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Diagnostic Study for Neurodegenerative Disorders Based on Handwriting Analysis

Leila Soleimanidoust [1], Abdalhossein Rezai *[2], Hamideh Barghamadi [1], and Iman Ahanian [3]

[1] Department of Medical Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran.
[2] Department of Electrical Engineering, University of Science and Culture, Tehran, Iran.
[3] Department of Electrical Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran.

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Abstract
One of the most frequently acknowledged personal behavioral traits in the biometric system is the handwritten exam. Numerous fields, including e-health, psychological issues, medical diagnosis, and many more, can benefit from handwriting analysis. In this study, a handwriting-based computer diagnostic method for identifying neurodegenerative disorders is established. The suggested computer diagnosis system uses the *SFTA* feature extraction approach, and the findings are classified using *SVM*, *kNN*, and D-Tree algorithms. MATLAB R2021b and the handwritten tests gathered at Botucatu Medical School, So Paulo State University—Brazil—are used to assess the performance of the suggested computer diagnosis method. The best results were related to two models of classifier, the Optimizable model of *SVM* and *kNN*. The accuracy, sensitivity, and specificity are 89.2%, 88.3%, and 90.0% for *SVM* and 89.2%,90.0%, and 88.3% for *kNN* over the Meander handwritten exam. These results indicate that the use of the *SFTA* feature extraction method, *SVM* classification algorithm, and handwritten database in the proposed computer diagnosis system gives acceptable results.

Keywords: Diagnostic study, Feature Extraction, Handwritten Exam, Neurodegenerative Disorder, Prediction disease.

1. INTRODUCTION

Neurodegenerative disorders may severely affect handwriting, which is produced through a complex network of cognitive, kinesthetic, and perceptual motor skills [1].

***Corresponding Authors Email:** rezaie@acecr.ac.ir

The association between neurodegenerative illnesses and the characteristics used to define patients' handwriting has been studied extensively in several papers published in the fields of medicine and psychology using this framework for instance using a tablet to collect handwriting for the study [2] or a study on Arabic handwriting [3]. The initial stage in medical practice, a proper diagnosis, is essential for wise clinical judgment. Once people exhibit cognitive deficits that are worse than those that would be statistically expected given their age and educational level, neurodegenerative disorders like Alzheimer's [2], Parkinson's disease [4], and Multiple Sclerosis (MS) [5] are identified. Neurodegenerative disorders primarily affect the central nervous system and have an impact on movement, such as the degree of immobility and tremors. In order to identify these diseases, clinicians analyze the controlled movements of their patients, particularly their handwriting. They also use imaging, electroencephalography, blood testing, and lumbar punctures. Unfortunately, noninvasive and accessible early diagnosis such as handwriting exams is less applied. Observing motor movements may help identify a condition because research has revealed that people with neurodegenerative disorders have decreased movement control and poor spatial organization. Handwritten trace is considered as a movement under control. So, analysis of a patient's handwriting is a well-known way to diagnose neurodegenerative disorders [1-5]. Recent research ignores the complex interactions between potential multiple features. When combined with other features, weakly linked single features to the target class can frequently be utilized to increase classification accuracy [6]. It is crucial to show the intricate relationships between the features extracted from people's handwriting in order to predict cognitive state [7]. The conclusions and recommendations of the feature investigation conducted on the handwritten exams collected at Botucatu Medical School, So Paulo State University – Brazil, are presented in this paper[8].

The primary contribution of this research is the ability to diagnose neurodegenerative disorders from patient-drawn handwritten. *SFTA* feature selection has been used to identify the most discriminating traits for disease diagnosis. On both Spiral and Meander handwritten, the effectiveness of three classifiers—Support Vector Machine, K Nearest Neighbor, and D Tree Algorithm—has been examined. With an accuracy of 90.0%, the mutual information gain feature selection strategy in conjunction with *SVM* classifiers yields the greatest results.

The other parts of this essay are arranged as follows. Section 2 presents related works. Section 3 (Materials and Methods) discusses the design process for the dataset. Following is a description of the suggested method for extracting visual characteristics from handwriting assessments. The experimental findings and discussion are presented in Section 4, and the conclusions and suggested future research are presented in Section 5.

