

# Diagnosis of Parkinson’s Disease Using Spiral Test Based on Pattern Recognition

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**Abstract.** Recently, Parkinson’s disease has become one of the most serious health problems. The incidence is significantly increased, especially in people over 65 years of age. The adverse effects of the disease on motor activities distract patients from social environments. Early diagnosis is important in Parkinson’s disease. In addition, the diagnosis of Parkinson’s disease is quite difficult. Therefore, computer-aided systems are used. The Parkinson’s spiral drawing test is one of these methods. Many researchers have classified these drawings with different approaches. In this study, the spirals drawn in the diagnosis of Parkinson’s disease were analyzed by pattern recognition methods. Patient and control group drawings were assumed to be characters. Thus, 123.066 features were obtained for each drawing. In this way, a high p low n problem occurs when the data set is converted. In order to overcome this problem, feature selection process with genetic algorithm was applied as a pre-process. k-nearest neighbor and decision trees were used for the classification process. The results are validated by a leave one out cross validation method. In this study, the data set prepared by the Department of Neurology in Cerrahpasa Faculty of Medicine, Istanbul University was used. The experimental results obtained show that the proposed method gives successful results. Specifically, accuracy value obtained 1.00 in the decision tree classification by selecting the feature with the genetic algorithm. These results showed that the proposed method can be used in the diagnosis of Parkinson’s disease.

**Key-words:** Artificial Intelligence; Medical Informatics; Parkinson’s diagnosis; Spiral test; Pattern recognition; Classification; Genetic algorithm.

## 1. Introduction

Parkinson’s disease is a neurological disorder that affects the nervous system, causing partial or complete loss of motor reflexes, speech, thinking, behavior and other vital functions [1]. An

estimated seven to ten million people worldwide are living with Parkinson's disease [2]. Parkinson's disease is a progressive and persistent disease. The most important symptom of the disease, which is aggravated by age and increasing in frequency, is the deterioration in sound and motor functions [3]. Symptoms such as illegible writing, small writing, speech disorder, low voice, slow walking, depression and distressed moods are common in Parkinson's patients. These symptoms prevent people from carrying out their work and daily activities in a healthy way. For this reason, in the early stages of the disease, it causes the patient to isolate from business and social life. This situation causes the patients to be affected psychologically.

The diagnosis of Parkinson's disease is particularly difficult in the early stages of the disease. In addition, early diagnosis of Parkinson's disease, which is caused by deformation in brain cells, is of great importance for drug treatment. Therefore, in recent years, computer-based solution research has been increased to support medical decision [4,5]. These studies are mainly focused on gait [6-8], speech [9-12] and spiral drawing [13-15]. In the diagnosis of Parkinson's gait analysis, Abdulhay et al. classified the Parkinson's and healthy individuals with the parameters in the gait cycle [6]. In addition, Gumuscu et al. suggested performing genetic algorithm feature selection on data in order to get more successful results from the diagnosis made from vocal analysis of Parkinson's patients. In this way, the number of features was reduced and the success rate of classification was increased [12]. While gait and vocal analysis have more procedures for diagnosis, spiral drawing is more practical and applicable everywhere. Therefore, in this study, the diagnosis of Parkinson's disease was handled with spiral drawing and the diagnosis was greatly improved. In recent studies on Parkinson's diagnosis, drawings on digital tablets have been used instead of drawings on paper. In one of these studies, Gemmert et al. performed a drawing-based analysis on 13 control subjects and Parkinson's patients aged 54 to 82 years. [16]. In this study, each patient was asked to draw 12 'llllllll' stencils with a length of 1.0, 1.5, 2.0, 3.5 cm. As a result of the measurements made on the drawn templates, it was observed that Parkinson's patients could not clearly achieve the desired length in 1.5 cm and above templates compared to the control patients. In addition, it was observed that the writing acceleration in Parkinson's patients was much lower than in the control group. However, it has been observed that the character dimension drawn for Parkinson's disease is effective in distinguishing between patients and healthy individuals [16]. In addition to these studies, Ünlü et al. tried to diagnose Parkinson's disease by using a special electronic pen that records pressure and hand movements in 3 coordinate axes while typing. [17]. They used 56 people (28 patients and 28 controls) in their study. They extracted a feature based on the difference in typing pressure in the x-y directions on the different templates. Using this feature, they aimed to distinguish between Parkinson's symptoms and normal tremor. Aly et al. conducted a similar study with [17] in real time on a digital tablet connected to the computer, aiming to preserve the traditional paper and pen environment [18]. The drawings exact time, x – y coordinates, pressure and shear on the input device were measured with a digital tablet. Fourier transform was applied to these data. According to the Unified Parkinson's Disease Rating Scale, it was aimed to classify the Parkinson's patient group and the control group of the same age as the people in the patient group. It was observed that the model used would not replace the clinical examination and evaluation but could help in the diagnosis stage. Unlike these studies, Wang et al. measured the harmony and performance of patients' motor reflexes using spiral drawing with electronic tablets [19]. In this study, they aimed to learn how much reflexes lost their function or how much they work, information about the disease and the possibility of early diagnosis. Thus, they were able to classify patients and control group. When the studies were examined, the drawings of

