Original Research Paper

Cloud Based Low Cost Retinal Detachment Screening Method Using Data Mining Techniques

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Abstract: The Electro-Oculogram (EOG) signal can be used for detecting the normality of the eye retina. A number of advantages including the flexibility of the recoding process for EOG signals have encouraged insight into EOG based research. This study proposes a new cloud based retinal detachment screening technique based on data mining techniques to diagnose the type of eye retina. The used recognition methods include: back propagation neural network, Kohonen neural network and support vector machine. The obtained results are classified as normal or abnormal eye retina. Given a training set of such patterns, the proposed system is trained how to differentiate a new case in the domain. The diagnosis performance of the proposed systems is evaluated using more than one performance measure such as statistical accuracy, specificity and sensitivity. The diagnostic accuracy of the proposed neural network has achieved a remarkable performance with 100% accuracy on training and test subsets. The main advantage of the proposed system is the high quality of the diagnosis process that help health team to take the suitable decision regarding the patient case. The proposed system may help reducing the cost of screening patients especially in rural areas where experts are not available through sending their data to a central site where the automatic system will help an expert to diagnose the suspected cases.

Keywords: Electro-Oculography (EOG), Signal Analysis, Cloud based Screening, Automatic Diagnosis, Telemedicine

Introduction

Vision is the most essential sense for human beings and the eye is the vital and main organ of sight. It has a number of elements. These elements include but are not limited to the iris, pupil, cornea, lens, retina, macula, optic nerve and vitreous. The cornea is the pure first window of the eye that transfers and focuses light into the eye whereas the retina is the nerve layer at the back of the eye and it covers the inside surface and holds both the ends of the optically sensitive nerve and the nerve fibers, which leave the eye through the optical disc (Sprelckelsen *et al*., 1994; Constable *et al*., 2017; Anirban *et al*., 2017). When the focused light by cornea and Iris reaches the retina, the rods and cones into a signal that travel through the optic nerve to the brain, to convert it. Several muscles are responsible for moving the eyes around to complete different types of responsibilities as focusing on objects that are right in front, and tracking moving of the objects in the sky. Each of these distinct tasks performed by the eyes requires a certain types of controlled activities. The EOG is an important bio-potential that can provide many facts about the eye system. There are several views that have been proposed as the mechanism of the EOG. The more public viewpoint is the cornea-retinal dipole model. Where an electric potential difference is formed between the positive charges that formed on the cornea and the negative charges on the retina like a weak battery, as shown in Fig. 1.

The electrical field is being measured by the EOG. If the eye move from side to the side, so does the dipole.

Figure 2, shows a description of how the vertical movements of the eye are recorded and the relation between the direction of the movement and the nature of the recorded wave. If the movement of the eyeball is to the top, the generated and recorded potential difference is positive whereas it is a negative if the movement of the eyeball is to the bottom.
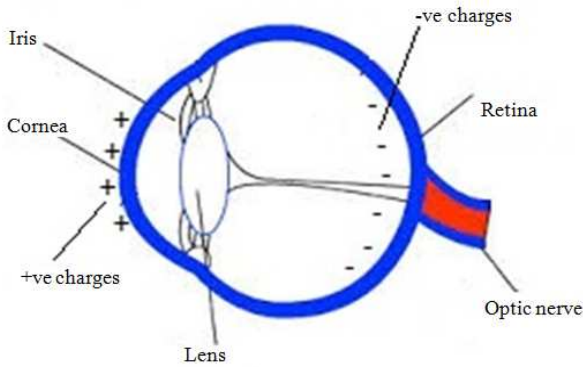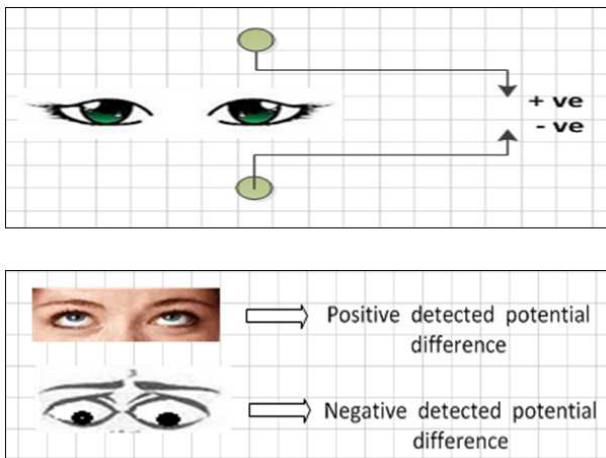
Fig. 1: Cornea-Retinal dipole

