RESEARCH ARTICLE

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A Comprehensive Review of Glaucoma and Stargardt Disease Detection using Retinal Images

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Abstract: Digital image processing permit ophthalmologists to discover and treat various eye diseases. Precise and early identification is important in biomedical and healthcare communities. Retinal imaging discovers several diseases in eye. Retinal images are essential in diagnosing ocular diseases such as diabetic retinopathy (DR), Glaucoma and Stargardt disease. These diseases lead to blindness if not identified precisely. Glaucoma is chronic, progressive neuropathy which damages optic nerve and neural fiber bundle that transmits visual information from eye to brain. Stargardt disease (STGD) is form of hereditary macular dystrophy in childhood damaging one among in 10,000 individuals. Several researchers performed their research on Glaucoma and STGD identification. But, accuracy and time consumption was not enhanced. To resolve these issues, several glaucoma identification methods are reviewed and drawbacks are detected.

Keywords: Digital Image Processing, Stargardt Disease, Glaucoma, Diabetic Retinopathy, Biomedical, Healthcare Communities.

1. Introduction

Glaucoma is an eye disease and it leads to blindness. It is categorized via optic nerve fibre loss with enhanced intraocular pressure (IOP) and/or loss of blood flow to optic nerve. Glaucoma is diagnosed through medical history of patients, determining IOP, implementing visual field loss test and carry out manual assessment of Optic Disc (OD) to scrutinize shape and colour of optic nerve. In fundus image, optic nerve head or OD are divided as two zones known as bright and central zone known as optic cup. A peripheral part is known as neuro-retinal rim. Early diagnosis of glaucoma is necessary for the treatment of patients. Medical offer criteria for diagnosis which focus on or around OD region.

This paper is ordered as follows: Section 2 describes various glaucoma detection methods, Section 3 provides study and analysis of conventional glaucoma detection methods, Section 4 portrays comparison between them. In section 5, the issues and discussion of conventional glaucoma detection techniques are discussed. Section 6 concludes the paper.

2. Literature Survey

In [1], a novel multi-task fully convolutional network (MFCN) technique was presented to extract features from retinal images. However, relationship among PPA difference and glaucoma improvement were not studied. For glaucoma evaluation, a new retinal image synthesizer and semi-supervised learning technique was introduced in [2]. But, the generated image quality and glaucoma classification was not increased.

A two-stage framework was presented in [3] to localize OD as healthy or glaucomatous. A computer-aided diagnosis system was introduced in [4] with optic disk localization, optic disk computation and cup height. However, disease detection accuracy was lower.

In [5], a patchbased Output Space Adversarial Learning framework (pOSAL) segments the OD and OC from various fundus images. But, no effort has taken to expand pOSAL framework. Automatic disc localization method was introduced in [6] for retinal fundus images. But, segmentation time was higher.

In [7], a glaucoma diagnosis technique was introduced with fundus eye images. But, diversity indexes and pattern recognition techniques were not utilized on various fundus eye image databases. For glaucoma diagnosis, a novel fully automated methodology was designed in [8]. A novel structure-preserving guided retinal image filtering (SGRIF) was designed in [9] to restore images based on attenuation and scattering model. But, it does not validate optic cup segmentation outcomes. The convolutional neural networks (CNN) were constructed in [10] to study discriminative features from raw pixel intensities. Disease detection time (DT) was higher.

3. Glaucoma Detection with Retinal Images

Glaucoma is diagnosed through medical history of patients, calculating IOP, implementing visual field loss test and assessment of OD by ophthalmoscopy to scrutinize shape and color of optic nerve. OD is cross sectional view of optic nerve linking to retina of each eye. It appears same as round spot in retinal fundus image. IOP affects nerve fibre comprises optic nerve. OD created cavity and expanded crater-like depression at nerve head known as Optic Cup (OC). Boundary of disc dilates and colour vary from healthy pink to pale. Cup-to-Disc Ratio (CDR) is foremost structural image cues considered for glaucoma detection.

3.1 Two-Stage Framework for Optic Disc Localization and Glaucoma Classification in Retinal Fundus Images using Deep Learning

Glaucoma is syndrome of eye disease outcomes in subtle, slow and total loss of vision if not treated. Disordered physiological processes connected with disease were multifactorial.

Glaucoma was linked with IOP in eye which outcomes from blockage of intraocular fluid drainage. A two-stage framework was designed for OD localization and categorization. OD was instrumental in scrutinize eye for various diseases. A fully automated disc localization method eliminated necessity for dataset-specific empirical or heuristic localization methods via exact localization across broad spectrum. First step was based on Region with CNN(RCNN) for localizing and obtain OD from retinal fundus image. Second stage employed Deep CNN to categorize disc into healthy or glaucomatous. A rule-based semi-automatic ground truth generation method was designed with annotations to present disc localization.