the patients were compared with the expected drawing in the diagnosis of Parkinson's with spiral drawing. In this study, unlike other studies, spirals were considered as characters and the problem of identification was handled as a character recognition problem [20]. Thus, machine learning algorithms were used in the diagnosis of Parkinson's and successful results were obtained. In the study, k-NN and Decision trees were used as machine learning methods. The results are validated by a leave one out cross validation method. The technical contributions of this study are summarized below:

1. A novel model framework is developed to accurately classify the Parkinson's spiral drawing images.
2. The impact of the genetic algorithm feature selection method on the Parkinson's spiral drawings classification was investigated.
3. Using the proposed system, accuracy value obtained 1.00 in the decision tree classification by selecting the feature with the genetic algorithm.

The rest of the article is organized as follows. All the algorithms used in the proposed method are summarized in section 2. In Section 3, the steps of the proposed method are discussed in detail. The results obtained with the proposed method are given in Section 4, and the results of the study are evaluated by comparing the results with other studies in the literature. In Section 5, the contributions of the article are highlighted.

## 2. Dataset

In this study, a new data set was created by using spiral drawing and dynamic spiral drawing data from 62 patients with Parkinson's disease and 15 healthy controls taken from UCI Machine Learning Repository data set [21]. In the drawing data, 6 Parkinson's patients were excluded from the data set due to the lack of static or dynamic drawing data. In this data set, drawings were taken with two different procedures, static and dynamic. The spiral image that needs to be drawn in static drawings is seen on the tablet. In dynamic drawings, the figure is shown by blinking. Fig. 1 illustrates how the drawing data is converted to a data set.

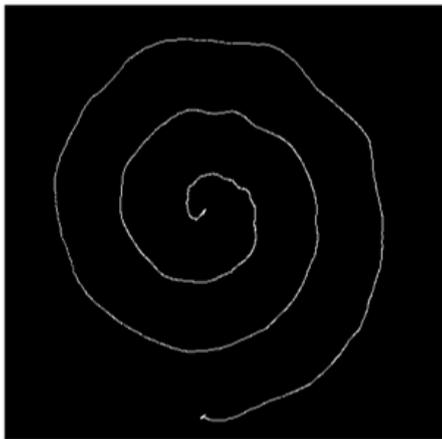
BSDA		BDDA		SDT	SPA	DTD	DPA	DL
010...	0	0	...010					
000...	0	0	...111	.	.	.	.	.
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101...	0	0	...101	.	.	.	.	.
010...	0	0	...011	SDT	SPA	DTD	DPA	DL

BSDA : Binary Static Draw Array  
 BDDA : Binary Dynamic Draw Array  
 STD : Static Draw Time  
 SPA : Static Pressure Average  
 DTD : Dynamic Draw Time  
 DPA : Dynamic Pressure Average  
 DL : Disease Label

