

Development of High Efficiency Optimization Algorithm based on New Topology in Particle Swarm Optimization for Parkinson's Disease

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Abstract

Parkinson's disease is a progressive neurodegenerative disorder, where new cells in the brain die slowly over time due to the loss of the substantia nigra causing the lack of dopamine. In order to tackle the accurate diagnosis of Parkinson disease issue, this research proposes to design of a new algorithm to efficiently discern Parkinson's disease patients from the healthy individuals using the binary particle swarm optimization method. The case-control study was designed to evaluate this algorithm by analyzing the electroencephalogram dataset of over 196 patients with Parkinson's disease and compare it with that of healthy controls of the same age and gender. The comparison includes other traditional deep learning, logistic regression and binary particle swarm optimization techniques to find out the most accurate one between the three methods.

Keywords.

Date of Submission: 22-11-2020

Date of Acceptance: 07-12-2020

I. Introduction

Parkinson Disease considered as the second of the most common neuro- degenerative disorders, the first one is Alzheimer's disease. More than 10 million people all over the world are diagnosed with PD, according to the Parkinson's Foundation, but no scan has been proved to definitively diagnose it. The disease more often appears in the ages after the age of 60 [1].

There is no specific therapy for Parkinson's disease despite extensive scientific research, however, early diagnosis can accelerate treatment procedures and help millions of people who are suffering from this disease around the world. Diagnosing Parkinson's disease in its early stages can be a great help in the process of synthesizing more effective drugs and enhance the life of patients with this disease [2][3]. Patients with Parkinson's have movement disorders. Although many machine learning techniques are proposed for diagnosing this disease, these techniques use EEG data set, clinical data, and so on for diagnosis. Neural network mapping and logistic regression are used for diagnosing. The current work describes these different issues in details aiming for early diagnosis of the disease through the analysis of electroencephalogram (EEG) data set electronically rather than manually, enabling rapid, and sensitive diagnosis [4][5].

The objective of this paper is to help diagnose the Parkinson disease (P-D) fast and in the early stages by applying the algorithm to the EEG data set of the patient to figure out whether he have the Parkinson or not, since it is done manually till it will take time to read and check all the parameters of all the patients. The main contributions of this study can be summarized as follows:

The paper includes a new algorithm to efficiently discern PD patients from healthy individuals using BPSO. The implementation of the algorithm is obtained using MATLAB software. The paper is organized in five sections; summarized as follows: Section 2 gives an overview of the algorithms used that used to diagnosis the PD in early stages. In addition, a survey of some useful algorithms is presented. Section 3 describes a developed algorithm to diagnosis the PD based on the PSO and EEG data-set. Section 4 gives the detailed experimental results of the developed algorithm. Furthermore, it includes a detailed comparison with pervious works. Section 5 concludes the main paper results and identifies areas where further research may be appropriate.

II. Parkinson's Disease

Parkinson's disease (PD); which is also named Paralytic Paralysis; is a progressive neurodegenerative disorder, identifies the lack of dopaminergic neurons. Dopamine is a neurotransmitter chemical that aids in passing messages between different sections of the brain. The primary function of dopamine is to control the

body movement. The cells that produce dopamine are damaged in people with Parkinson disease. Figure 1 depicts the Parkinson's neuron versus healthy (normal) neurons [6].