3.2 A New Convolutional Neural Network Model for Peripapillary Atrophy Area Segmentation from Retinal Fundus Images

Peripapillary atrophy (PPA) is a clinical finding, which reproduces atrophy of retina layer and pigment epithelium. Size of PPA area is medical indicator as it was related with various diseases. PPA area segmentation task was transformed as segmenting tasks with regular and uniform shapes. A new MFCN model extracts retinal images. The segmentation of two areas was presented with normal and uniform shapes for PPA segmentation task. The designed model achieved improved results and permit PPA related feature generation via various medical services. Accurate segmentation permit creation of PPA related features via various medical services. PPA differences were explored among glaucomatous and physiologic large cup cases for glaucoma diagnosis. A new learning strategy segmenting the objects with complicated shapes.

3.3 Retinal Image Synthesis and Semi-Supervised Learning for Glaucoma Assessment

A retinal image synthesizer and semi-supervised learning technique was presented for glaucoma assessment depends on Semi-Supervised Deep Convolutional Generative Adversarial Networks (SS-DCGAN) by adversarial model on less glaucoma-labelled and huge unlabelled database. The glaucoma was identified via scrutinize OD and surroundings where images cropped around optic disc. SS-DCGAN includes improvement on vanilla GAN. Among replacement of pooling layers with strided convolutions in discriminator and fractional-strided convolutions in generator, batch normalization was utilized in generator and discriminator. The replacement of fully connected hidden layers was performed for each layer except output and LeakyReLU activation for each layer in discriminator. Unsupervised loss function was determined to discriminate real training and fake images.

4. Performance Analysis on Glaucoma Detection with Retinal Images

The glaucoma detection methods are compared with number of retinal images. An experimental evaluation is executed in MATLAB Software with private database named ACRIMA with 705 retinal images to train models in this work (https://figshare.com/search?q=%3Akeyword%3A%20ACRIMA%20database&searchMode=1). ACRIMA have 396 glaucomatous images and 309 normal images. Python scripts are employed to obtain presented outcomes. The traffic prediction is enhanced by diverse metrics,

- Sensitivity,
- Specificity and
- Detection Time

4.1 Impact on Sensitivity

Sensitivity (Se) is measured as ratio of number of normal images which are correctly detected to total number of images. It is measured in percentage (%) and given by,

$$Se = \frac{\text{Number of normal images that are correctly identified}}{Total\ number\ of\ retinal\ images} \times 100 \quad (1)$$

From (1), the sensitivity is measured.

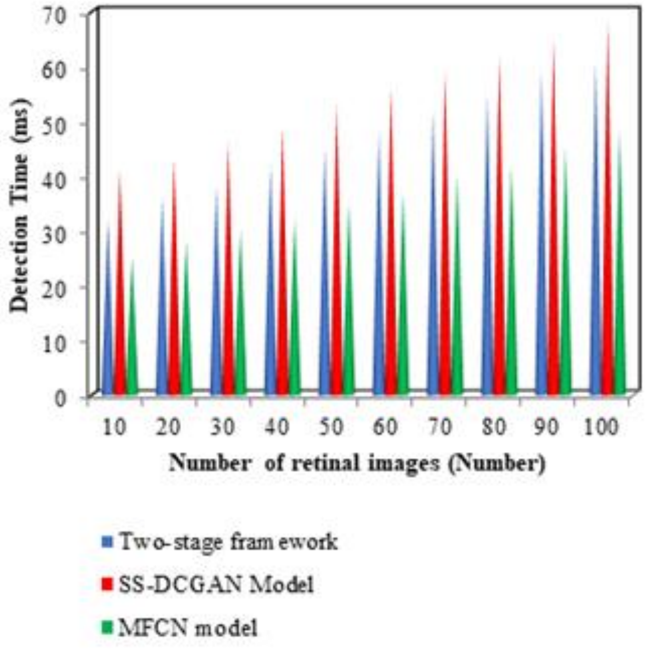

Figure 1. Measurement on sensitivity

The results of sensitivity are illustrated in Figure 1 with number of retinal images for three different methods. From figure 1, the sensitivity using SS-DCGAN Model is higher than other methods. This is because of utilization of fully linked hidden layers with average pooling, ReLU activation in generator for each layer except output and LeakyReLU activation in discriminator for each layer. The unsupervised loss function was utilized to categorize real training images and fake images. This enhances sensitivity of SS-DCGAN Model. The sensitivity analysis of SS-DCGAN Model is enhanced by 14% and 8% as compared to other two conventional methods.

4.2 Impact on Specificity

Specificity (Sp) is measured as ratio of number of glaucomatous images which are precisely detected to total number of images. It is calculated in percentage (%) and given by,

$$Sp = \frac{\text{Number of normal images that are correctly identified}}{Total\ number\ of\ retinal\ images} \times 100 \quad (2)$$

From (2), specificity is measured.

Table 1. Tabulation For Specificity

Number of Retinal Images (Number)	Specificity %		
	Two Stage Framework	SS-DCGAN Model	MFCN Model
10	80	73	65
20	83	76	67
30	86	78	69
40	89	82	71
50	87	75	68
60	89	77	71
70	92	80	74
80	94	83	76
90	96	86	79
100	97	89	81

Table 1 demonstrates specificity of three different methods with number of retinal images ranging from 10 to100.