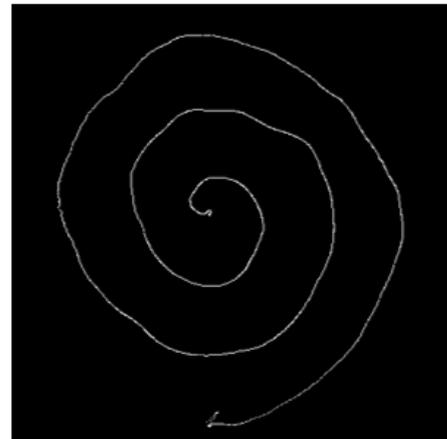
**Fig. 1.** Structure of the data set.

In the data set prepared by Isenkul *et al.*, there are X and Y coordinates, time data and pressure values of the points where the drawing is made. [21]. As shown in Fig. 1, with the help of these values, a matrix of 450 x 450 was formed and "1" data was added to the coordinates of the pen and "0" to the other points. The same procedure was performed for dynamic drawing data.

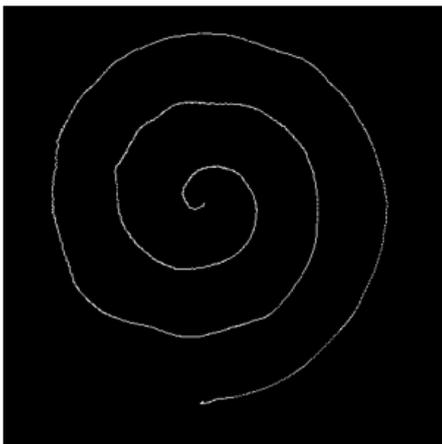
Static Spiral Test (SST) drawing of a Parkinson's patient, Dynamic Spiral Test (DST) drawing of a Parkinson's patient, SST drawing of a healthy person, DST drawing of a healthy person is given in Fig. 2. In addition to drawing data, the drawing completion time and pressure average data are added. This data is added separately for static and dynamic drawings.



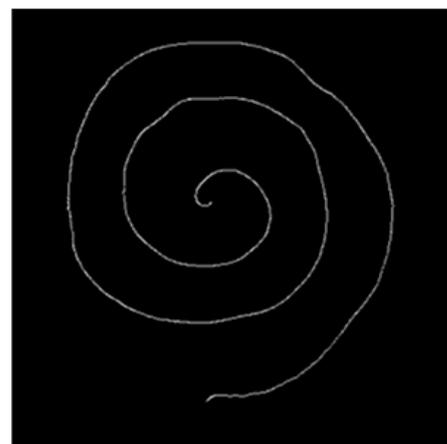
a. SST of Parkinson's Patient



b. DST of Parkinson's Patient



c. SST of Healthy Person



d. DST of Healthy Person

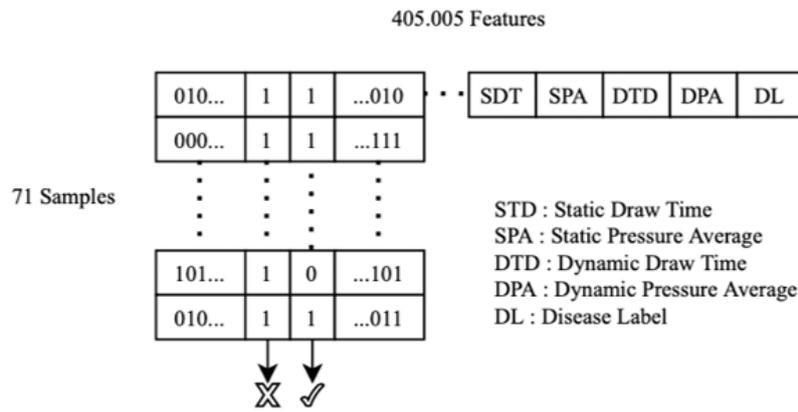
**Fig. 2.** SST and DST Drawings.

