal and glaucoma affected, respectively. The network consists of Convolutional layers, Batch normalization, Max pooling, ReLU used for feature detection. The fully connected layers and softmax function is used for classification (see Fig. 1). The Dropout layer and data augmentation also employed in our proposed deep learning architecture [21].

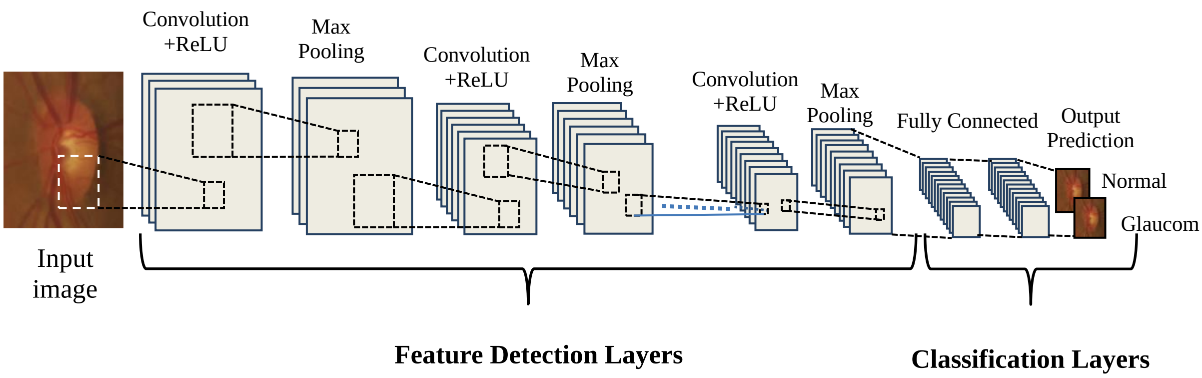


Fig 1: The overview of feature detection and classification layer

2.1 Feature Detection Layers

2.1.1 Convolutional layer: A 3D convolutional filer mask is applied to an input image which activates certain feature maps from the input image. A square filter mask having $f^{[l]}$ rows is convolved with a padded input image with a set stride value of $s^{[l]}$ to extract feature maps that are fed to the next layer. A convolutional layer l, takes a square image having $n^{[l-1]}$ rows, pads it with $2p^{[l]}$ rows, $2p^{[l]}$ columns and gives out a square image with $n^{[l]}$ rows determined by Equation (1) [22].

$$n^{[l]} = \left[\frac{n^{[l-1]}+2p^{[l]}-f^{[l]}}{s^{[l]}} + 1\right] \quad (1)$$

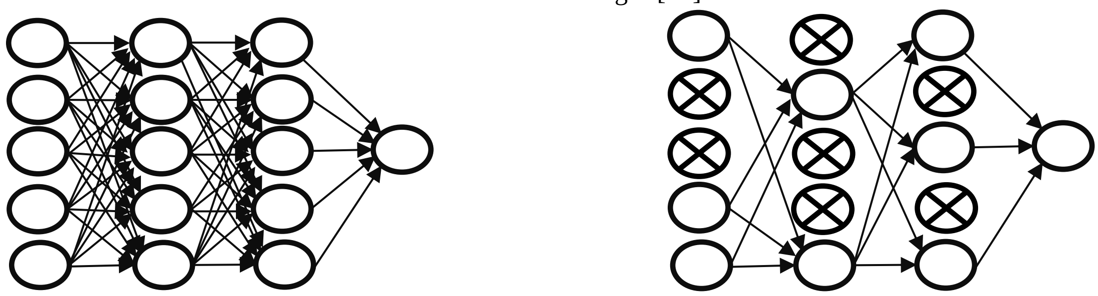
2.1.2 Batch normalization: It is a technique for improving the speed, performance, and stability of CNN by setting the mini batch mean zero and variance one.