Fig. 2: Vertical movements and nature of the recorded potential
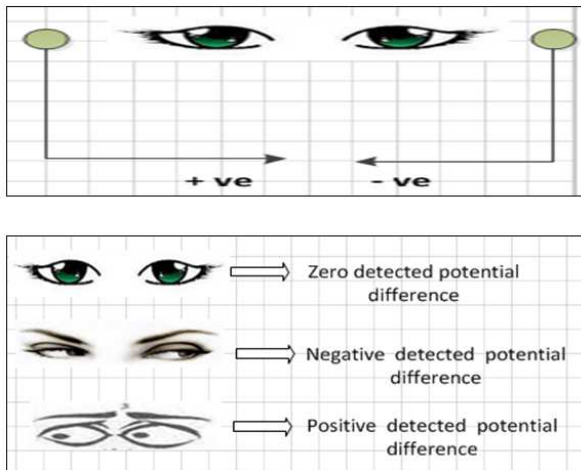

Fig. 3: Horizontal movements and nature of the recorded potential

The relation between the recorded potential difference and the horizontal movements of the eyeball is shown in Fig. 3. It is noted that if eyeball is at the center, the recorded potential equals zero, if the eyeball moves to right, the recorded potential is positive and it will be negative if the eyeball moves to left side.

Researchers have performed many trials to understand how the eye movements can help in diagnosing eye diseases and the EOG is one of the observed phenomena (Constable *et al*., 2017).

An analysis of eye movement for activity recognition using electrooculography is described in (Bulling *et al*., 2011). A real time EOG signal Deterministic Finite Automata (DFA) classifier for microcontrollers is proposed in (Trikha *et al*., 2007). A new low-cost real-time communication assistive system for disabled people is proposed in (Lopez *et al*., 2014). A wireless EOG-based HCI device is used for detection of eye movement in four directions in (Supraja, 2014). In (Peng *et al*., 2013) the author has implemented a system based on EOG-feature based methods and LVQ algorithm to control locations of the cursor of the mouse. A proposed system to control and direct mobile robots is presented in (Barea *et al*., 2000) and (Al-Haddad *et al*., 2011). A new technique is used for measuring the evolution of neurodegenerative diseases and state of alertness in healthy persons in (Al-Haddad *et al*., 2011). The relationship between driver eye movements and different real driving situations by EOG signals in a fully controlled experiment is described and implemented in (Ebrahim *et al*., 2013). The Standard Clinical EOG method, definitions, explanations, instrument specifications, and testing strategies are given in (Brown *et al*., 2006).

The rest of the paper is organized as follows. Section 2 gives a description of the used materials and methods. Section 3 introduces Experimental results and discussion. Finally, the paper is concluded in Section 4 with a short summary and future work.

Materials and Methods

Dataset Description

This study uses dataset delivered by PhysioNet (https://physionet.org/mimic2/Signals_Class/eog.shtml) which give a free web access to large groups of recorded physiologic signals called Physio Bank and is supported by the National Institute of General Medical Sciences (NIGMS) and the National Institute of Biomedical Imaging and Bioengineering (NIBIB).