A disease tag has been added to the last column of the data set. As a disease label, "1" was added for Parkinson's patients and "0" for healthy people. Thus,  $1 \times 405.005$  sized matrix for a person and totally  $71 \times 405.005$  sized matrix data was obtained. Table 1 summarizes the description of the data set.

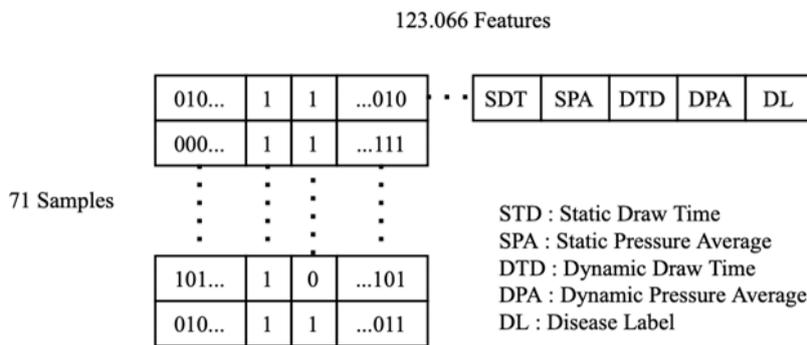
**Table 1.** Data set descriptions

Feature Description	Number of the features
Static Drawing Data	202.500
Dynamic Drawing Data	202.500
Static Drawing Time	1
Static Drawing Pressure Mean	1
Dynamic Drawing Time	1
Dynamic Drawing Pressure Mean	1
Disease Label	1
Total	405.005

Considering the data set and the absence of any drawing on many points of the Parkinson’s spiral drawings, all samples with the same value were removed to reduce the number of features and to clear the data set from unnecessary data. Thus, the features with the same value on all the drawings in the data set were removed and the obtained features were considered as information containing differences. This process is described using Fig. 3.



**Fig. 3.** Feature extraction process.



**Fig. 4.** Feature extraction process.

As a result; A data sized 71x123066 was obtained. Considering that the number of samples is 71 and the number of features is 123066, it is understood that feature selection algorithms should be used in the data set obtained. Fig. 4 shows the final of the data set.

### 3. Genetic Algorithm–based Feature Selection

In the data sets where the number of samples is low and the number of attributes is very high, machine learning algorithms do not provide very successful results. In addition, the high number of features increases the hardware requirements [22]. To obtain more successful results, more valuable features are used to create models of machine learning algorithms by feature selection [23].

Feature selection methods are generally examined in three main topics in the literature. They can be listed in the form of filters, wrapper and embedded. Wrapper model feature selection methods generally aim to select the most ideal features with meta-heuristic algorithms [23].

In contrast to the high success rate of the wrapper model feature selection methods, the processing time in the data sets with a high number of features is a problem. Operators such as selection, mutation and crossover are used to achieve the specified function. Fig. 5 illustrates the process flow of the wrapper model feature selection method.

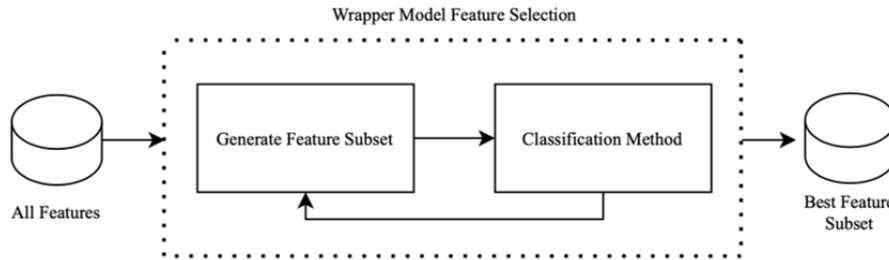


Fig. 5. Structure of the final data set.

