Detection of Abnormality in Human Body by Observing Change in Iris using Optimized Support Vector Machine Classifier

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Abstract

In modern biomedical trend, it has been proved that the abnormalities in the system of human body can be diagnosed by the analysis on the change in anatomy of the human iris. Due to the fact that there is a direct relationship between human health and changes in the anatomy of the iris, this type of diagnosing methodology becomes trustworthy. The internal alteration in the properties of irises are used to diagnose the abnormalities. These internal alterations in iris is main focus of our iris recognition process. From the literature survey, it is found that modern technology also fails in lot of cases to diagnose disease correctly. Thus the diagnosis is made using ancestors irido-diagnosis technique with modern technology. Research on computerized iridology had been done before. This paper presents a computerized iridology system for detecting abnormality conditions in the body. Which is designed with help of image processing through several stages such as pre-processing, feature extraction, classification using SVM based on Greywolf optimization algorithm. This system produces a better accuracy rate which is relatively higher than the existing noninvasive models.

Keywords: Iridology, Computerized iridology, Image processing, Pre- processing, Feature extraction, Greywolf optimization algorithm

1. Introduction

By examining the iris patterns of an human being, iridologists are capable of recognizing the current status of health and wellness of the human body more precisely. Iridology is a holistic endeavor in that it addresses the person's whole being in the reading. Human eye anatomy is given in figure1.

The range of information gleaned encompasses physical, emotional, mental, and spiritual aspects of the person's health picture [3]. In addition to assessing the person's general level of health, readings can reveal other data, including energy quotients, internal areas of irritation, degeneration, injury, or inflammation, nutritional and chemical imbalances, accumulation of toxins, life transitions and subconscious tensions [4]. Iridologists maintain that the eyes reveal information about the person's physical and emotional constitution, such as inherited weaknesses and risks to which the person may be prone. Strengths may also be revealed, including inherited emotional tendencies from which the person derives particular talents. Cleansing and healing can be verified by changes in the iris.

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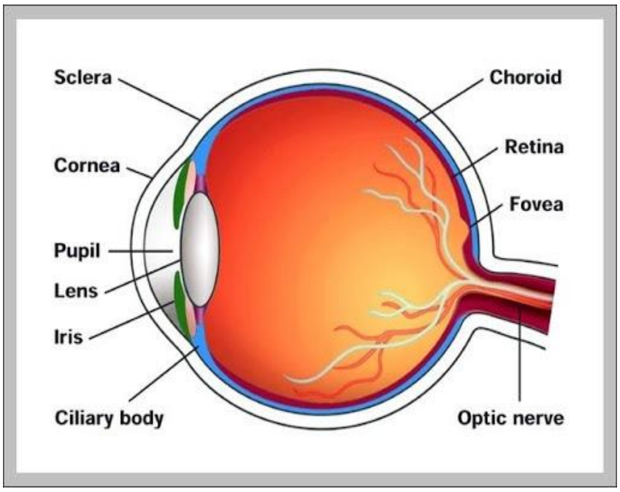

Figure 1. Anatomy of Human Eye

By looking for certain signs such as healing lines, iridologists obtain information about previous health problems and injuries and discover what may have gone wrong in the person's past. An iridology reading reflects the causes of problems, not symptoms. It may, iridologists claim, reveal that organs or systems are overstressed or predisposed to disease before clinical symptoms even develop. By predicting future problems, iridology can be used as a preventive tool. People can use the information from iridology readings to improve their health and make better behavioral choices in the future, thereby heading off problems before they occur. Combining iridology and image processing produce a computerized health detection system to the body through the iris. Several studies have been conducted to analyze the iris through a computer. A high percentage of success rate will depend on the successfully taking appropriate iris image from the original image.