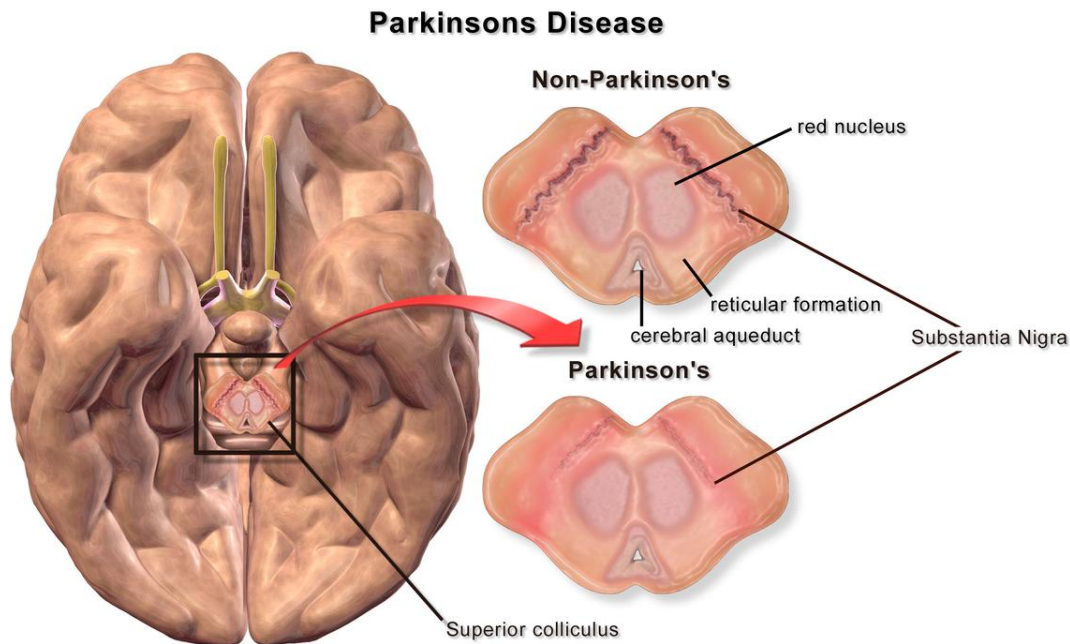


Figure 1. Effect of Parkinson Disease on a Human Brain

PD was first discovered by Dr. James Parkinson on the second most common neurodegenerative disease, the disease was described in 1817 where James Parkinson wrote a book called ICN Shaking Palsy, after that the famous French neurologist Jean Martin Charcot decided to name this disease after James Parkinson [7][8].

There are several causes of P-D, like Genetics (some researchers suggested that genes play important role in Parkinson almost 15% of the people that have Parkinson have history of the disease in their family, the hybrid genes that are responsible of producing the dopamine and specific proteins substantial to the brain [9][10].

Environment: some evidence proved that the environment effects through the chemical exposure also drinking water in little amounts.

Lewy bodies which are a clump of abnormal proteins was found in the brains of the people that have Parkinson, as shown in Figure 2.

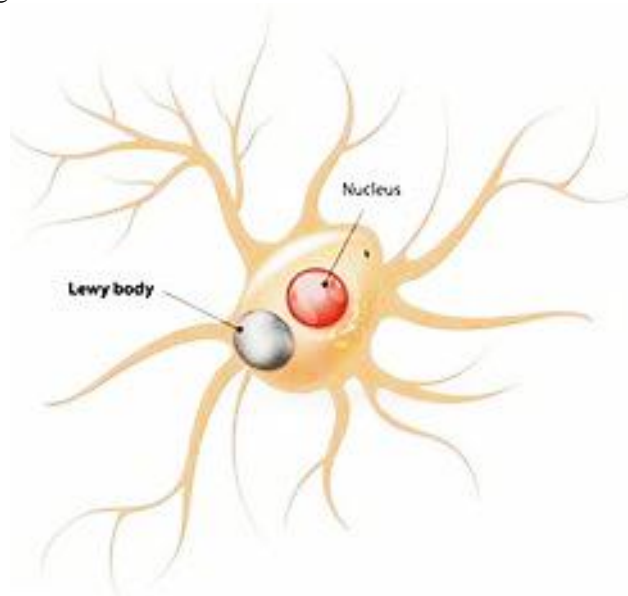


Figure 2. Lewy Bodies in Parkinson- Disease (PD)

These clumps contain protein that the cells unable to break it, which causes them to surround the brain cells causing obstruction of the brain functions, these clumps diagnose with time because of the motor coordination [11].

Age and gender also effects, where evidence shows that age is the most effective factor in Parkinson, also gender is considered one of the factors where men are more likely to have it than women [12].

P-D is hard to diagnose, especially during early stages, because the symptoms are subtler and more sporadic. Patients with this disease exhibit many motor symptoms like tremors, difficulty walking, cramped or small handwriting, loss of smell, sleep problems, poor balance, bradykinesia, facial masking, voice changes, stooping or hunched posture, constipation, psychological symptoms, weight loss [13][14].