In this study, the following classification error rate is employed as the genetic algorithm fitness function [24]:

$$FitnessFunction = ClassificationErrorRate(Feature). \tag{1}$$

The fitness function in (1) is also the objective function involved in the optimization problem solved by the genetic algorithm. The optimization problem aims the minimization of this objective function. In order to be able to select the feature by the genetic algorithm, a number of bits is created up to the number of features. This array's value can be either logical 1 or logical 0. If the value is logic 1, the feature corresponding to the bit is selected, and the logic 0 means that the feature corresponding to the bit is not selected. Genetic operators are applied to this created binary number and it is changed iteratively in each generation. This process is repeated until the optimum feature set is found.

## 4. Parkinson's Disease Classification using Machine Learning Methods

### 4.1. k-Nearest Neighbors Classification Method

One of the easiest but effective classification methods is the k-nearest neighbors (k-NN) [25]. This method classifies the unspecified sample class by its neighbor, the closest Euclidean distance. The Euclidean distance formula is:

$$d(x, y) = \left( \sum_{i=1}^n (x_i - y_i)^2 \right)^{1/2} = \sqrt{(x_1 - y_1)^2 + \dots + (x_n - y_n)^2}. \quad (2)$$

The variable  $d(x, y)$  given in (2) represents the Euclidean distance of the  $x$  and  $y$  points.  $x_i$  and  $y_i$  are notated as the  $i$ th features of  $x$  and  $y$ . In the k-NN method, the nearest k neighbor is determined. When determining this proximity, the absolute distance of points in the selected training set is checked. After determining the distance of the k neighbor, where this distance is the minimum, the classes of all neighbors are examined and the class with the highest weight is selected. The k-nearest neighbor method is very sensitive to outliers.

### 4.2. Decision Tree Classification Method

*Decision Trees* (DT) are a popular in Supervised Machine Learning if data is iteratively divided according to a specific parameter [26]. DT can be explained by two building elements named as decision nodes and leaves. Decision nodes show how data is divided and leaves are decisions or final results. DTs are a widely used method since they can be easily explained in classification. DT are entropy-based classification methods. According to Quinlan, when the data is divided according to a feature, the best choice is made if the uncertainty of each data set obtained is minimum and thus the information gain is maximum. Accordingly, the individual feature vectors are examined and the feature with the highest information gain is preferred for branching the tree [27]. In the first step of each iteration, the entropy of the class vector is determined. The class vector's entropy formula is:

$$H(X) = \sum_{i=1}^n P(x_i) \cdot \log_2 \left( \frac{1}{P(x_i)} \right) = - \sum_{i=1}^n P(x_i) \cdot \log_2 (P(x_i)), \quad (3)$$

where  $H(X)$  represents the class entropy, Besides,  $P(x_i)$  represents the probability of class  $i$ . Then, the class dependent the feature vectors' entropies are calculated and subtracted from the entropy calculated in the first step. The value obtained in this way is the feature vector's information gain value. The measure of the difference in entropy before and after the set  $X$  is split on a feature  $A$ , with the notation  $IG(X, A)$  is computed in terms of:

$$IG(X, A) = H(X) - \sum_{i=1}^n P(i) \cdot H(i) = H(X) - H(X|A), \quad (4)$$

where  $H(X)$ ,  $P(i)$ ,  $H(i)$  are the class entropy, the probability of the number of elements in  $A$  on the set  $X$ , and the feature entropy, respectively. The feature with the highest gain performs the branching of the tree determined in that iteration. DT structure is formed by branching iteratively. The tree structure created is used in the decision-making phase for the samples [26].

### 4.3. Parkinson's Disease Classification

This section describes the algorithm used to determine Parkinson's disease. The data set was tested with two different classification algorithms, k-NN and DT. In this case, the data set is firstly converted to spiral drawing data. The unnecessary features were eliminated from the data set. The data set was sent to the machine learning algorithm for classification. In addition, the Genetic algorithm was used to test the effect of feature selection. The genetic algorithm-based feature selection is illustrated in Fig. 6.