This paper presents a method for selecting features that used as input data for classifiers and the best parameters for SVMs via applying an optimization algorithm. Selecting these parameters correctly guarantees to obtain the best classification accuracy [6]. SVMs have two types of parameters, and the values of these parameters affect the performance of SVMs [7]. Accordingly, this paper adopts GWO to present a novel GWO-SVM hybrid optimized classification system for detection of abnormalities in human body. The obtained experimental results obviously indicate significant enhancements in terms of classification accuracy achieved by the proposed GWO-SVMs classification system compared to classification accuracy achieved by the typical SVMs classification algorithm and Genetic Algorithm with SVM (GA-SVM).

The rest of the paper is organized as follows Section 2 deals with related works. The Greywolf Optimization is discussed in Section 3. Section 4 presents the proposed GWO-SVM methodology in detail. Experiment and results are illustrated in Section 5. Section 6 concludes our work.

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2. Related Works

Qiang et al., (2017), proposed a framework by integrating an improved grey wolf optimization (IGWO) and kernel extreme learning machine (KELM), termed as IGWO-KELM, for medical diagnosis. The proposed IGWO feature selection approach is used for the purpose of finding the optimal feature subset for medical data. In the proposed approach, genetic algorithm (GA) was firstly adopted to generate the diversified initial positions, and then grey wolf optimization (GWO) was used to update the current positions of population in the discrete searching space, thus getting the optimal feature subset for the better classification purpose based on KELM. The proposed approach is compared against the original GA and GWO on the two common disease diagnosis problems in terms of a set of performance metrics, including classification accuracy, sensitivity, specificity, precision, G-mean, F-measure, and the size of selected features. The simulation results have proven the superiority of the proposed method over the other two competitive counterparts.

Kulvir et al., (2016), presented different methods used which recognizes the iris samples. This work uses 50 samples of Iris which were collected by 25 known people where each includes 2 samples. For this Irislet and GA based Irislet is used which shows that GA based Irislet recognizes efficiently all the samples even when samples are noisy. Because irislet fails to recognize noisy samples accurately. Because irislet fails to recognize noisy samples accurately. The results show that Irislet gives 100% accuracy with original samples but 56% accuracy with noisy samples which decreases its performance. This proposed GA-based Irislet achieve 100% accuracy for noisy samples also. It means if a person's sample while authentication affected with any kind of external noise then GA-based Irislet is able to recognize that sample/person.

Farhan (2018), proposed an algorithm and implemented using Genetic based Hough Transform algorithm (GACHT) to implement the first stage of iris recognition system with the developed Genetic Algorithm. GACHT was used to detect the Iris and Pupil segments which in turn is a outer and inner circles, the accuracy of any Iris recognition system should be depend on the right region of the Iris, which is done in this paper using and evolutionary algorithm called GACHT algorithm. The objective of this study is to use Hough transform to detect the Iris and Pupil segments which in turn is an outer and inner circles, the accuracy of any Iris recognition system should be depend on the right region of the Iris, which is done in this paper using and evolutionary algorithm called GACHT algorithm. The proposed algorithm succeeds to find and accurate circles in a very god time compared to the original Circular Hough Transform. This gain has very important benefits in case of online recognition system. The selected image has different radii in noisy environment.

Akashi et al., (2016), discuss that high tolerance in human head movement and real-time processing that are needed for many applications, such as eye gaze tracking. The generality of the method is also important. We use template matching with genetic algorithm, in order to overcome these problems. A high speed and accuracy tracking scheme using Evolutionary Video Processing for eye detection and tracking is proposed. Usually, a genetic algorithm is unsuitable for a real time processing, however, we achieved real-time processing. The generality of this proposed method is provided by the artificial

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iris template used. In our simulations, an eye tracking accuracy is 97.9% and, an average processing time of 28 milliseconds per frame.

