

European Journal of Science and Technology Special Issue, pp. 412-416, September 2020 Copyright © 2020 EJOSAT **Research Article** 

# Diagnosis of Glaucoma Disease by Analyzing the Visual Field with Deep Learning

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#### Abstract

Glaucoma, commonly known as eye pressure or blackwater, is an important health problem caused by increased intraocular pressure and can cause vision loss. In generel, eye pressure, the most common cause of blindness in people over the age of 60, occurs with the accumulation of fluid in the anterior part of the eye. In addition to eye pressure, glaucoma disease may appear when problems occur in the visual field. In patients, glaucoma disease can be diagnosed by analyzing the visual field. The analysis process can be performed very precisely by image processing methods and image processing methods can extract important features from the image. The features extracted from the image are used for training the deep learning algorithm. Deep learning algorithms have not lost their use value in various fields such as engineering, banking, and agriculture. Moreover, Deep learning algorithms are used in the medical field for diagnosing many diseases. In this study, glaucoma disease is diagnosed by the proposed deep learning algorithm. Firstly, the visual field of the eye is analyzed by the mean absolute deviation method, and then a glaucoma diagnosis decision system is formed by the deep learning algorithm is trained with the visual field image. In the experimental results, the classification criteria Sensitivity, Specificity, Precision, Accuracy, F1 Score, and False Positive Rate has been obtained by 10-fold cross-validation. As a result, the proposed deep learning algorithm based glaucoma diagnosis decision system designed has successfully diagnosed glaucoma disease by analyzing the visual field image.

Keywords: Deep learning, Diagnose, Glaucoma, Visual field

# Derin Öğrenme ile Görme Alanının Analiz Ederek Glokom Hastalığının Teşhisi

#### Öz

Genellikle göz tansiyonu veya karasu olarak bilinen glokom, göz içi basıncının artmasının neden olduğu önemli bir sağlık sorunudur ve görme kaybına neden olabilir. Genel olarak, 60 yaş üstü kişilerde en sık görülen körlük nedeni olan göz tansiyonu, gözün ön kısmında sıvı birikmesi ile oluşur. Göz tansiyonuna ek olarak görme alanında problemler oluştuğunda glokom hastalığı ortaya çıkabilir. Hastalarda görme alanı analiz edilerek glokom hastalığı teşhis edilebilir. Analiz işlemi, görüntü işleme yöntemleri ile çok hassas bir şekilde gerçekleştirebilir ve görüntü işleme yöntemleri, görüntüden önemli özellikleri çıkarabilir. Görüntüden çıkarılan özellikler, derin öğrenme algoritmasının eğitilmesi için kullanılır. Derin öğrenme algoritmaları mühendislik, bankacılık ve tarım gibi çeşitli alanlarda kullanım değerini kaybetmemiştir. Ayrıca tıp alanında birçok hastalığın teşhisinde derin öğrenme algoritmaları kullanılmaktadır. Bu

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çalışmada, glokom hastalığı, önerilen derin öğrenme algoritması ile teşhis edilmektedir. Öncelikle, gözün görme alanı ortalama mutlak sapma yöntemi ile analiz edilir, ardından analiz edilen görsel alan görüntüsü ile derin öğrenme algoritması eğitilerek glokom tanı karar sistemi oluşturulur. Önerilen derin öğrenme algoritmasının öğrenilmesi 337 görsel alan görüntüsü analiz edilerek gerçekleştirilmiştir. Deneysel sonuçlarda, Duyarlılık, Özgünlük, Kesinlik, Doğruluk, F1 Score ve Yanlış Pozitif Oran sınıflandırma kriterleri, 10 kat çapraz doğrulama ile elde edilmiştir. Sonuç olarak tasarlanan derin öğrenme algoritması tabanlı glokom tanı karar sistemi, görsel alanı görüntüsünü analiz ederek glokom hastalığının başarılı bir şekilde teşhis edilmesini sağlamıştır.

Anahtar Kelimeler: Derin öğrenme, Glokom, Görme alanı, Teşhis.