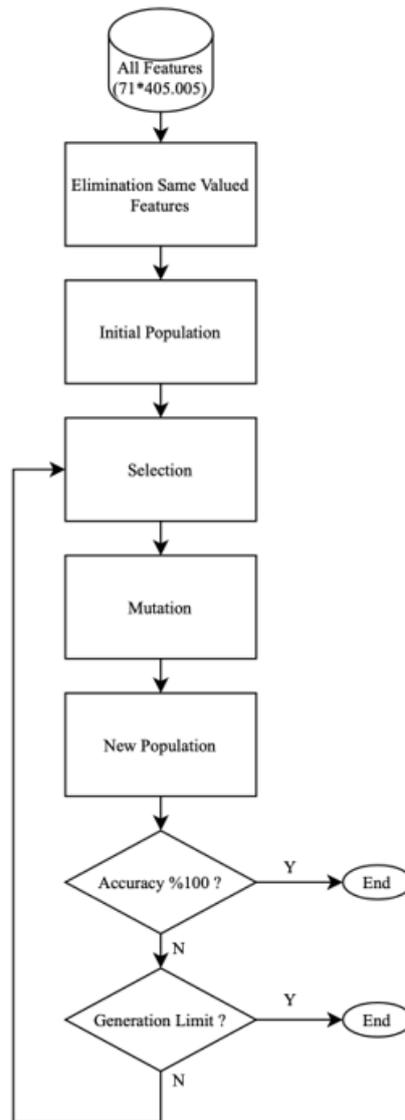


Fig. 6. Process of genetic algorithm-based feature selection.

The above steps have been applied separately for k-NN and DT. The termination of the feature selection process takes place in two situations. When the 100% success rate is reached and the generation limit is reached, the feature selection process is terminated. The proposed method is summarized in Algorithm 1.

Algorithm 1. Pseudocode of Proposed Method

```

for i=1:sample
    p=load ("Isenkul_Dataset")
    for j=1:static_draw_end
        static_draw (p(j,1),(p(j,2))=1;
    end
    for k=static_draw_end:dynamic_draw_end
        dynamic_draw (p(k,1),(p(k,2))=1;
    end
    data(i,:)=[static_draw dynamic_draw p(static_draw_time) p(static_pressure)
    p(dynamic_draw_time) p(dynamic_pressure) p(label)];
end
for i=1:feature
    feature_array=data(:,i);
    if feature_array=same
        Eleminate_Feature();
    end
end
    FS_GA_Out = GA_FS (data,200,100,0.8,0.1);
    [GA_FS(data,PopSize,Generation,SelRate,MutRate)]
    Results=Machine_Learning (FS_GA_Out);
end

```

As seen in Fig. 6, firstly, the initial population is created for the Parkinson's data set. New populations are created with genetic operators such as selection and mutation from this population. At this stage, the number of individuals in each population was determined as 200, the selection rate was 0.8, and the mutation rate was 0.1.

## 5. Results and Discussion

In this study, the Parkinson's disease classification from the spiral drawings drawn to the patients with Parkinson's disease is discussed. It is decided whether people with Parkinson's disease are drawn from spiral images. The results obtained were calculated according to the success parameters (Sensitivity, Specificity, Accuracy, Precision) in the literature.

Sensitivity, Specificity, Accuracy, Precision indices are used to evaluate the success of the diagnosis of Parkinson's disease. To calculate these performance indices, *True Positive* (TP) number of correctly predicted patients, healthy persons classified as Parkinson's disease *False Positive* (FP), the number of patients not classified as Parkinson's disease is *False Negative* (FN) and the number of people who are not classified as Parkinson's disease is correctly *True Negative* (TN). The definitions of these performance indices are:

$$Sensitivity = \frac{TP}{TP + FN}, \quad (5)$$

$$Specificity = \frac{TN}{FP + TN}, \tag{6}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{7}$$

$$Precision = \frac{TP}{TP + FP}. \tag{8}$$

The results were performed on a computer with an Intel Core i7 processor with a frequency of 2.8 GHz and 8 GB of RAM. The k value of the k-NN classification method is 1.

In this study, k-NN classification without feature selection (k-NN), Decision Tree classification without feature selection (DT), k-NN classification with genetic feature selection (GA-k-NN), Decision Tree classification with genetic feature selection (GA-DT) has been applied. The confusion matrices are given in Table 2. Results obtained in Table 2 validated by Leave One Out Cross-Validation method. The validation method ensures that the training and test data are selected with a certain procedure. Thus, the data obtained in this study can be obtained by everyone.

