Avrupa Bilim ve Teknoloji Dergisi
Özel Sayı 43, S. 1-5, Kasım 2022

Araştırma Makalesi

www.ejosat.com ISSN:2148-2683

European Journal of Science and Technology
Special Issue 43, pp. 1-5, November 2022

Research Article

Determination of Glaucoma Disease with Gray Level Co-occurrence Matrix Features

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(4th International Conference on Applied Engineering and Natural Sciences ICAENS 2022, November 10 - 13, 2022)

(**DOI:** 10.31590/ejosat.1202569)

ATIF/REFERENCE: Sadık Şahin, E., (2022). Determination of Glaucoma Disease with Gray Level Co-occurrence Matrix Features. European Journal of Science and Technology, (43), 1-5.

Abstract

Glaucoma is a disease that causes an abnormal increase in intraocular pressure and therefore causes permanent damage to the optic nerves. Early and accurate diagnosis of the disease, known as the most "insidious" disease among eye diseases, is important. In this study, glaucoma prediction application was performed from high-resolution fundus photographs taken from an open-source database. Correlation, energy, homogeneity, contrast and entropy features were extracted from the segmented photographs using the gray-level co-occurrence matrix. Extracted features were divided into 66% test and 33% training after taking their average values. A 3-fold cross-validation was applied to the data and a feedback artificial neural network, classification and regression trees algorithm and k nearest neighbor algorithm were trained using 66% of the data. Classification success was also tested with 33% of test data. As a result, glaucoma and healthy individuals were classified with an average of 86.7% accuracy with the k nearest neighbor algorithm, an average of 87.8% accuracy with the decision trees, and an average of 96.7% accuracy with the artificial neural network algorithm. According to the results obtained, it was seen that glaucoma disease could be detected with high accuracy with the gray-level co-occurrence matrix features of glaucoma disease.

Keywords: Artificial Neural Network, Fundus, Classification and Regression Tree, Glaucoma, Gray level Co-occurrence matrix, K-nearest neighbor.

Gri Seviye Eş Oluşum Matrisi Öznitelikleri ile Glokom Hastalığının Tespit Edilmesi

Öz

Glokom, göz iç basıncının anormal bir biçimde artmasına neden olan ve bu sebeple görme sinirlerinde kalıcı hasara yol açan bir hastalıktır. Göz rahatsızlıkları içerisinde en "sinsi" hastalık olarak bilinen hastalığın erken ve doğru teşhisi önemlidir. Bu çalışmada, açık kaynak bir veri tabanından alınan yüksek çözünürlüklü göz dibi (fundus) fotoğraflarından glokom tahmini uygulaması gerçekleştirilmiştir. Segmente edilmiş fotoğraflardan gri seviye eş oluşum matrisi kullanılarak korelasyon, enerji, homojenlik, kontrast ve entropi öznitelikleri çıkarılmıştır. Çıkarılan öznitelikler, ortalama değerleri alındıktan sonra %66 test ve %33 eğitim olarak ayrılmıştır. Verilere 3 kat çapraz doğrulama uygulanmış ve verilerin %66'sı kullanılarak geri beslemeli bir yapay sinir ağı, sınıflandırma ve regresyon ağaçları algoritması ve k en yakın komşuluk algoritması eğitilmiştir. %33 test verisi ile de sınıflandırma başarısı test edilmiştir. Sonuç olarak, k en yakın komşuluk algoritması ile ortalama %86,7 doğruluk, karar ağaçları ile ortalama %87,8 doğruluk ve yapay sinir ağı algoritması ile de ortalama %96,7 doğruluk ile glokom ve sağlıklı bireyler sınıflandırılmıştır. Elde edilen sonuçlara göre glokom rahatsızlığının gri seviye eş oluşum matrisi öznitelikleri ile glokom hastalığının yüksek doğrulukta tespit edilebildiği görülmüştür.

Anahtar Kelimeler: Yapay Sinir Ağı, Göz Dibi Fotoğrafı, Sınıflandırma ve Regresyon Ağacı, Glokom, Gri seviye Eş oluşum matrisi, K-en yakın komşuluk.