We have used 40 samples 20 of them are for normal eyes and 20 for abnormal. Seventy five percent of the available data was used for training and twenty five percent for testing. The Data recording method was done as follows (https://physionet.org/mimic2/Signals_Class/eog.shtml):

- Electrodes are placed beside the two eyes horizontally (right, left) or vertically (upper, lower) and a reference electrode is placed on the forehead to measure the horizontal or vertical movements
- The patient keeps his or her head still while moving the eyes back and forth alternating between the two red lights
- The examination occur first at dark and then at light around 15 min for each phase
- The potential decreases for 8-10 min in darkness. Subsequent retinal illumination causes an initial fall in the standing potential over 60-75 s (the Fast Oscillation (FO)), followed by a slow rise for 7–14 min (the light response)" as shown in Fig. 4

Classification Methods

The proposed system is shown in Fig. 5. We propose measuring the EOG signal and sending it using a raspberry PI device connected to a GSM module or mobile device equipped with a GPRS data that will eventually send the EOG signal to a server on the cloud. The cloud-based server has a web service that will utilize data analysis techniques and classification methods to automatically diagnose the EOG signal and classify it to whether normal or abnormal. The diagnosis of the suspected abnormal cases only is then sent to the expert to be evaluated based on other symptoms of the patients and extra analysis by the expert.

This proposed method can be used as a screening method to be used in rural areas where experts are not available, or to reduce the number of suspected cases that will be further analyzed by the expert to save the expert time and hence reduce the cost of the service.

At the server side, we have implemented an automatic diagnosis system that analyze the EOG signal and extract the following features: Light peak, Dark trough, Arden ratio, Mean and Standard deviation of the whole signal.

The light peak feature is calculated as the maximum value of the EOG signal that occur during the light phase as shown on Fig. 4 and denoted by *Lp*. The dark trough feature is the minimum value of the EOG signal that occur during the darkness phase as shown on Fig. 4 and denoted by Dt. The relative ratio of amplitudes in dark and light gives an index of the eye response to ionic changes. This ratio is called the Arden Ratio (AR) = light peak/dark trough. The mean and standard deviation features are calculated for the whole EOG signal using the standard statistical equations.

The proposed system, as illustrated in Fig. 6, incorporates six stages: reading the EOG signal, sending it to the cloud server, feature extraction, automatic classification process, and send the abnormal classified signal to the expert for further investigations. Finally, the diagnosis result is sent to the patient.

Figure 7 shows the two types of the EOG signal for normal and abnormal retina.

We used three different classifiers to classify the EOG feature vectors.

The following subsections will discuss each one of them in details.

Multilayer Perceptron Neural Network

Artificial Neural Networks (ANNs) are widely used in classification by simulating the biological human brain and it is highly used as diagnostic techniques. They are widely used in modelling extremely complex non-linear functions. ANNs are formally defined as techniques that are used to analyze and model data after the processes of learning in the cognitive system and the neurological functions of the brain and can predict new patterns from other patterns after executing a process called learning from existing data (Haykin, 2009). Multilayer Perceptron Neural Network (MLPNN) with back-propagation is the most popular ANN architecture. MLPNN is known to be an excellent function approximator for prediction and classification problems
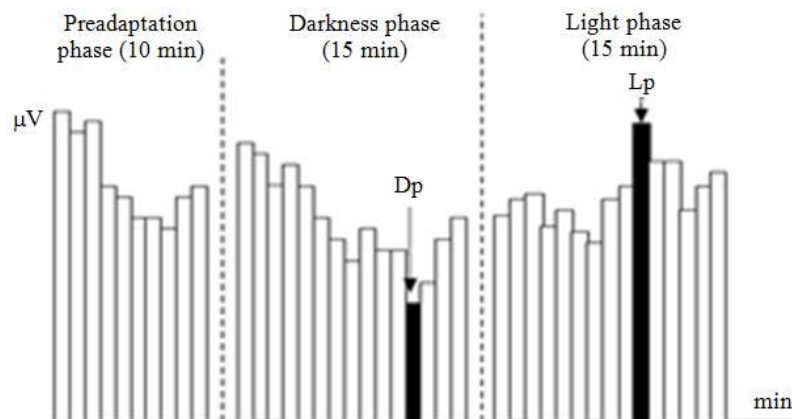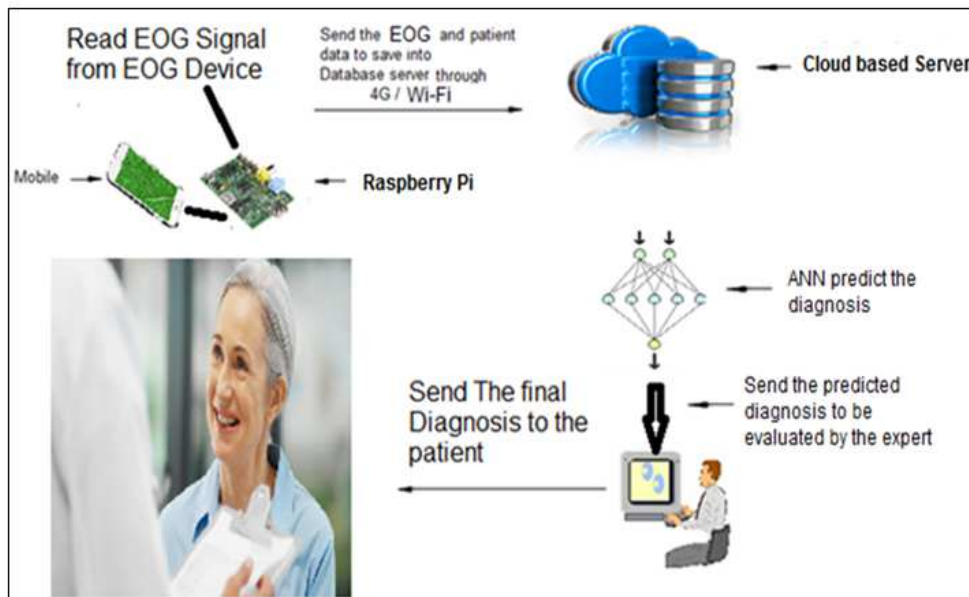