# 1. Introduction

In recent years, various studies have been carried out on the availability of some new and helpful classifiers, decision support systems and decision-making tools in the diagnosis of diseases. Glaucoma is a common eye disease that affects millions of people. In the glaucoma disease, the fluid pressure in the eye may rise to levels that can damage the eye nerve. Glaucoma is especially at risk for people over 40 years of age and a cause loss of vision if it remains without treatment. Studies on classification, prediction, and diagnostic algorithms are increasing and these algorithms are used in various fields such as engineering [1], banking [2] and medicine [3]. In the diagnosis of the glaucoma disease, doctors make decisions based on their knowledge, experience, visual field testing, and the laboratory results. However, the decisions of doctors may be misdiagnosed and many decision support systems or artificial intelligence based medical diagnosis systems can be used to overcome this problem. Visual field testing is an important factor in the glaucoma diagnosis because it provides a direct measure of the underlying visual function of the treatment. In the literature, many studies have been proposed to diagnose glaucoma disease based on artificial intelligence classification algorithms. Henson et al. proposed an artificial neural network (ANN) based method to perform visual field analysis using the Kohonen self-organising feature map for glaucoma diagnosis. According to the experimental results, visual field defects may be classified by the ANN-based method and may be used to assist clinical assessment [4]. Belghith et al. proposed the usage of kernel-based support vector data description (SVDD) classifier approach to diagnosing the glaucoma disease. The proposed SVDD classifier has provided high specificity between normal and non-progressing eyes [5]. Sacchi et al. designed a class balancing technique to balance the glaucoma disease dataset and classified this dataset with the naïve bayes (NB) classification algorithm. The results showed that the classification model was not adversely affected by the inclusion of less reliable tests in the training process [6]. Huang et al. developed an automated classifier based on adaptive neuro-fuzzy inference system (ANFIS) to differentiate between normal and glaucomatous eyes. They obtained retinal nerve fiber layer thickness and optic nerve head topography measurements from the data reports of the Stratus optical coherence tomography. They used the orthogonal array for feature extraction and they trained ANFIS by the back-propagation gradient descent method. In this decision-making mechanism, first, the feature extraction was applied using the orthogonal array then the eye is classified as glaucomatous or normal by the adaptive neuro-fuzzy inference system which is trained by the back-propagation gradient method. According to the experimental results, they increased the receiver operative characteristic area with ANFIS method [7]. Diagnostic glaucoma systems use the optical coherence tomography, scanning laser polarimetry (SLP), and heidelberg retina tomography (HRT) scanning methods which are expensive. Mookiah et al. proposed a novel low-cost automated glaucoma disease diagnostic system using digital fundus images and a novel integrated index which is called glaucoma risk index (GRI). The proposed glaucoma disease diagnostic system used a support vector machine (SVM) data mining classification algorithm. According to the experimental results, the proposed glaucoma disease diagnostic system was able to identify glaucoma and normal images automatically with a 95% accuracy, 93.33% sensitivity and 96.67% specificity [8]. Liu et al. offered an automatic fundus image-based cup-to-disk ratio measurement system which provides strong support for using the fundus image as a modality for automatic glaucoma recognition [9]. Jagadish et al. provided a new method for glaucoma detection using digital fundus images in their work. Digital image processing techniques such as pre-processing, morphological processing and thresholding are widely used for optical disinfection, automatic detection of blood vessels and calculation of properties. The experimental results indicated that the features are clinically significant in the detection of glaucoma and the system is able to classify glaucoma automatically with a 100% sensitivity and 80% specificity [10].

The paper is organized as follows: In section 2, the material and method are used in the glaucoma diagnosis decision system are explained. The proposed glaucoma diagnosis decision system for diagnosing glaucoma diseases is explained in section 3. The results of the proposed glaucoma diagnosis decision system are demonstrated and discussed in section 4. The conclusion of the study is given in section 5.

# 2. Material and Method

# 2.1. Diagnosing Glaucoma Disease

In this study, we proposed a decision system for diagnosing glaucoma disease by analyzing the visual field that depended on deep learning and image processing algorithms. In image processing phase the image of the visual field has been converted to numerical data and these numerical data has been used to learning the deep learning algorithm. The deep learning and image processing algorithms are detailed in subsection 2.1.1 and 2.1.2.