1. Introduction

Glaucoma is a disease caused by increased intraocular pressure, which damages the main optic nerve of the eye, called the optic nerve. Glaucoma is an insidious disease that requires careful examination, which can be noticed in the very last stages of the disease. When glaucoma is detected late, it can cause serious damage to the optic nerves that cannot be compensated. If the necessary early intervention is not performed, it may result in blindness. It usually occurs when the eye nerves are negatively affected by this pressure, as a result of the inability of the intraocular fluid to drain from the eye canals and the increase in intraocular pressure. (Balci, Eraslan ve Temel, 2015). It is estimated that more than 67 million people worldwide are affected by glaucoma and 10% of these patients are at risk of blindness. It is estimated that 79.6 million people in the world may be affected by glaucoma by 2020 and 11% may be at risk of blindness. (Şatır, 2015). There is no known cure for the progression of glaucoma. In the loss of nerve tissues, they cannot be regenerated and are irreversible. Vision may be lost. In advanced cases, only treatments aimed at preserving the patient's remaining vision can be applied. Therefore, early diagnosis of the disease is vital (Ozkava et al., 2018).

Glaucoma detection can usually be done with very expensive methods such as Optical Coherence Tomography (OCT) and Hidelberg Retinal Tomography (HRT) (Nayak, Acharya U., Bhat, Shetty ve Lim, 2009). In order to be an alternative to these methods and to make an automatic diagnosis of glaucoma, glaucoma detection was performed by using fundus images and machine learning methods in this study. Medical innovations that increase the average life expectancy and quality of today's people mostly owe their development to the applications of the breakthroughs in technology in the field of medicine. For example, the development of medical imaging, image processing and data analysis techniques provides great convenience in the diagnosis and diagnosis of diseases. In addition, the use of classifier systems in medical diagnosis is increasing. Recent developments in the field of artificial intelligence have also led to developments in medical applications. Moreover, in recent years, computing tools have been designed to enhance the experience of doctors and medical professionals in making decisions about their patients. Expert opinion is still the most important factor in the diagnosis in the evaluation of the data obtained from the patients. However, today, it is tried to develop supporting tools for experts by using different artificial intelligence techniques. Classification systems can help diagnoses work more efficiently as well as increase the accuracy and reliability of diagnoses and minimize potential errors. Studies in the literature on these issues are increasing day by day (Abhishek et al., 2012; Delican et al., 2011; İlkuçar, 2015; Rouhani & Haghighi, 2009; Tomar & Agarwal, 2015).

In this study, it was aimed to distinguish the disease by using data obtained from high-resolution fundus images of healthy people diagnosed with glaucoma. The average of the gray level co-occurrence matrix features extracted from the fundus photographs of patients and healthy individuals were taken and compared with 3 different classification methods. In the second part of the study, the database used, the gray level co-occurrence matrix and the classification methods used are introduced, and in the third part, the analyzes are given. In the last section, the results and evaluations are presented.

2. Material and Method

As can be seen in Figure 1, the study consists of creating the data set, extracting the features, and classification. As a result, it is expected that glaucoma and normal eye images can be distinguished.

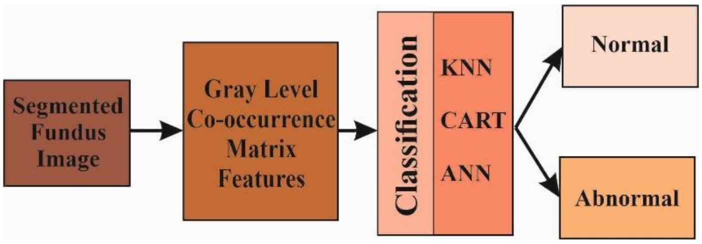

Figure 1. Block diagram of the study.

2.1. Dataset

In this study, images belonging to the "High Resolution Fundamental Images (HRF) Database" provided as open source by Friedrich-Alexander University Erlangen - Nürnberg were used. A research group created this database to support comparative studies on retinal fundus images using automatic segmentation algorithms. The dataset contains 30 images, 15 of which are healthy and 15 of which are from glaucoma patients. The images were captured with a Canon CR-1 fundus camera with a 45° field of view (Budai, Bock, Maier, Hornegger ve Michelson, 2013). Sample eyeball images of healthy and sick people in the database are shown in Figure 2. In the figure, the photo of the fundus of the eye with glaucoma, the photograph of the fundus of the healthy individual and the segmented forms of these photographs are given. The features used in the study were extracted from the segmented images.

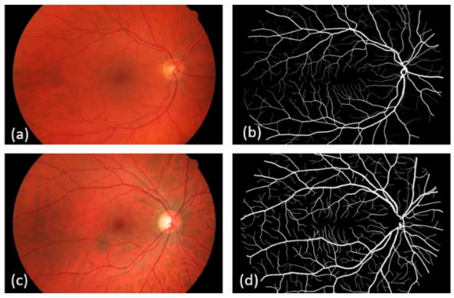

Figure 2. a) Fundamental image of an individual with glaucoma, b) Segmented image of the fundus of the eye with glaucoma, c) Fundamental image of a healthy individual, d) Segmented image of the fundus of the healthy eye.