Aruna and Jaya, (2019), aimed to gain the advantages of feature level fusion in multi-algorithmic iris recognition system and to investigate whether data transformation technique PCA or Optimization technique Genetic Algorithm (GA) will produce good amount of reduction with prominent recognition accuracy. The claimed eye image has been preprocessed to get fixed dimension iris image by performing localization using canny edge detection and Hough transform followed by Daugman's rubber sheet model for normalization. Then three different algorithms based on 2D-Gabor filter, Haar Wavelet, and 2D-Log Gabor filter have been applied to extract features from normalized iris. Then three feature reduction approaches called PCA, GA, and Hybrid approach, which is the application of PCA followed by GA have applied. The reduced feature vector has been matched with the stored iris template database using either Euclidean distance based matching or classification based matching to identify genuine or imposter claim.

Lavanya et al., (2018), presents a computerized iridology system for detecting abnormality conditions in the body. Which is designed with help of image processing through several stages such as pre-processing, feature extraction, classification using threshold Algorithm, binary image conversion and disease detection algorithm. This system produces accuracy rate of 86.4% which is relatively higher than the existing noninvasive models. Iridology is one of the most popular treatments. To perform iridology and computation process needs a good cropping of iris image is required. This application has the higher percentage of success result than the existing system.

3. Grey Wolf Optimization (GWO)

Grey Wolf Optimizer (GWO) is a new meta-heuristic technique [16]. For solving optimized problems, it can be applied and achieves excellent results [17,18]. In nature, The GWO algorithm resembles the guidance ranking and hunting strategy of grey wolves. Grey wolves are of different types. They are alpha (α), beta (β), delta (δ) and omega (ω). Those four kinds can be employed for simulating the guidance ranking. In this methodology, the hunting (optimization) is guided by three wolves (α, β and δ). The wolves follow them these three wolves [17].

3.1. Encircling Prey

To hunt a prey, grey wolves encircling it. Mathematically, this encircling behavior is modeled by the following equations [17-19].

$$D = |C.X_P(t) - X(t)|$$

$$X(t+1) = X_P(t) - A.D$$

where t is the current iteration, A and C are coefficient vectors, X_p is the vector of the prey position, and X indicates the vector of the grey wolf position. A and C vectors can be calculated as follows:

$$A = 2a.r_1 - a$$

$$C = 2.r_2$$

where components of a are linearly decreased from 2 to 0, over the course of iterations and r_1, r_2 are random vectors in [0,1].

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3.2. Hunting

To simulate the hunting process of grey wolves, assume that the α (the best candidate solution), and δ have better knowledge about the possible position of prey. Therefore, the best obtained three solutions are saved so far and oblige other search agents (including ω) to update their positions according to the position of the best search agents. This updating for the grey wolves positions is as in the following equations [17,18]:

$$D_\alpha = |C_1.X_\alpha - X|$$
$$D_\beta = |C_2.X_\beta - X|$$
$$D_\delta = |C_3.X_\delta - X|$$

$$X_1 = X_\alpha - A_1.(D_\alpha)$$
$$X_2 = X_\beta - A_2.(D_\beta)$$
$$X_3 = X_\delta - A_3.(D_\delta)$$
$$X(t+1) = \frac{X_1 + X_2 + X_3}{3}$$

3.3. Support Vector Machine (SVM)

SVM is an efficient classifier in the domain of life science for the observation of abnormalities from biomedical indicators. In this work, to assess the effectiveness of the proposed mechanism we are having four test cases with two different sets of class so we preferred this classifier for better accuracy results. The structural formation of the SVM depends on the following: first, the regularization parameter, *C*, is used to control the trade-off between the maximization of margin and a number of misclassifications. Second, kernel functions of nonlinear SVMs are used for mapping of training data from an input space to a higher dimensional feature space. All kernel functions like linear, polynomial, radial basis function and sigmoid having some free parameters are called hyper parameters. To date, the kernel generally used in Brain-Computer Interface research was the Gaussian or radial basis function (RBF) kernel with width σ

$$K(x, y) = \exp\,(-\|x - y\|^2/2\sigma^2)$$

where, K(x,y) is termed as the kernel function, which is built upon the dot product of two invariant x and y. Suitable trade-off parameter *C* and the kernel parameter σ are required to train SVM classifier and usually obtained by the K-fold cross-validation technique. We have employed ordinary 10-fold planning to get preeminent performance accuracies.