Parkinson Disease is diagnosed by using the EEG signals. The EEG is regarded as a non-invasive method that measures the electrical field generated by the neural electrical activity of the brain, and it has good temporal resolution and high test-retest reliability, which is found as an essential feature of cortical integrative functions. The functions of the cortical and subcortical parts of the brain can be easily recognized with the help of the EEG.

The EEG signals are complex and nonlinear in nature, therefore, several linear feature extraction approaches were found to be unable to characterize these signals accurately; as shown in Figure 3.

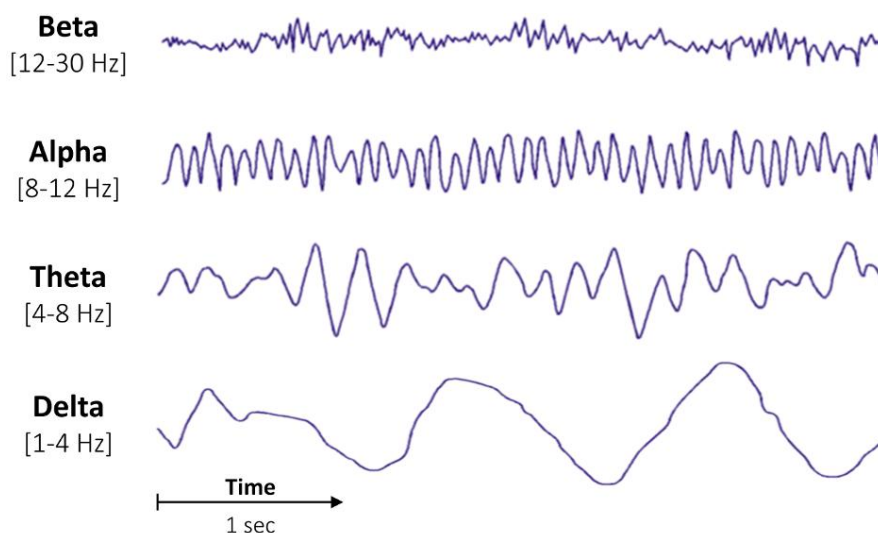


Figure 3. EEG Frequency Band Signals

It was observed that with aggravation of PD, the EEG signal displays complexity. This is attributed to the nonlinear components that are present in the EEG signals [15]. Therefore, the analysis of nonlinear features extraction techniques would be useful in the differentiating EEG signals of the normal from that of PD.

III. Formulation of Equations for PSO

The fitness value of the randomly has been selected for the good values of location and velocity and is formulated as follows:

$$Fit_i = \frac{1}{1+Fun_i} \tag{1}$$

In this equation Fun_i is the function that related to the problem state, and Fit_i is the fitness value of the resolution i who is relative to the quantity of the food resource in the location i and T is the number of food resources, which is equal to the number of worker bees.

An onlooker bee estimates the food resources information to utilize from each of the workers and elects a food resource with a possibility associated to it is food resources best quantity with this formula:

$$P_i = \frac{Fit_i}{\sum_{j=1}^T fit_j} \tag{2}$$

Once the study is achieved by all the worker bees, the onlooker bees utilizing the roulette wheel possibility fitness values for any function is selected.

$$Z_{i,j} = y_{i,j} + RAND_{i,j} \cdot (y_{i,j} - y_{k,j}), i = 1,2, N, j = 1,2, \dots, D \tag{3}$$

For Ant Bee Colony optimization algorithm $Z_{i,j}$, is the j th measurement of i th food resource, i th being the worker bees. $y_{i,j}$ And $y_{k,j}$ is the minimum and maximum bounds of the j th measurement, ($RAND_{i,j}$) is a random range [0-1].

The values of a fresh food resource and every food resource originated by the worker bees are measured by the equation (4),

$$y_{i,j} = LB_{i,j} + rand(0,1) \cdot (UB_{i,j} - N_{i,j}) \quad (4)$$

Here $LB_{i,j}$ is Lower Band and $UB_{i,j}$ is upper band. If the fitness of a food resource does not enhance when a position is bound, it is deserted and exchanged with an arbitrarily produced food resource by the scout bees; they itemize them similar to the feedback mechanism and variation feature of PSO.