2.2. Gray Level Co-occurrence Matrix

The Gray Level Co-occurrence matrix method is based on a second-order statistical image prediction that deals with the relationship between pixels or groups of pixels. It is a method of extracting features from RGB images to detect and classify images. In the method described by Haralick, 14 different image features are extracted for gray level differences between two pixels (Haralick, Shanmugam ve Dinstein, 1973). In this study, it was tried to classify patients and healthy people by using correlation, contrast, homogeneity, energy and entropy features. The expressions of the features used can be listed as follows:

- Correlation: It is a measure of gray level dependencies in the image as expressed by equation (1). Shows how pixels relate to their neighborhoods. Where σ_x and σ_y are the mean of the rows and columns of the probability density function P_{ij} used in the equations, σ_x and σ_y are the standard deviation of the rows and columns of the probability density function P_{ij}.

$$\frac{\sum_{i,j} P(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{1}$$

- Contrast: It examines the intensity and gray level changes of pixels in the image and their neighboring pixels. It is expressed by equation (2).

$$\sum_{i,j} |i-j|^2 P(i,j) \tag{2}$$

- Homogeneity: It is a measure of the distribution and closeness of the elements in the gray-level co-occurrence matrix of the image. It is shown by equation (3).

$$\sum_{i,j} \frac{P(i,j)}{1+|i-j|} \tag{3}$$

- Energy: It is a measure of homogeneity of the image as expressed by Equation (4). Energy varies in direct proportion to homogeneity.

$$\sum_{i,j} P(i,j)^2 \tag{4}$$

- Entropy: Indicates the level of spatial irregularity of the gray levels in the image. It shown by equation (5).

$$-\sum_{i,j} P(i,j) \log P(i,j) \tag{5}$$

Sample eyeball images of healthy and sick people in the database are shown in Figure 2. In the figure, the photo of the fundus of the eye with glaucoma, the photograph of the fundus of the healthy individual and the segmented forms of these photographs are given. The features used in the study were extracted from the segmented images.

2.3. Artificial Neural Network (ANN)

Artificial neural network (ANN) is a system that tries to imitate the working logic of the brain. ANN consists of layers. Weighted connections are used and parallel and distributed computing is done with interconnected processing elements. It can be realized with electronic circuits as hardware or as software in computers. (Basheer ve Hajmeer, 2000).

2.4. Classification and Regression Tree (CART)

The classification and regression tree method was first developed by Breiman et al. in 1984. (Breiman vd., 1984). The classification and regression tree method is a non-parametric statistical method that uses categorical and continuous variables. When the dependent variable used is categorical, the CART is a classification tree, when continuous, it is a regression tree (Deconinck vd., 2005).

The CART algorithm basically creates a structure called a "decision tree" using historical data. Then it can classify the new data using the decision tree (Kantardzic, 2011). The most basic condition to be able to use CART is that you need to know the number of classes beforehand. CART uses historical data, which we can call learning data, whose classes we know, when constructing the decision tree. The decision tree basically consists of yes/no questions that break down the learning data into smaller pieces at each step (Rutkowski, Jaworski, Pietruczuk ve Duda, 2014). Learning data can continue to be split until each branch of the tree points to a class. A CART analysis usually consists of three steps. In the first step, a tree is created that closely describes the training set. This tree is called a maximal tree and is grown using the binary split procedure. In the next step, the overgrown tree is pruned. During this procedure, a set of less complex trees is derived from the maximum tree. In the last step, the tree with the most suitable tree size is selected using the cross validation procedure (Breiman vd., 1984).

The CART method is stable against outliers in the input data. Another advantage of the CART algorithm is that it is independent of the individual transformations applied to the input data. For example, the user can use the logarithmic expression or square root of a variable, if necessary. This transformation will not affect the decision tree. However, the CART algorithm can generate an unstable tree structure in some cases. For example, removing a few critical values from the input data can lead to very serious differences in the structure of the decision tree. In addition, since the CART method performs division by a single variable at each node, the decision tree can become complex in some cases, especially when it has non-linear input data.