2.1.3 ReLU Layer: Rectified Linear Unit activation function referred to as ReLU, this function work as a linear for values greater than zero and zero for negative values Eq. (2). This function preserves many of the properties of gradient based models and used default activation function.

$$\varphi(x) = \begin{cases} x, & x > 0 \\ 0, & x \leq 0 \end{cases} \qquad (2)$$

2.1.4 Max Pooling layer: This layer performs down sampling by reducing the number of parameters needed to learn about.

2.1.5 Dropout and Data Augmentation: It is a regularization technique in which randomly selected neurons are dropped-out with set probability during training (see Fig. 2). This improve generalization because force your layer to learn with dissimilar neurons the same "concept". Drop out layer prevent the network from overfitting. Data augmentation is a technique applied to preprocess images before training to artificially increased the dataset by performing random resizing, reflation and rotation on input images and preserving the labeling of images [23].



(a) (b)

Fig 2: An illustration of CNN structure a) before and b) after dropout

2.2 Classification Layer

2.2.1 Fully connected layer (FC): it is next-to-last layer that outputs a vector of K dimensions where K is the number of classes that the network will be able to predict. This vector contains the probabilities for each class of any image being classified.

2.2.2 Softmax: this is the last layer in CNN architecture which provide the classification output. Mathematically, defines as a normalized exponential function, which takes the input vector K real numbers and normalize the data set into a probabilistic distribution with values that sums to one.

Table.3 is the summary of proposed architecture of CNN with detail of layers, kernel size, activations and other parameters like set stride and padding value, which are derived through trial and error process.

Table 3: The details of CNN model used in this research

Layers	Type	Kernel Size	Activations	Other Parameters
1.	Image Input	512×512×3	512×512×3	Stride = 1, Padding ‘same’
2.	Convolution	3×3×3	512×512×8	
3.	Batch Normalization	8 channels	512×512×8	
4.	ReLU		512×512×8	
5.	Max Pooling	2×2	256×256×8	Stride = 2, Padding ‘valid’
6.	Convolution	3×3×8	256×256×16	Stride = 1, Padding ‘same’
7.	Batch Normalization	16 channels	256×256×16	
8.	ReLU		256×256×16	
9.	Max Pooling	2×2	128×128×16	Stride = 2, Padding ‘valid’
10.	Convolution	3×3×16	128×128×32	Stride = 1, Padding ‘same’
11.	Batch Normalization	32 channels	128×128×32	
12.	ReLU		128×128×32	
13.	Max Pooling	2×2	64×64×32	Stride = 2, Padding ‘valid’
14.	Convolution	3×3×32	64×64×64	Stride = 1, Padding ‘same’
15.	Batch Normalization	64 channels	64×64×64	
16.	ReLU		64×64×64	
17.	Convolution	3×3×32	64×64×128	Stride =1, Padding ‘same’
18.	Batch Normalization	128 channels	64×64×128	
19.	ReLU		64×64×128	
20.	Dropout		64×64×128	50%
21.	Fully connected		1×1×2	2 fully connected layer
22.	Softmax		1×1×2	softmax
23.	Classification Output Cross enteropyex with classes ‘Normal’ and ‘Glaucoma’			

3. Experiment

3.1 Image dataset

All the three releases of the publically available RIM-ONE are combined to form the dataset used for the training as well testing phases of the experimental work [24]. RIM-ONE r3 images are stereo images taken in different angles in a single shot of the same eye [25]. We dealt each one in the pair as a separate unit in the dataset. Table 4 describes the composition of RIM-ONE dataset.