At every iteration, every particle in the group of bees moves to a new position in the study space. The new position of particle (i) in iteration $k + 1$, and $x_i(k + 1)$, is calculated by the accumulation of a velocity, $V_i(k + 1)$, to the current location $X_i(k)$.

$$X_i(K + 1) = X_i(K) + V_i(K + 1) \cdot \Delta t \quad (5)$$

Where Δt is a time increment and by using the normal PSO implementations, let the value of time be $\Delta t = 1$. This may be well-known, but, the current work confirmed enhanced results using variable Δt . The new particle velocity, $v_i(K + 1)$, is added to the current location to achieve the new position vector, $x_i(K + 1)$, as presented in equation (5). The local best particle was utilized in the calculation of the particle velocity and position of the PSO from the equations below:

$$V_k^{new} = M \times V_i^{old} + K_1 Rand_1(Pbest_i - X_i^{old}) + K_2 Rand_2(gbest_{is} - X_i^{old}) \quad (6)$$

The position update rule remains unchanged from the equation below:

$$X_i^{new} = X_i^{old} + V_k^{new} \Delta t \quad (7)$$

Where V_k^{new} is the new velocity of the particle i , and M is the inertia weight, V_i^{old} is equal to the previous step of velocity i , and $X_{old} i$ is the old position of the particle, $K1 = K2$ values between [0, 1]. From the equations (7), i is the particle index, V_k^{new} : Particle velocity, X_i^{old} : Particle position, $Pbest_i$: The best singular particle location, $gbest_{is}$: The most "remembered" swarm position.

r_1, r_2 : Random range [0 – 1], $Rand_1, Rand_2$: Random range from – 1 to 0, and

K_1, K_2 : Cognitive and social parameters, M : Inertia weight.

If a particle's velocity goes, on the other side of its particular highest velocity, this velocity is grouped in the value V_{Max} and after that modified before the position update by,

$$V_i^{t+1} = \min(|V_i^{t+1}|, V_{max}) \quad (8)$$

If the maximum velocity is full, the particles may move randomly and be closer to the best resolution. Then again, if it is also minor, the particle's movement is imperfect and the swarm may not search sufficiently enough, or the swarm can develop confinement in a local optimum resolution.

Every super swarm particle appears as the set of the PSO factors to be optimized. The function of every super swarm particle based on the number of analysis optimization issues are measured and on the number of repetitions of the sub swarm optimizations. By using the PSO algorithm, every pixel in the image is categorized into a cluster dependent on the highest fitness function.

IV. Simulation Result

The flow chart of proposed method for Leukemia Cell recognition is shown in figure 4.

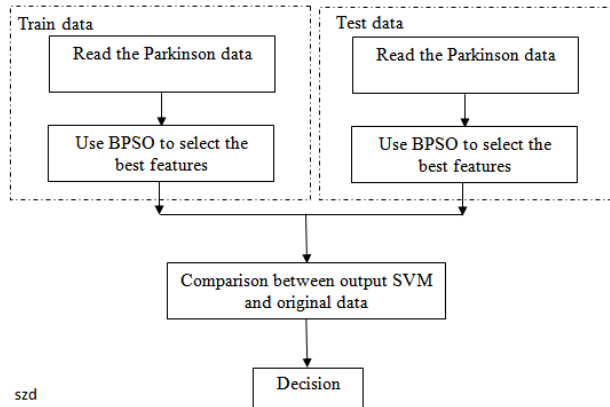


Figure 4. Flow chart of proposed method

The parameters that used for BPSO is shown in table 1.

Table 1. parameters for BPSO

Parameter	Name of parameter	Value
N	Number of particles	10
T	Maximum number of iterations	100
C1	Cognitive factor	2
C2	Social factor	2
V_{max}	Maximum velocity	0.9
W_{max}	Maximum bound on inertia weight	0.4
W_{min}	Minimum bound on inertia weight	6

The flowchart for the PSO is shown in figure 5.