Fig. 4: Data recording phases
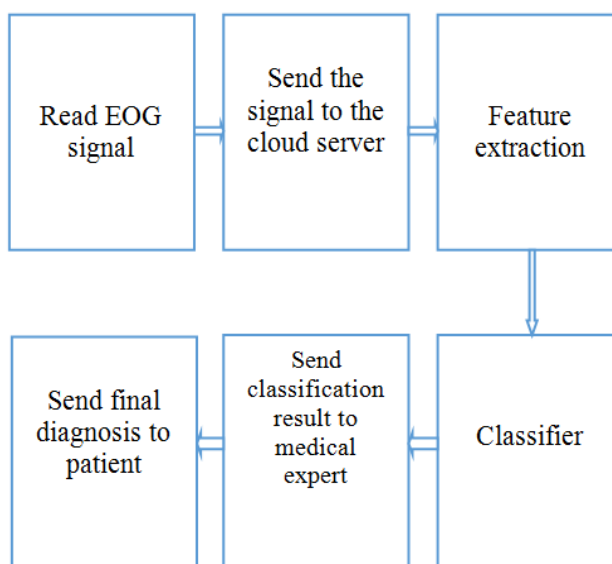
Fig. 5: The proposed system

Fig. 6: Block diagram of the proposed system

MLPNN's consists of layers of neurons, namely called input layer, output layer and hidden layer. There is at least one hidden layer, where the actual computations of the network are processed. Each neuron in the hidden layer calculates its output y_j using Activation Function (AF) of the sum of its input attributes xi after multiplying them by the strengths of the respective connection weights w_{ij}. AF may range from a simple threshold function, or a sigmoidal, hyperbolic tangent, or Radial basis function Equation 1:

$$y_i = f\left(\sum w_{ij}x_i\right) \tag{1}$$

where, f is the activation function. Back-Propagation (BP) is the popular training technique for MLPNN. Back Propagation algorithm works by giving each input patterns to the network and the estimated output is computed by performing weighted sums and transfer functions. The Error of the network E is computed as the squared differences between the desired and estimated values of the output neurons and is defined as:

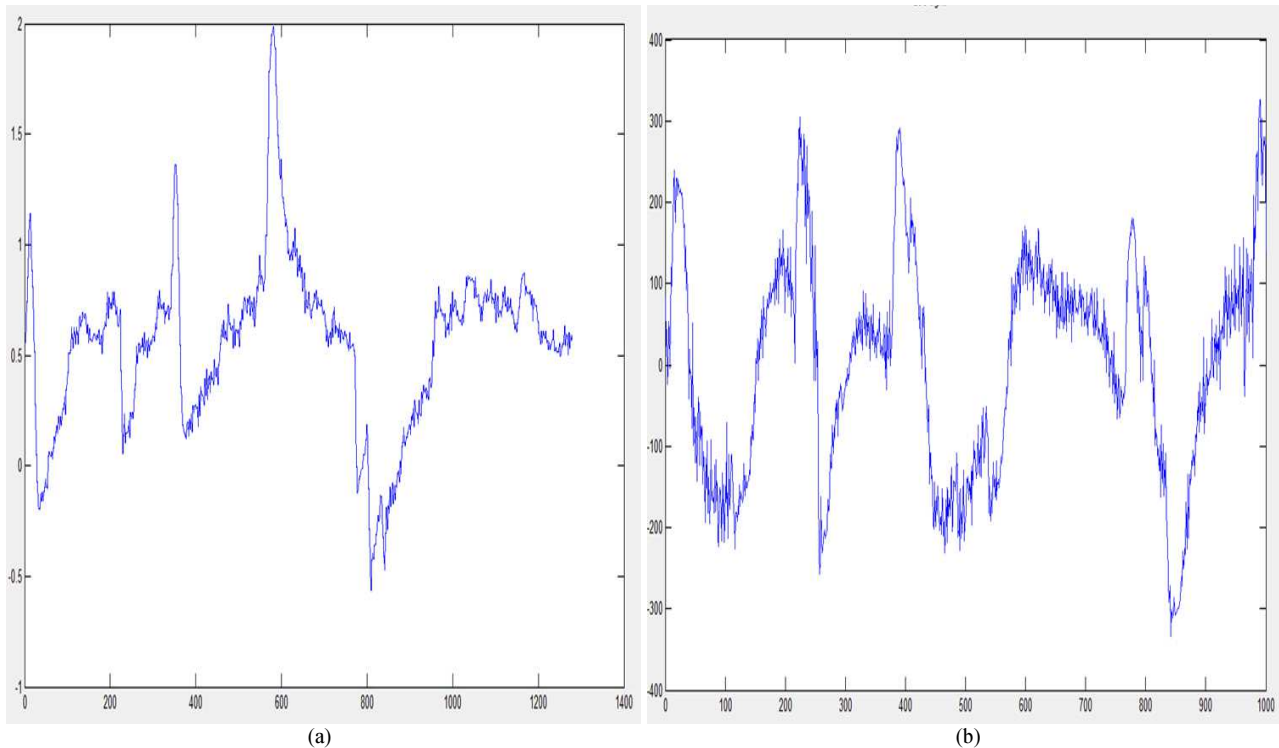$$E = \frac{1}{2}\sum_i \left(y_{dj} - y_i\right)^2 \tag{2}$$

(a)

(b)

Fig. 7: EOG signals. (a) Normal (b) Abnormal

where, y_{dj} is the desired value of output neuron j and y_j is the estimated output of that neuron. In Equation 1, each weight wij is adapted to minimize the error of Equation 2 as fast, quickly as possible. BP applies a weight correction to minimize the difference between the estimated outputs of the network and the desired ones; i.e., the neural network can learn and can thus decrease the future errors (Berry and Linoff, 1997) and (Quinlan, 1993).

Kohnon Network

Kohonen's networks are one of the most common forms of self-organizing neural networks. The ability to self-organize allow the network to offer new possibilities-adaptation to formerly unknown input data. It is considered to be the most natural way of learning, which is used in human brains, where no patterns are pre-defined. Those patterns are created during the learning process, which is combined with normal work. The Kohonen Net has a competitive layer of neurons and an input layer. The input layer is fully linked to the competitive layer. The entities in the competitive layer sum their weighted inputs to find a single winner neuron (Jain *et al*., 1994).

Support Vector Machine

Support Vector Machine (SVM) is one of the most known classifiers formally defined by a separating hyperplane. Its fundamental idea is based on finding the hyperplane surface that provides the largest minimum length to the training patterns. The ideal separating hyperplane maximizes the margin of the training data. Where the separating hyperplane can be defined by:

$$f(x) = \beta_0 + \beta^T x \qquad (3)$$

where, β is known as the weight vector and βo as the bias (Smola and Schölkopf, 2004).