4. The Proposed GWO-SVM Classification Approach

For the purpose of classification, we present GWO-SVM mechanism in this paper. The objective of this approach is to optimize the SVM classifier accuracy by effortless approximating the optimal feature subset and best values of the SVM parameters for the SVM model. The proposed classification approach consists of four main phases. In the first phase, data sets are pre-processed by to decompose into five sub-band signals using four levels decomposition. In the second phase, useful features like Entropy, Min, Max, Mean, Median, and Standard deviation, Variance, Skewness, Energy and Relative Wave Energy (RWE) are derived from each sub-band of wavelet coefficients. In the third phase, the relevant features are selected from the extracted features and the parameter values (C, σ) of SVM are dynamically optimized by GWO for EEG signals classification. After that,

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selected features are applied as an input to SVM-RBF classifier for epilepsy classification task with the obtained optimal parameter values. Finally, the obtained results are evaluated using five different measurements such as classification accuracy, sensitivity, specificity, precession, and F-Measure.

4.1. Pre-processing and Feature Extraction

To attain better outcomes in feature separation, wavelet decomposition has been employed as a pre-processing stage for EEG segments to separate five physiological bands, delta (0–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–60 Hz). Since our dataset is in the range 0–60 Hz, coefficients D1, D2, D3, D4 and A4 corresponding to 30–60 Hz, 15–30 Hz, 8–15 Hz, 4–8 Hz and 0–4 Hz respectively were separated, that are almost standard physiological sub-bands. Fig.2. illustrate the proposed GWO based SVM.