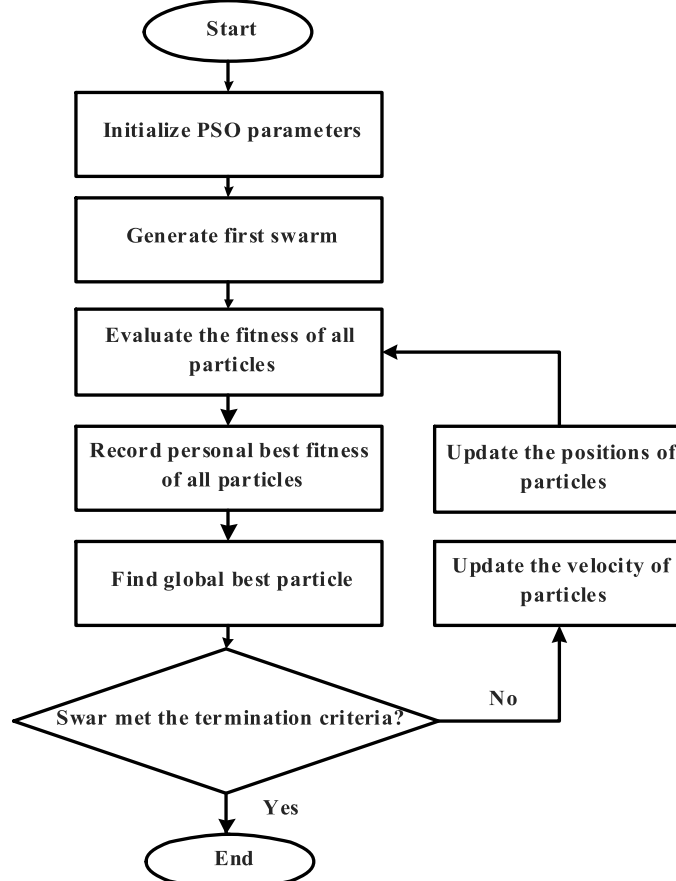


Figure 5. Flowchart of PSO

A Support Vector Machine (SVM) classifier is formally separated by a hyper plane defined. In other words, according to the data of the tag (teaching supervision), the algorithm outputs an optimal hyper plane that by classifying new samples. It is in hyper plane sense that the desirable? If the training data is linearly separable, we can select two parallel hyperplanes that separate the two classes of data, so that the distance between them is as large as possible. The region bounded by these two hyperplanes is called the "margin", and the maximum-margin hyperplane is the hyperplane that lies halfway between them. Some example of SVM is shown in figure 6.

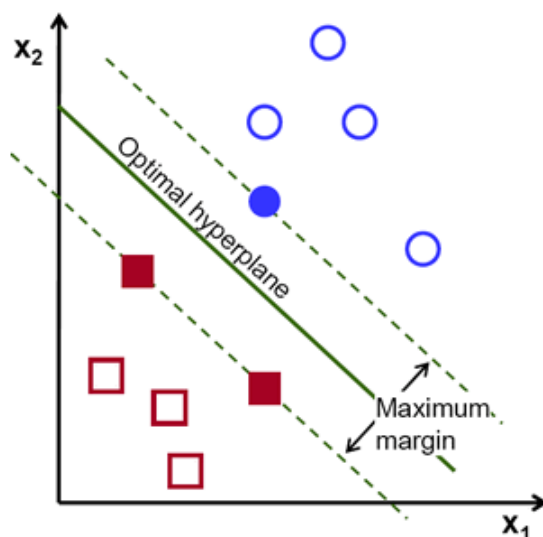


Figure 6. SVM for classification of data

In this thesis the different kernel function are used for SVM. These kernels are linear, Quadric, Polynomial Radial Basis Function (RBF) and Multilayer Perceptron (MLP). The best result is get for linear. We used svmtrain for training of data and svmclassify for classification of data. The Convergence curve, fitness value against of the number of iterations is shown in figure 7.