2. RELATED WORK

Numerous methods have been proposed to anticipate the presence of the disease at its primary stage because neurodegenerative diseases (NDDs) have a significant global impact. In 2013 [9], Radial Basis Function (RBF) and Multi-Layer Perceptron (MLP), two dissimilar forms of feed-forward networks, were used to identify patient data using Artificial Neural Networks (ANNs). A comprehensive review of the current computational methods used across the entire neurodegenerative spectrum has been published by Tautan, et al. [10]. In addition to offering a thorough examination of the numerous modalities and decision-making processes used for each disease, they have offered a taxonomy of the specific clinical aspects and the current computational approaches. In contrast to the fact that most machine learning techniques have weaknesses as a result of congenital comments, they enabled an interpretable diagnosis of NDDs [11]. In [12], The potential for predicting neurodegenerative disorders using handwriting signatures has been discussed by Pirlo, et al. With a bagging cart classification tree, the sigma-lognormal model has been taken into consideration for handwritten signature analysis and specific important features that are employed for the early diagnosis of neurodegenerative disorders.

Neurologists and medical facilities could use ANNs in automatic disease diagnosis systems because of the results, which showed that the RBF exhibits less accuracy than MLP. By identifying the similarity between the exam pattern and the patient's handwritten trace using the Structural Co-occurrence Matrix (SCM), De Souza, et al. [13] suggested a method in 2018 to diagnose disease. To evaluate this strategy and the patient's handwriting traces, numerous exam templates were developed and put to use. The Nave Bayes (NB), Optimum-Path Forest (OPF), and Support Vector Machine (*SVM*) classifiers were used collectively to apply each of the modifications. The results suggest that this method can assist in the diagnosis of Parkinson's disease (PD) with high *SVM* accuracy, 85.54% for spiral data and 82.23% for meander. In [14], Convolutional Neural Network (CNN), a deep learning approach used to extract information from handwritten tests, has been used to identify diseases. Particle Swarm Optimization (PSO), Bat Algorithm (BA), and Firefly Algorithm (FA) were used to enhance the CNN restrictions. When compared to spiral images, they prove that meandering images produce the greatest results. Tom Quisel and co. [15] noticed in 2017 that many variables might affect a character's health, making it challenging to anticipate a person's medical state. Wearable sensors and smart devices have been utilized to make it feasible to collect a few parameters with a minimal impact on people by passively and continually tracking actions and environmental factors. In 2011, neurodegenerative disease was identified using data mining methods [16]. In order to discover the classifier algorithm with the best accuracy while utilizing the Tanagra data mining tool, a study of the most recent knowledge detection techniques in databases employing data mining algorithms has been offered. The data mining project employed in this study is open-source. It's noticeable that the dataset's feature relevance was assessed before the classifiers were applied to it. In 2018, Wroge, et al. [17] suggested a diagnosis method built on voice recognition and machine learning. This system's goal is to examine how well it can accurately diagnose patients with disease by using supervised classification methods like deep neural networks. It was achieved that using some features such as noninvasive voice biomarkers, the disease diagnosis prediction technique is capable. A PD system prediction that was based on the Internet of Things (IoT) position in the medical field was introduced by novelists in [18]. Through the extraction of Kinematic Features (KF) from spiral handwritten drawings and classification using the AdaBoost classifier, Lamba R., et al. [19] offered a methodical strategy to identify disease in 2021, achieving 96.02% accuracy.

3. MATERIALS AND METHODS

This section presents the standard methods that are employed to resolve the problem that is being examined. The work scope is to consider the handwritten exam images as the input data (meander and spiral separately), at that point the *SFTA* method is used for extracting features. After feature extraction, three different algorithms, *SVM*, *kNN* and D-Tree, are employed in order to classification of results. This method is used two-time, first time for Meander exam and second time for Spiral exam. Figure 1 depicts the suggested system design.

Four basic pieces of the suggested system architecture are discussed in this section. The entire set of experiments was carried out using MATLAB R2021b on a machine with 4GB of RAM and a 3.20 GHz processor, it should be emphasized.