Table.4. Composition of RIM-ONE Database

	Healthy Eye	Glaucoma	Total
RIM-ONE r1	118	40	158
RIM-ONE r2	255	200	455
RIM-ONE r3	2×85=170	2×74=148	318
Total	543	388	931

3.2 Experimental Results

Complete dataset comprises a total of 931 fundus images, of which 543 represent healthy eyes and 388 represent glaucoma-affected eyes. We resized all the datasets of 512 x 512 to capture the detail information, because smaller image may loss the detail. Half of the images are used for the training and validation and the remaining half for the testing purpose. We perform manifold training and testing of random selection of images and this experimental setup is repeated five times with learning rate 0.001 and 200 epochs. In this paper we present our results of five-manifold training and testing (See Table.5). In this work we utilize statistical measures sensitivity, specificity, overall classification accuracy (OCA) and equal error rate to evaluate the performance of glaucoma diagnosis.

Table.5. The Classification results of across all five-fold.

No. of Exp. units	OCA	Sn	Sp	ERR
1	**0.88**	**0.85**	**0.92**	**0.12**
2	0.85	0.86	0.84	0.15
3	0.80	0.74	0.86	0.20
4	0.87	0.81	0.91	0.13
5	0.83		0.87	0.17
Average results	**0.85**	**0.80**	**0.88**	**0.15**

4. Conclusion

In this research work we design a deep learning architecture for automated diagnosis of glaucoma based on CNN. CNN is able to learn features and perform classification in one step without going to preprocessing steps. Drop out and data augmentation is applied to reduce overfitting problems. Our architecture presents optimum results with average over all classification accuracy 0.85, sensitivity 0.80, specificity 0.88 and equal error rate of 0.15. Our proposed method has efficiency of 0.84. In future work we plan to recognize the different stages of glaucoma using deep learning architecture.

5. Results and Discussions

This is the first work that utilized all three releases of RIM-ONE database. As it is mentioned earlier in database description that proposed method utilizes 930 fundus images, Training and testing performed on different validation datasets distribution. In proposed method K fold cross validation, training and testing is performed, and we end up with results that our model performance is consistence. Our OCA and specificity is higher than 0.80 and sensitivity is higher than 0.74 in each number of experimental Units. And best classification results in 1st experimental unit with OCA 0.88, sensitivity 0.85, specificity 0.92 and less equal error rate 0.12 (see Table.5). Our proposed method utilized data augmentation and dropout layer techniques to ovoid overfitting problem. Batch normalization layer is added to speed up the process as training performed on CPU.

Conflicts of interest

There is no conflict of interest in this research work.

Biography

Engr. Iqra Memon is Research Associate in the of Department of Biomedical Engineering at Mehran University of Engineering and Technology Jamshoro, Sindh, Pakistan. She received her first degree in engineering from Liaquat university of Medical and Health Sciences, Pakistan in 2016. Her Masters in Biomedical Engineering is in progress. Her research interests include Image Processing, Signals and Systems, and Deep Learning.

Dr. Ahsan Ahmad Ursani is Professor and Chairman of Department of Biomedical Engineering at Mehran University of Engineering and Technology Jamshoro, Sindh, Pakistan. He received his first degree in engineering from the same university in 1995. He received his PhD from Institute National des Sciences Appliquees, Rennes, France, in 2008. His research interests include Medical Imaging, Image Processing, Speech Processing, Biomedical Signals processing, Biomedical Instrumentation, and Remote Sensing.

Engr. Muhammad Ali Bohyo is Director of Institute of Biomedical Engineering and Technology, LUMHS, Pakistan. He received his first degree in Electronic engineering from Mehran University of Engineering and Technology Jamshoro, Sindh, Pakistan in 2000. He received his Masters of Engineering in Communication Systems and Networks from the parent university in 2008 and Post graduate courses from DepPaul University Chicago in 2005. His research interests include Network management, Event correlation systems, Machine learning and Deep learning.

Engr. Rabia Chandio is Assistant Professor in the of Department of Biomedical Engineering at Mehran University of Engineering and Technology Jamshoro, Sindh, Pakistan. She received her first degree in Biomedical engineering in 2007 and Masters in Telemedicine and e-Health Systems in 2015 from the same university. Her PhD is in progress in from the same university. Her research interests include Biological Signals and Systems, E-Health monitoring and Biomechanics.

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