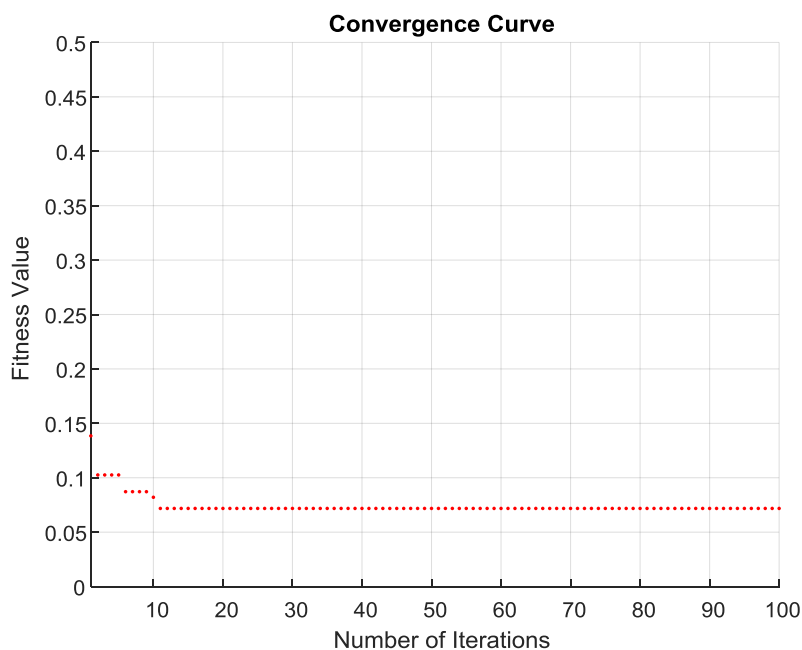


Figure 7. Convergence curve, fitness value against of the number of iterations

The Area under Curve is shown in figure 8.

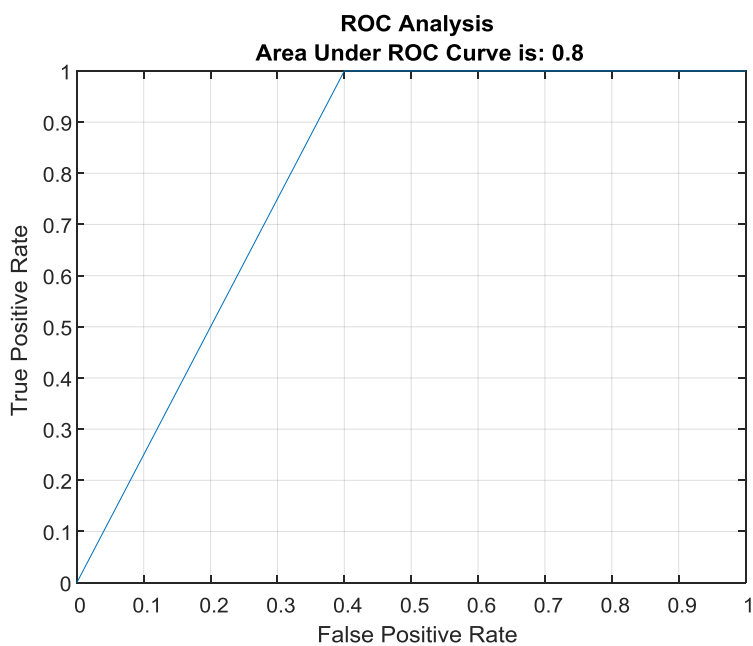


Figure 8. Area under Curve

The Confusion matrix is shown in figure 9.