**Table 2.** Confusion matrices

		Actual Values	
		P	N
Predicted Values (k-NN)	P	45	10
	N	11	5
Predicted Values (DT)	P	54	12
	N	2	3
Predicted Values (GA-k-NN)	P	53	5
	N	3	10
Predicted Values (GA-DT)	P	56	0
	N	0	15

Table 2 shows the confusion matrices obtained as a result of classification. The success parameters calculated according to the equation (5-8) are given in Table 3.

**Table 3.** Classification results

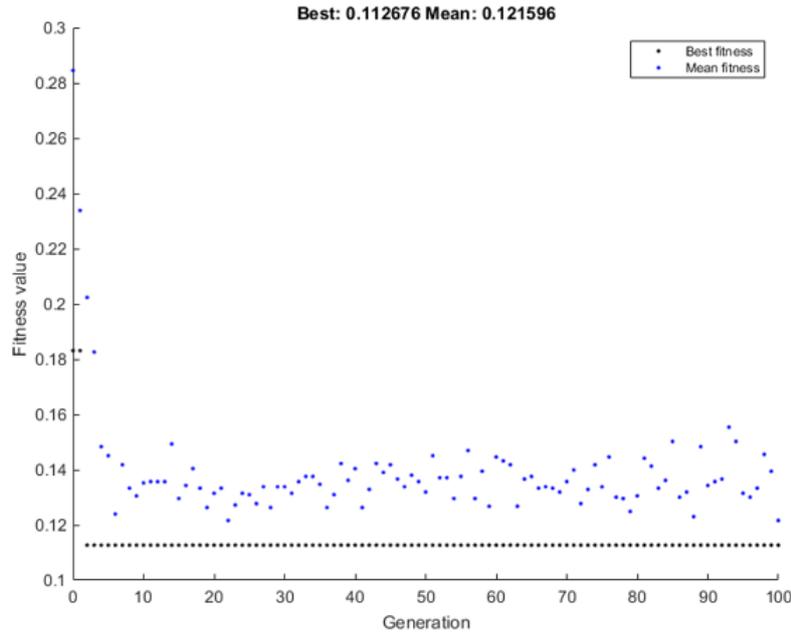
Classification Method	Feature Selection	Accuracy	Sensitivity	Specificity	Precision
k-NN	-	0,7042	0,8035	0,3333	0,8181
DT	-	0,8028	0,9642	0,2000	0,8181
GA-k-NN	GA	0,8873	0,9464	0,6666	0,9137
GA-DT	GA	1	1	1	1

According to Table 3, according to spiral drawings, the most successful condition was obtained by GA-DT method. Specifically, it can be said that feature selection processes contribute significantly to the classification success rate. Besides, when GA-DT classification success rates are considered, it is seen that all the samples are correctly predicted without an incorrect estimation. Table 4 shows the comparison of the processing times.

**Table 4.** Classification results

	Feature Selection	FeatureSelection Processing Time (second)	Classification Processing Time (second)	TotalTime (second)
k-NN	-	-	7.38	7.38
DT	-	-	42.50	42.50
GA-k-NN	GA	14340.66	1.94	14342.60
GA-DT	GA	26497.95	16.36	26514.31

In Table 4, it is seen that feature selection with GA has a significant negative impact on processing time. However, it is seen that the classification after the feature selection process is completed in a shorter time. While improving the classification performance with the genetic algorithm, the different best value and the average value of the generation are calculated in each generation. The generation based performance values for the k-NN classification are given in Fig. 7.

**Fig. 7.** k-NN classification error rate with GA feature selection.

As seen in Fig. 7, the lowest error rate was 0.112676, the generation average was 0.121596, and the number of generations was 100 in the operations performed with the GA feature selection and k-NN classification method. The generation-based performance values for the DT classification are given in Fig. 8.