Figure 2 portrays specificity versus number of retinal images. From the figure, the specificity using two-stage framework is higher than the other methods. This is because the utilization of RCNN. Deep CNN categorizes extracted disc as healthy or glaucomatous. A rule-based semi-automatic ground truth generation technique presents disc localization in RCNN based model using suitable annotations. The specificity of two-stage framework is enhanced. Specificity of two-stage framework is enhanced by 12% and 24% as compared to other methods.

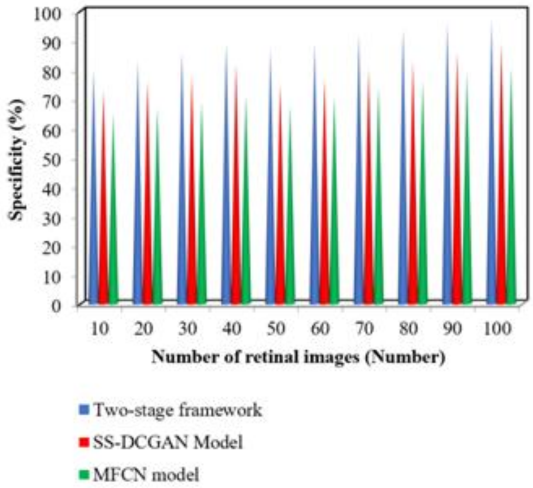

Figure 2. Measurement on Specificity

4.3 Impact on Detection Time

DT is measured as amount of time consumed for glaucoma disease Detection from input retinal images. It is calculated in milliseconds (ms) and formulated as,

Detection time = Ending time - Starting time for glaucoma detection (3)

From (3), DT is calculated. Table 2 portrays DT analysis of three methods for number of retinal images.

Table 2. Tabulation For Detection Time

Number of Retinal Images (Number)	Specificity %		
	Two Stage Framework	SS-DCGAN Model	MFCN Model
10	32	41	25
20	36	43	28
30	38	46	30
40	42	49	32
50	45	53	35
60	48	56	37
70	52	59	40
80	55	62	42
90	59	65	45
100	61	68	48

The DT results of three different techniques are portrayed in Figure 3 with number of retinal images. From figure 3, DT using MFCN model is minimal than the other techniques. This is due to segmenting PPA-Disc area and Disc area with normal and uniform shapes. The initial object was transformed to several objects for identification. This assists to lessen the DT. DT of MFCN model is minimized by 23% and 34% as compared to other existing methods.

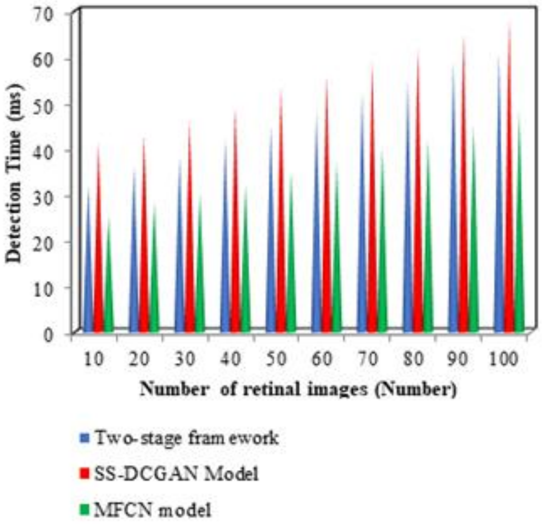

Figure 3. Measurement on Detection Time

5. Discussion and Limitation on Glaucoma Detection with Retinal Images

SS-DCGAN created images synthetically and provide labels. Synthetic images were calculated using t-SNE plots of features with images. An anatomical consistency was determined via calculate proportion of pixels corresponding to anatomical structures around optic disc. However, advance generative adversarial network was not built for retinal image synthesis and semi-supervised learning to increase images quality and glaucoma classification.

To identify and localize OD, A two-stage framework was designed for categorizing images into healthy or glaucomatous. At first, localization and extraction of OD was performed from retinal fundus image. Deep CNN classify disc as healthy or glaucomatous. The retinal fundus image offer bounding box ground truth necessitated for disc localization. Fine grained discriminative details were lost with enhance in network hierarchy.

A novel MFCN model extract features through the segmentation task with normal and uniform shapes. Accurate segmentation permit PPA area linked feature generation via various medical services. MFCN enhanced precision and lessen the error rate. Relationship among PPA differences and glaucoma enlargement were not studied.

5.1 Future Direction

The future direction of work is to carry out effective glaucoma identification by using machine learning and deep learning methods with greater accuracy and minimal time consumption.

6. Conclusion

A survival study of various glaucoma detection methods is performed. From that, DT was higher by MFCN. Two-stage framework does not enhance the sensitivity while identifying glaucoma disease. The advance generative adversarial network was not built for retinal image synthesis and semi-supervised learning to increase generated images quality and glaucoma categorization. The experiments on conventional glaucoma detection techniques compare outcomes and discuss their issues. From the result, the research work is performed by machine learning and deep learning techniques for glaucoma detection with retinal images to enhance accuracy and lessen time consumption.

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Conflict of interest

The Author have no conflicts of interest to declare that they are relevant to the content of this article.

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