Experimental Results and Discussion

Classification using Feed-Forward Network

In this method, we have divided the 40 samples data signals into 70% for training, 15% for validation, and 15% for testing. Figure 8 shows the validation performance of the classifier. The figure shows that the mean square error of the network has reached the best validation performance of 9.0938×10^{-8} at epoch 18, which is a good result that indicates the capability of the network to learn the classification task efficiently.

The training state is shown in Fig. 9. It indicates that the network gradient has reached 8.264×10^{-8} at epoch 18, which is a very small value. This means that the training has reached its goal with no more network weights update.

Figure 10 shows the Receiver Operating Characteristic (ROC) curve which offers a graphical illustration of the sensitivity (true positives) as the y axis and the specificity or False Positive Rate (FPR) as the x axis for weighing the performance of diagnostic trials.
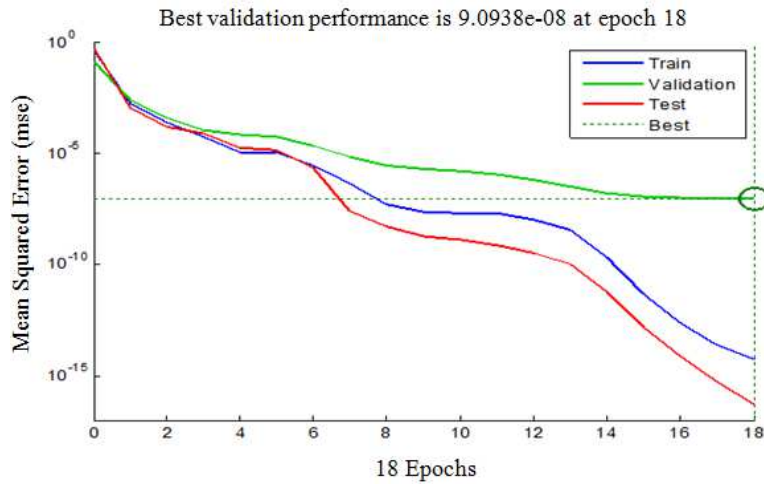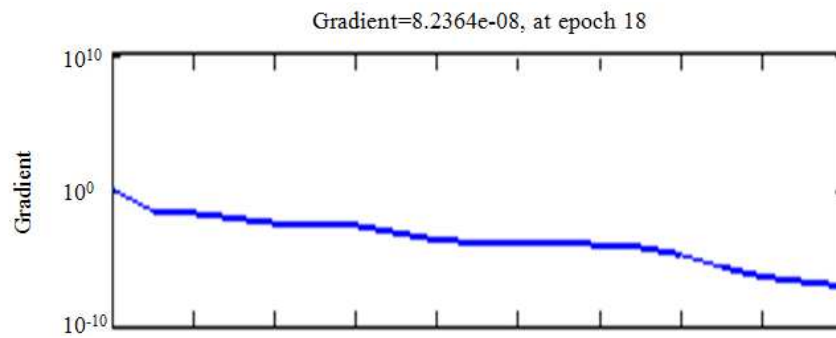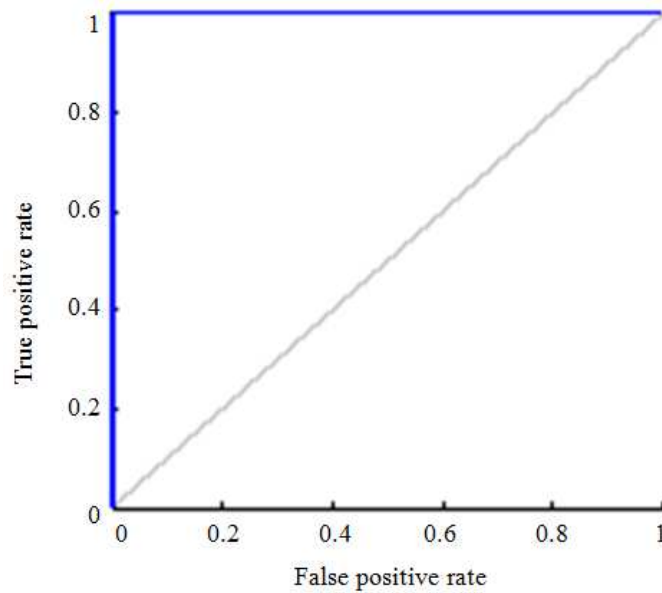
Fig. 8: Validation performance