As seen in Fig. 8, the lowest error rate was 0, the generation average was 0.0389671, and the number of generations was 51 in the operations performed with the GA feature selection and DT classification method.

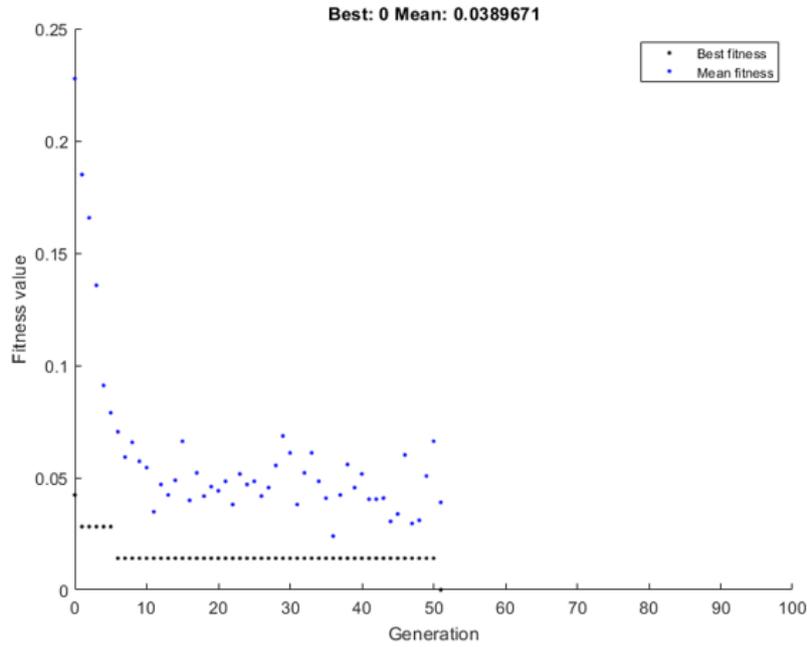


Fig. 8. DT classification error rate with GA feature selection.

## 6. Conclusion

Nowadays, early diagnosis the Parkinson's disease is of great importance. The difficulty in diagnosing Parkinson's disease increases the need for helpful tools for diagnosis. In this study, Parkinson's disease diagnosis was made by Parkinson's spiral test analysis. In addition, the Parkinson's spiral test was considered as a recognition problem, unlike studies in the literature. The proposed method was tested using the data set created in the Department of Neurology in Cerrahpasa Faculty of Medicine, Istanbul University. When the results are considered, it is seen that the results are successful.

When the classification success rates are examined, it is seen that the Decision Tree classification process with the genetic algorithm gives the best results in accuracy, sensitivity, specificity, precision parameters. Better results were obtained in the accuracy and sensitivity parameters of the classification method with the Decision Tree without the feature selection process.

If the processing times are examined, it is seen that the feature selection methods affect the total processing times negatively. It has been determined that while the duration of the feature selection process with the genetic algorithm is quite high, it reduces the classification time. Considering that the feature selection process with the genetic algorithm will be done once, the long processing time will not affect the test times. When a new sample is considered, tests will be made only on the features we have determined. It will have a positive effect when it is considered that it reduces the classification time even more due to reducing the number of features.

The number of features, which was 123,066 at the beginning, decreased to 60,954 in the process performed with the Genetic algorithm feature selection and k-EK classification method, and to 60,768 in the process performed with the Genetic algorithm feature selection and Decision

Tree classification method. While reducing the number of features reduces the processing times, it has led to an increase in classification success rates

In terms of time, it has been observed that feature selection methods have a negative effect on total processing time. But when the classification success parameters are examined, it can be said that feature selection methods contribute to success rates. In addition, successful results can be obtained with pattern recognition methods in the Parkinson's spiral test. The diagnosis of Parkinson's disease, which is very difficult to diagnose at an early stage, can be determined more effectively by this method.

In future studies, the usability of the spiral test used in the study can be investigated on the Parkinson's patients' monitoring. In addition, it can be researched that the drug interaction of Parkinson's patients can be measured with this method.

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