3.1. Handwriting Dataset

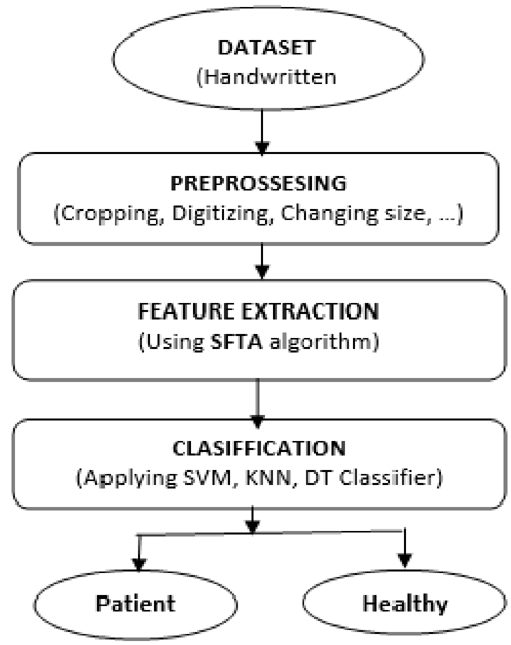

***Fig. 1. The proposed system architecture*.**

We utilize the handwriting images dataset presented in [8]. To build this handwriting images dataset of neurodegenerative disease, Pereira et al. in [8] have designed a protocol and collected handwriting exams with the purpose of describing individual aids at Brazil, the Sao Paulo State University, and the Faculty of Medicine of Botucatu. The idea behind the test was to ask a person to draw while they were taking a handwriting test, such as "meanders" in Figure 2 and "spirals" in Figure 4.

The applied dataset consists of screenshots from 92 people's handwriting evaluations separated into two groups: (i) The first group, known as the control group, conducts 18 examinations on healthy individuals. It consists of 6 men and 12 women; (ii) another group was made up of 74 exams of persons who had the disease; as a result, the name "patient group" was chosen for this group, which has 59 men and 15 women as subjects. As a result, 19.56% of the dataset is made up of control individuals, while 80.44% of the dataset is made up of patient individuals. Although the dataset's distribution is skewed, adding more control people than patients will allow for similar results. The control group consisted of 2 left-handed people and 16 right-handed people, with an average age of 44.22±16.53 years. Regarding the patient group, there have been 69 right-handed people with an average age of 58.75±7.51 years and 5 left-handed people. As a result, the dataset is not age-skewed, providing an intriguing scenario for learning. It should be taken into account that the dataset was sufficiently inclusive to include a 38-year-old male patient. 240 photos from handwriting examinations are chosen from the dataset and divided into four groups. The Meander Control Set (CS) contains 60 images with samples displayed in subfigures 2(a), 2(b), 2(c), and 2(d). The Meander Patient Set (PS) has 60 photos with samples displayed in subfigures 3(a), 3(b), 3(c), and 3(d). The third set includes 60 photos of the Spiral Control Set with samples shown in 4(a), 4(b), 4(c), and 4(d). while the fourth set includes 60 images of the Spiral Patient Set with some examples displayed in 5(a), 5(b), 5(c), and 5(d).

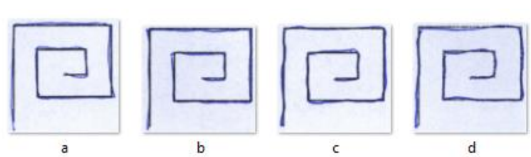

Fig. 2. Meander Control Images Samples.

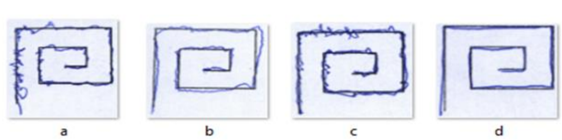

Fig. 3. Meander Patient Images Samples.

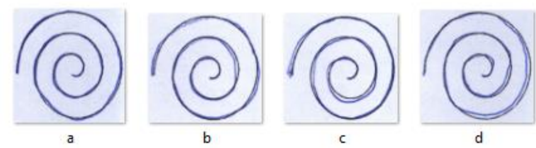

Fig. 4. Spiral Control Images Samples.