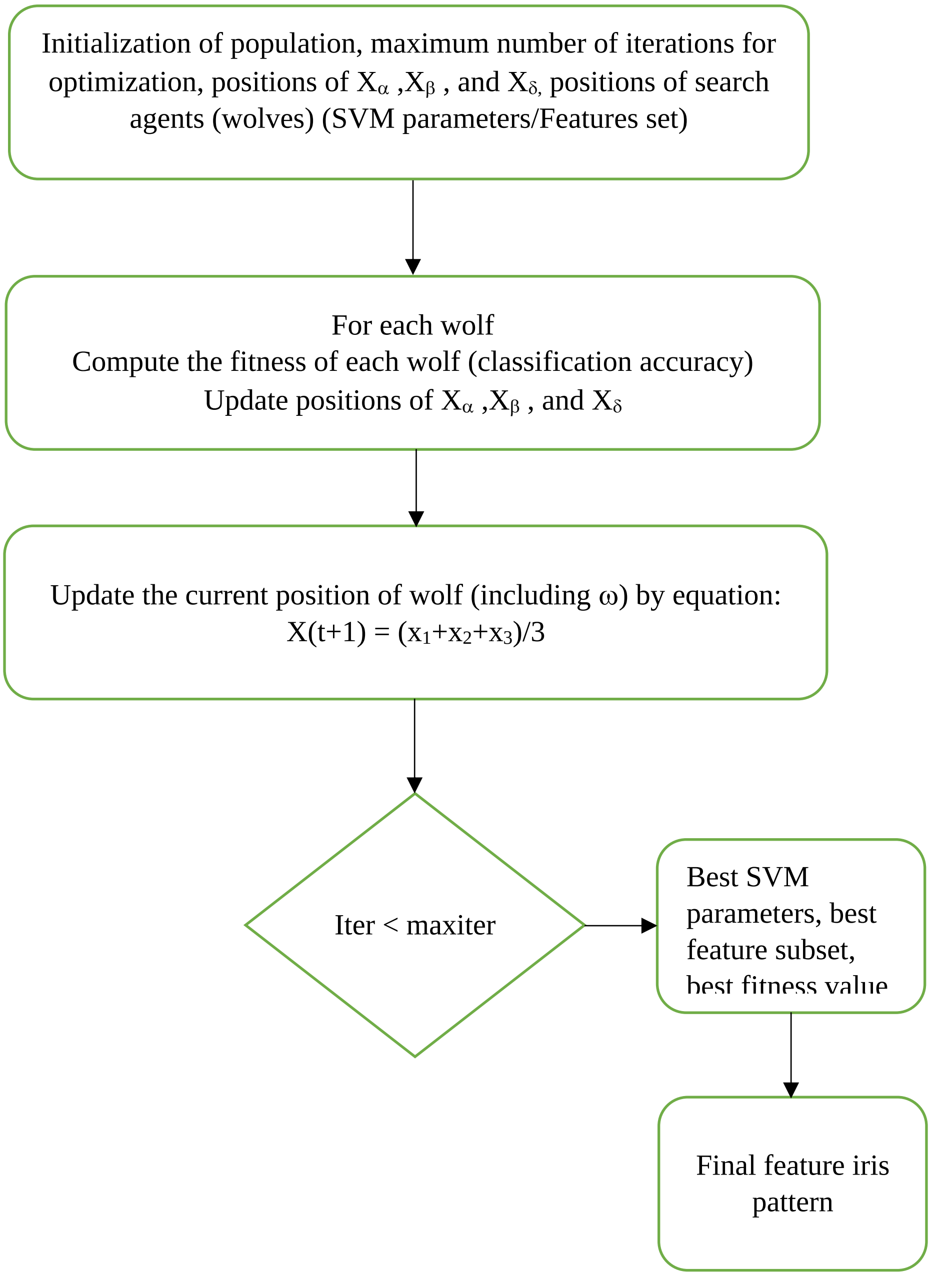

Figure 2. Proposed GWO/SVM Mechanism

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4.2. Features Selection and Parameters Optimization Using GWO

An efficient outcome may be attained by extracting irrelevant and recurring data while keep up the discriminating power of the data by choosing the feature. GWO is capable to produce both the optimal feature subset and SVM parameters simultaneously. Parameters configuration of SVM have a crucial effect on its classification precision. Unsuitable parameter configurations will cause inappropriate classification outcomes. The parameters that should be optimized include the parameter *C* and the kernel function parameters σ for the radial basis kernel.

4.3. Fitness Function

The classification precision is selected as the result qualifier through the hunting procedures. Categorization precision lie between the interval of [0; 1], every wolf (Search Agent) express a number of precisions depend on cross-validation methodology. In addition, each wolf express ten precision values for each fold and all precision values for all folds are taken to calculate mean to return fitness value to the search algorithm as expressed in the following equation.

$$f(w,t) = \sum_{k=1}^{N} acc_{w,t,k}/N$$

where $f(w, t)$ the fitness value for wolf w in iteration t, N represents the number of folds selected for cross validation and $acc_{w,t,k}$ is the accuracy resultant.

5. Experimental Results

The performance results of Proposed Greywolf optimization - SVM are evaluated by MATLAB simulation tool. From the obtained results the abnormal condition of human beings can be identified based on automatic iris scanning.

TABLE I
ABNORMALITY DETECTION

	Number of Images	Detection Rate
Normal	40	(35/40) 87.5%
Abnormal	75	(75/75) 100%
Total	115	93.5% (Total Abnormality Detection)

The iris database is derived from The Chinese Academy of Sciences - Institute of Automation (CASIA) eye image dataset of (version 1.0) consist of total 115 images. The abnormality detection of human beings can be identified from the obtained classifier results based on iris which shows the normal and abnormal datasets. Table 1 shows overall detection rate which is a sufficient result for abnormality detection system.

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TABLE II
CONFUSION MATRIX

		Predicted class	
	Total Population	Prediction Positive	Positive Negative
Actual Class	Condition Positive	True Positive (TP)	False Negative (FN)
	Condition Negative	False Positive (FP)	True Negative (TN)

From the table it is clear that the abnormality detection rate is high for implemented proposed GA/SVM Classifier. It shows 93.5% for total number of images. The overall sufficient detection rate is sufficient for proposed abnormality detection system. To validate the efficient performance of proposed GA/SVM, it is necessary to compare its performance with other classifiers such as K-Nearest Neighbor [9], Navies Bayes, Back Propagation Network (BPN), Probabilistic Neural Network (PNN), Support Vector Machine and Fuzzy SVM in terms of accuracy, sensitivity and specificity.