# 2.1.1. Deep Learning

Deep learning is a common technique of supervised machine learning [11]. Moreover, is used in many various recognition and diagnosis applications. In supervised learning, deep learning algorithms learn to predict values from the training dataset. Deep learning algorithms can be helped us to classification objects. After the learning phase, the deep learning algorithms can be made inferences from the input data that is not labeled. The major challenges that come with traditional machine learning models is feature extraction. The

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features of objects to be looked out forgiven to the learning algorithms by the users. And these specific features help the learning algorithms to make decisions. The deep learning structure is consists of at least three layers, input layer, hidden layers, and an output layer, the deep learning structure is given in Figure 1 [12].



Figure 1. The deep learning structure

#### 2.1.2. Image Processing

In this stage, we analysed the visual field images by the mean absolute deviation method is given in Equation 1 [13].

$$F = \frac{1}{N} \left( \sum_{i=1}^{N} |a(x, y) - m| \right)$$

$$1$$

In Equation 1, N is the number of pixels in the image and m is the average of all pixel values in the image. a(x, y) is the pixel value at point (x, y) [14]. In the analysing phase, we convert the image of the visual field to the numerical value. The normal and abnormal visual field image is given in Figure 2 [15].



Figure 2. The normal and abnormal visual field image

# 3. The Proposed Deep Learning

In this section, the proposed glaucoma diagnosis decision system for diagnosing glaucoma diseases is explained. The proposed glaucoma diagnosis decision system consists of an image processing feature extracting and deep learning algorithm. The proposed glaucoma diagnosis decision system for diagnosing glaucoma diseases is given in Figure 3.



Figure 3. The normal and abnormal visual field image

As shown in Figure 3, the proposed glaucoma diagnosis decision system, firstly, the visual field image feature is extracted by the mean absolute deviation method. The trained proposed deep learning algorithm makes a decision as normal or abnormal by analyzing the visual field image.

# 4. Results and Discussion

## 4.1. Results

In this section, the results obtained from the proposed deep learning algorithm for diagnosing glaucoma disease has been given. The proposed deep learning algorithm was written in visual studio C# and applied on the windows 10. The over view of the proposed deep learning algorithm program is given in Figure 4.

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Figure 4. The over view of the proposed deep learning algorithm program

As shown in Figure 4, the training of the proposed deep learning algorithm has been performed well. The classification criteria Sensitivity (Sen), Specificity (Spe), Precision (Pre), Accuracy (Acc), F1 Score, and False Positive Rate (FPR) has been obtained by 10-fold cross-validation. The results obtained from the proposed deep learning algorithm for training and testing phase is given in Table 1 and 2, respectively.

Table 1. The Results	of	`Training	Phase
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Phase	Best accuracy	Worst accuracy	Average accuracy	Standard division			
Training	0.98	0.97	0.97	0.01			
Table 2. The Results of Testing Phase							

Phase	Sen	Spe	Pre	Acc	F1 Score	FPR
Testing	0.98	0.95	0.98	0.97	0.98	0.05

# 4.2. Discussion

In this section, the results obtained from the proposed deep learning algorithm for diagnosing glaucoma disease has been given. When we analysed the Table 1 and 2, the proposed deep learning algorithm for diagnosing glaucoma disease has performed the training phase with 0.97 % training accuracy. The SSE value is a very important factor in the training deep learning algorithms, in the training phase, SSE value must decrease regularly. As seen in Figure 5, the proposed deep learning algorithm for diagnosing glaucoma diseases performed this task very well.

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Figure 5. Training SSE results

The performance of the deep learning algorithm testing phase depends on the training phase and the proposed method is trained very well. As seen in table 2, in the test phase the proposed deep learning algorithm has obtained 0.98, 0.95, 0.98, 0.97, 0.98, and 0.05 values in Sen, Spe, Pre, Acc, F1 Score, and FPR, respectively. These promising results demonstrate that the proposed deep learning algorithm can be used in several prediction problems.

## 5. Conclusions and Recommendations

Glaucoma is a very hazardous disease, to prevent hazard of glaucoma we must diagnose glaucoma disease early. There are a several method has been proposed by the researchers for diagnosing the glaucoma disease in the literature. In this study, we proposed deep learning algorithm for diagnosing glaucoma disease, the proposed deep learning algorithm diagnose the glaucoma by analysing the visual field image. According to the experimental results, the proposed deep learning algorithm has diagnosed the glaucoma disease very well.

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