2.5. K Nearest Neighborhood Method (KNN)

The KNN algorithm was first developed in 1967 and is a supervised, sample-based algorithm used for both classification and regression (Cover T ve Hart P, 1967). The KNN algorithm is one of the most basic and simple classification methods and can be one of the first choices for a classification study when there is little prior knowledge about the distribution of the data. The KNN algorithm is mathematically quite simple compared to other algorithms. It can determine the class of test data according to the positions of the training data in the sample space. For this, it uses the Euclidean distance relation mathematically. The KNN algorithm does not need a learning process and a classification relation after the learning process, so it is very fast. The implementation of the KNN algorithm is quite easy. All it needs is to determine the value of k and determine the positions with the distance function. However, the KNN algorithm may encounter performance loss in very large datasets, multidimensional datasets and datasets with outliers.

3. Results and Discussion

Classification results with artificial neural network, decision support trees algorithm and k nearest neighbor algorithm using gray level co-occurrence matrix features are as given in Table 1. Feed forward back propagation ANN model was used in the study. The tangent sigmoid was chosen as the transfer function. A single hidden layer with two neurons is used. Features extracted from masked images input; glaucoma/healthy (1/0) targets were used as outputs. The image of the ANN model performed in the MATLAB environment is given in Figure 3. The data were separated into training and test data by k-fold cross validation. The k value of 3 is chosen. 66% of the data is reserved for training data and 33% is reserved for test data. As a result of the training of the Artificial Neural network, 96.7% accuracy was found using the test data.

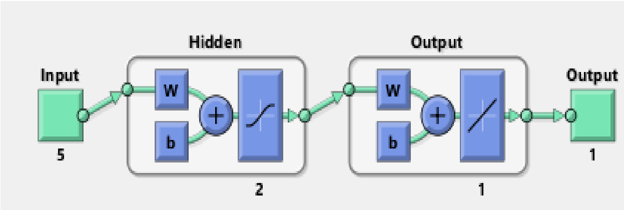

Figure 3. ANN model used in the study.

In K nearest neighbor classification, the data are separated as training and test data with k-fold cross validation. 66% of the data is reserved for training data and 33% is reserved for test data. As a result of classification, 86.7% accuracy was found by using test data.

In the decision tree classification, the data are divided into training and test data with k-fold cross validation. 66% of the data is reserved for training data and 33% is reserved for test data. As a result of classification, 85% accuracy was found using test data.

In Figure 4, the box plot showing the accuracy of the classification algorithms is given. The box plot gives a graphical representation of the obtained accuracy values based on quartiles. The box in the figure extends from the lower quartile to the upper quartile. The lines outside the box indicate the smallest accuracy value and the largest accuracy value obtained. The bed line inside the box shows the median accuracy value. As can be seen from the box plot, the classification accuracy obtained with the three classification algorithms deviated the most in the KNN algorithm. The highest accuracy value was obtained with ANN with an average of 96.67%.

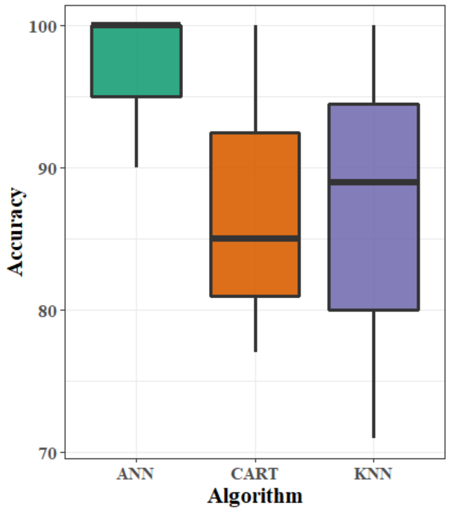

Figure 4. Box plot showing the accuracies of classification algorithms.

4. Conclusions and Recommendations

In this study, with the help of gray level co-occurrence matrix features from masked high resolution fundus photographs, the fundus photographs of healthy people and those with glaucoma were classified with the help of artificial neural networks, k nearest neighbor algorithm and decision trees algorithm. The classification results are as given in Table 1. K-fold cross-validation was performed in the classification and results were given for k=3. When the results obtained are examined, it is clearly seen that the highest accuracy is obtained with the ANN method. The good results presented demonstrated that ANN is a valuable alternative to classifying fundus images for glaucoma detection. With the help of the proposed method, glaucoma was detected with high accuracy. In future studies, performance improvement experiments can be made using more data, different features and other machine learning methods.

Table 1. Comparison of classification results.

k value	ANN Accuracy (%)	K-NN Accuracy (%)	CART Accuracy (%)
1	90	89	77
2	100	100	85
3	100	71	100
Mean±SD	96.7±5.77	86.7±14.6	87.8±11.7

5. Acknowledge

Part of the results of this study was presented as a summary paper at the 4th International Conference on Applied Engineering and Natural Sciences (ICAENS) 10-13 November 2022.

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