The effective measures calculated from confusion matrix output from the Table 2, which are True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN). Due to randomness in selecting the training and test data, the classifiers are executed on iris database and the obtained results as abnormalities are taken for consideration.

5.1. Performance Analysis

To evaluate the performance of a GWO-SVM classifier based on the risk score, employ the widely used measures of classification Accuracy, Specificity and Sensitivity.

5.1.1. Accuracy

The accuracy of a measurement system is how close it gets to a quantity actual (true) value

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})}$$

5.1.2. Specificity

Specificity measures the proportion of negatives which are correctly identified as such the percentage of normal healthy people who are correctly identified as not having the condition, sometimes called the true negative rate.

$$\text{Specificity} = \frac{\text{TP}}{(\text{TP} + \text{FP})}$$

5.1.3. Sensitivity

Sensitivity also called the true positive rate or the recall rate in some fields. It measures the proportion of actual positives which are correctly identified as such the percentage of DR people who are correctly identified as having the condition

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})}$$

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Table III shows the performance comparison of Various Classifiers for abnormality Detection.

TABLE III

Performance comparison of Various Classifiers for Abnormality Detection

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)
KNN	73	62	89.5
Navies Bayes	79	68.5	83.2
BPN	82	73.5	81.4
PNN	87.5	76.5	78.6
SVM	94.7	86.1	74.2
Fuzzy SVM	96.4	92.3	72.6
GA-SVM	98.6	95.4	71.6
Proposed GWO-SVM	98.8	97.8	70.2