Fig. 9: Training state

Fig. 10: ROC Curve

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Fig. 11: Confusion Matrix

Table 1: Kohonen network results Vs previous work (Giiven and Kara, 2006)

Group type	Proposed Kohnen network	Previous Work (Giiven and Kara, 2006)
Negative (normal)	18	15
TN	16(88.89%)	14(93.3%)
FN	2(11.11%)	1(6.7%)
Positive (subnormal)	9	17
TP	9(100%)	16(94.1%)
FP	0(0%)	1(5.9%)
Total	27	32
True	25(92.59%)	30(93.75%)
False	2(7.04%)	2(6.25%)
Sensitivity	81.2%	94.1%
Specificity	100%	93.3%
Positive productivity	100%	94.1%

Table 2: Comparison between the proposed approach and other approach

	Method	Accuracy	Sensitivity	Specificity
The proposed approach	Feed Forward Network	100%	100%	100%
	Kohonen Network	100%	81.2%	100%
	SVM	100%	100%	100%
	Giiven and Kara (2006)	94.1%	93.3%	94.1%

The confusion matrix is shown in Fig. 11. It indicates that the performance of the classifier has reached 100%. The classification accuracy for the feed forward network was 100%. The sensitivity and specificity are 100%. Which is a superior result compared to previous work.

Classification using Kohonen Network

We have used 75% of the data for training and the rest for testing. Table 1, shows the results of the kohonen network Vs the previous work achieved in (Giiven and Kara, 2006).

Classification using SVM

We have used SVM classifier to classify each row of the data in the testing set into one of the groups in the TRAINING set using a 'linear' separator for the two-classes, which separates the data by a hyperplane and uses a Gaussian radial basis function as the kernel function. The accuracy of the SVM classifier is 100%. The sensitivity and specificity are 100%.

Comparison with the existing systems is a hard issue since various authors have used different datasets with a different number of mammograms for experimentation. Besides, different works use different parameters to evaluate their performance. Table 2 summarizes the performance of the proposed classification techniques and the existing method in (Giiven and Kara, 2006).

These results guided us to use both of back propagation classifier and SVM based classifier in our implemented cloud based system to determine whether the case is normal or abnormal. If any of the two classifiers has detected abnormality, the case is sent to the expert for further investigations.

Conclusion

The proposed technique can be used in an embedded system that can be attached to a regular EOG device to assist physicians in diagnosing. The main advantage of the proposed system is the high quality of the diagnosis process that help health team to take the suitable decision regarding the patient case. It can be used as a screening method to be used in rural areas where experts are not

available, or to reduce the number of suspected cases that will be further analyzed by the expert to save the expert time and hence reduce the cost of the service.

The proposed system may help reducing the cost of screening patients especially in rural areas where experts are not available through sending their data to a central site where the automatic system will help an expert to diagnose the suspected cases. Also, the objective of this study was to design a computer aided diagnosis system that can be used by the physicians as a second opinion that will help him diagnosing with higher confidence. Three different classification models have been evaluated. The proposed techniques have used five features namely, Light peak, Dark trough, Arden ratio, Mean, and Standard deviation to classify the unknown EOG signal to one of the two classes; normal and abnormal. The classification accuracy has reached 100% which is a superior compared to previous methods that has used only two features for classification and a back propagation classifier and achieved 94% accuracy.

Future systems using Internet Of Things (IOT) technology can be established using the proposed system to act as a low cost screening method for early detection of eye diseases.

Acknowledgement

Author's Contributions

Mahmoud A. Fakhreldin: Designed the study, collecting the literature, collecting the datasets from databases and analyzed the data, then prepared the original draft the manuscript.

Ahmed F. Seddik: Guided the analysis and the interpretation of the results, validated the experimental results and made discussion. All authors reviewed and approved the manuscript.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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