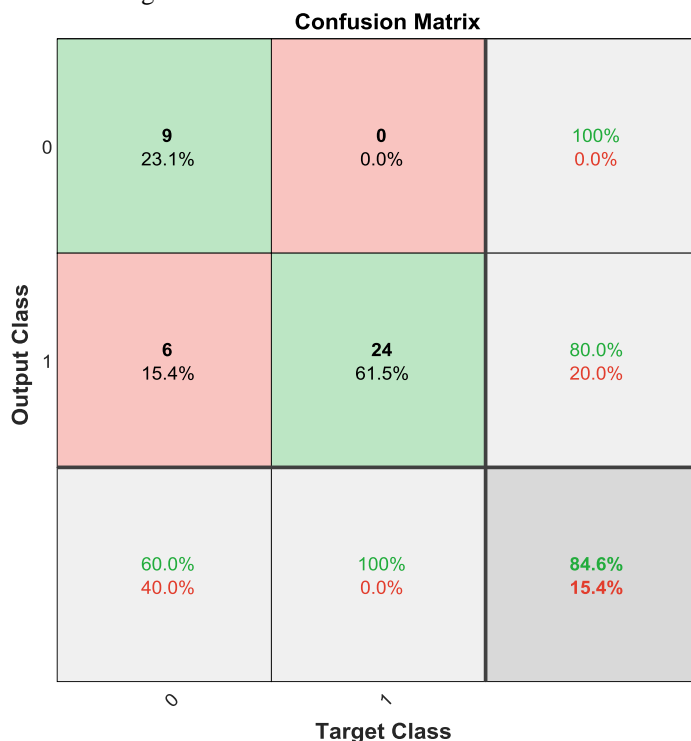


Figure 9. Confusion matrix

The Sensitivity, Specificity, Precision and Accuracy is shown in figure 10.

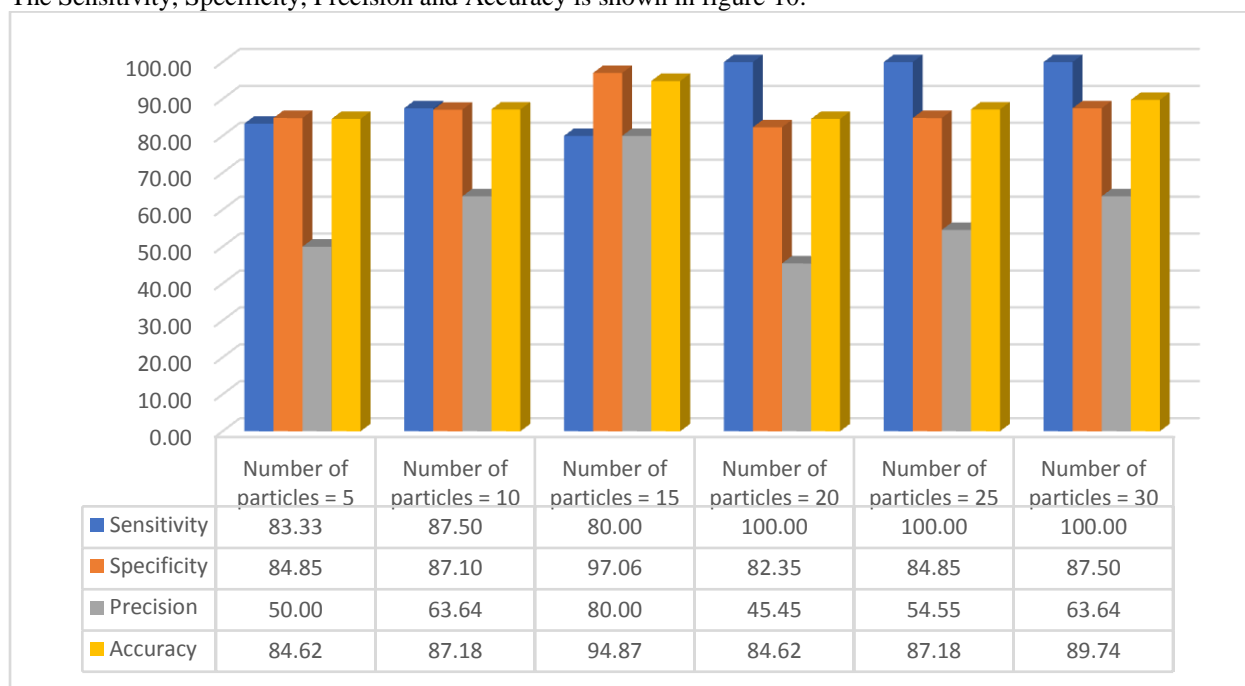


Figure 10. Sensitivity, Specificity, Precision and Accuracy

V. Conclusion

In this paper, particle swarm optimization is used to minimize the number of the features for predict the Parkinson's disease. We used 195 voice recordings that obtained from the dataset which consists of voice measurements of 32 people which of 24 have the Parkinson's disease. In the experiment, in addition to particle swarm optimization for binary classification to be able to make comparison between PSO and other methods. The highest average accuracy is obtained as 97.15 from the SVM classification algorithm while the highest average algorithm is 86.89% from the other classifier.

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