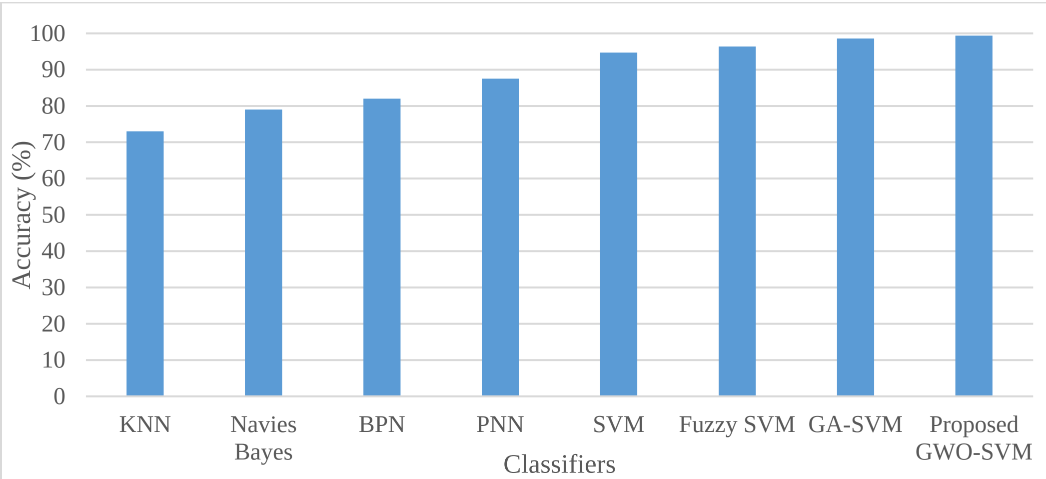

Figure 3. Accuracy Comparison of Various Classifiers for Abnormality Detection

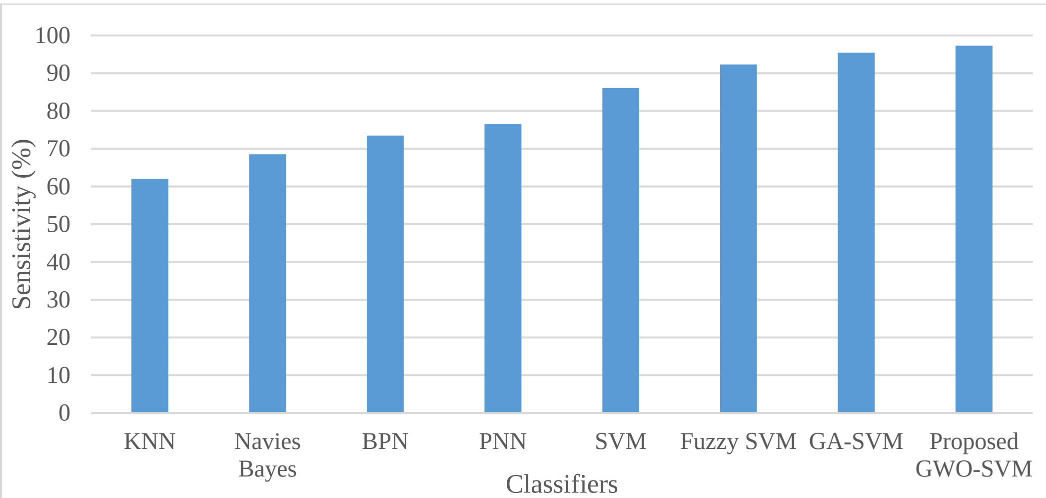

Figure 4. Sensitivity Comparison of Various Classifiers for Abnormality Detection

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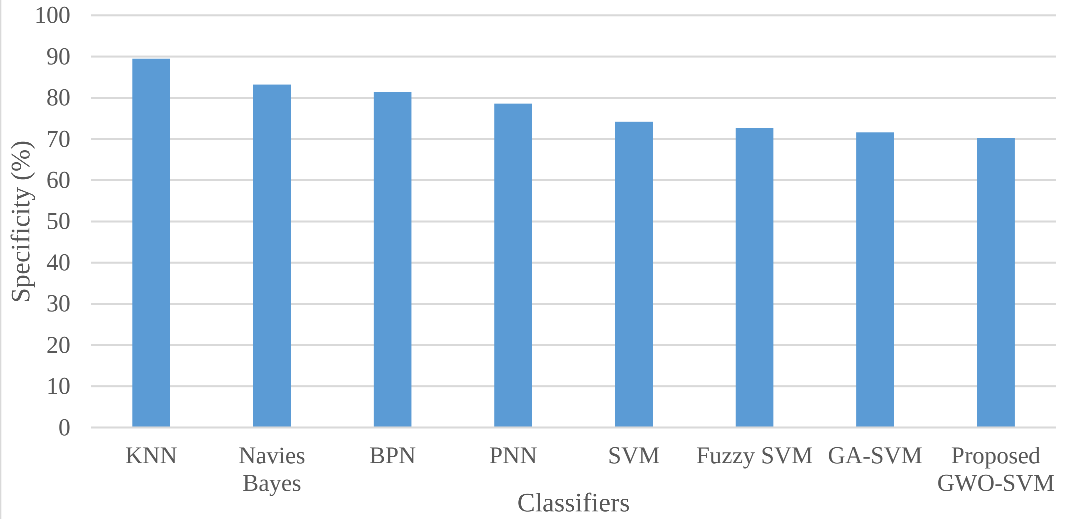

Figure 5. Specificity Comparison of Various Classifiers for Abnormality Detection

Figure 3, 4 and 5 shows the comparison of various classifiers for abnormality detection in terms of accuracy, specificity and sensitivity. It is clear that the proposed GWO-SVM shows better results when compared to other techniques.

TABLE IV
EER COMPARISON OF VARIOUS CLASSIFIERS

Classifiers	Equal Error Rate(%)
KNN	1.47
Navies Bayes	1.22
BPN	1.10
PNN	1.02
SVM	0.86
Fuzzy SVM	0.77
GA-SVM	0.75
Proposed GWO-SVM	0.71

Table IV shows the Equal Error Rate for different classifiers. It is the measurement parameter to monitoring the abnormality detection. In general, the smaller the EER is, the more accurate the proposed method. It shows that the proposed GA-SVM has less EER when compared to various classifiers.

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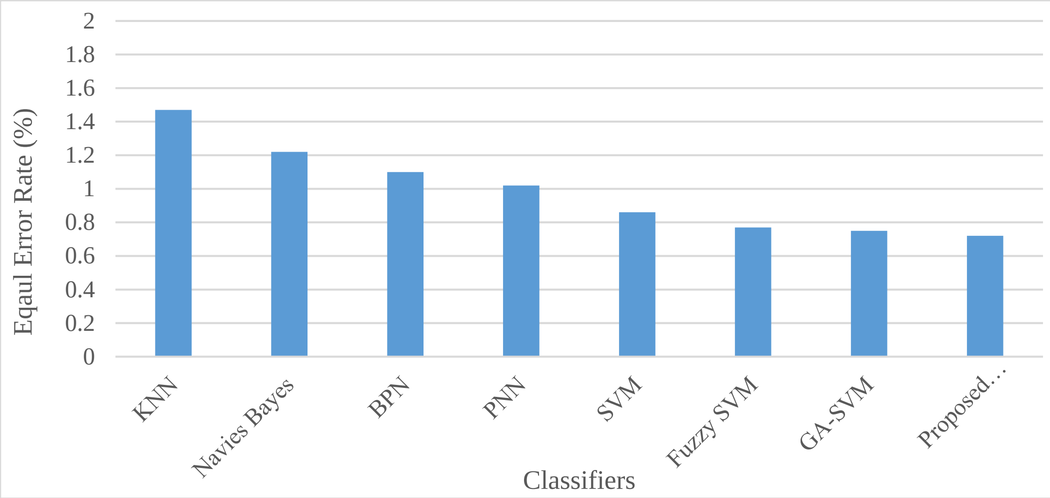

Figure 6. EER Comparison of Different Classifiers

Figure 6 shows the comparison of different classifiers with respect to selected threshold values. It shows that Proposed GWO-SVM has less EER when compared to various classifiers. The Abnormal detection for 75 images based proposed GWO-SVM shows error rate of 0.71. The performance results classify the iris dataset as normal and abnormal and further it is used to find the abnormality detection in human health condition. The experimental results prove that the proposed GWO-SVM outperforms well in classification accuracy when compared to other classifiers.

6. Conclusion

In this paper, GWO-SVM is used for analysis of iris to diagnose health abnormalities. This paper develops an approach using GWO for feature selection with SVM parameters optimization. Almost 100% classification accuracies are obtained using GWO-SVM. These results illustrate the effectiveness of using GWO and SVM classifier for iris based abnormality detection. The success of the proposed method is verified by comparing the performance of classification problems as addressed by other researchers. Also, experimental results indicated that the proposed GWO-SVMs approach outperformed GA-SVM and the typical methodologies.

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Dr Pushpa Rani is a vibrant teaching professional besides an internationally applauded Researcher whose focus dwells on the Research domains; Gait Analysis, Adaptive Learning Systems and Machine Learning. Dr Pushpa perused her PhD from Madurai Kamaraj University, India, for her innovative research on Gait Analysis. She currently serves as the Professor and Chairperson in the department of Computer Science of Mother Teresa Women's University, India. In addition, she is entrusted with many additional Positions such as University Syndicate Member, Academic Council member, Dean of Science, IQAC Co-ordinator, Director & Academic Co-ordinator. She authored four books to her credit, published more than 85 research papers in reputed International Journals, contributed around 75 book chapters and presented at least 140 technical papers in International/National Conferences. She has been honoured with a number of National and International awards, recognizing her Academic & Research caliber. She has been bestowed with three International Awards; 'Glory of India' , 'Distinguished Woman in Science' and 'Research Innovation Award', and 6 more Awards at National Level.

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