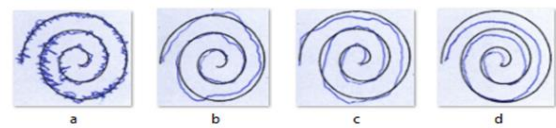

Fig. 5. Spiral Patient Images Samples.

Each subject was asked to complete a form with various activities, such as drawing circles, spirals, and meanders, in order to create the dataset. Each person had to complete six different tasks, each of which involved repeating a number of actions in line with specific drawings. The forms have been scanned after being filled out in order to further extract spirals and meanders. Each drawing is cropped to or almost to its minimum bounding box during this manual process. The focus of the image analysis will be on creating spirals and meanders that follow the template. We alter the size of each image to 640×480 and the image format to PNG (from JPG) to achieve better results when using MATLAB algorithms to analyze photos and extract features. We then separated the cropped photos into four groups, each consisting of 60 patient spiral images, 60 control spiral images, 60 patient meander images, and 60 control meander images. For more technical information regarding the dataset's arrangement, the reader may go to the HandPD home page [20].

3.2. Preprocessing

Choosing a valid dataset [8] which contained handwriting exam images from both meanders and spirals and the test was the first step. Images from digital handwritten examinations have been adjusted. We changed the size of each image to 640×480 and also the format of the images into PNG (from JPG). Soon after, we divide the cropped images into 4 groups: 60 patient spiral images, 60 control spiral as well as 60 patient meander images, and 60 control mender images. With these changes over the handwritten exam, the proposed approach was able to extract both the handwritten trace and the template from each exam automatically.

3.3. Feature Extraction

The segmentation-based fractal texture analysis (*SFTA*) method [۲۱] is used in this paper to extract features. The *SFTA* algorithm is shown in Figure 6 to aid with comprehension.

In fact, a gray level image and the number of threshold levels must be used in order to run the *SFTA* algorithm. Two essential steps are taken into consideration when the *SFTA* algorithm is implemented. Applying the OTSU multilevel thresholding algorithm to the gray level image with the total number of threshold levels yields the multi-threshold levels in the first phase. The vector T $=t_1, t_2, t_3, ..., t_n$ will be used to store the discovered n thresholds. To the vector $T_A = (\mathrm{Min}_{\mathrm{GrayValue}}, t_1), (t_1, t_2), \dots (t_{n-1}, t_n)$, these thresholds are inserted in pairs. The threshold levels will be placed in the vector T_B as $T_B = (t_1, \mathrm{Max}_{\mathrm{GrayVal}}), (t_2, \mathrm{Max}_{\mathrm{GrayVal}}), \dots, (t_n, \mathrm{Max}_{\mathrm{GrayVal}})$ after T_A is finished.

The gray level image is converted into binary images by applying these threshold pairs in an unconnected manner on the gray image using the Two Threshold Binary Decomposition (TTBD) technique.

$$I_b(x,y) = \begin{cases} 1, if\ t_{lower} < I_g(x,y) \leq t_{upper} \\ 0, \quad\quad otherwise \end{cases} \tag{1}$$

Thus, a variety ofsubbinary images is created from our participation image. I_b: $binary\ image$, I_g: $gray\ image$, t_{lower} and t_{upper} values stand for threshold pairs.

By ingesting these binary images, the features will be retrieved in the second stage.

$$\Delta(x,y) = \begin{cases} 1,\ if \exists\ (\acute{x},\acute{y}) \in\ N_8[(x,y)]: \\ I_b(\acute{x},\acute{y}) = 0 \wedge I_b(x,y) = 1 \\ 0, \quad\quad Otherwise \end{cases} \tag{2}$$

The binary picture border is represented by $\Delta\ (x,\ y)$, and $N_8\ [(x,\ y)]$ stands for the eight pixels connected to (x, y). Each of the generated images has edge pixels, and

Feature Extraction Algorithm

Require: Grayscale image I and number of thresholds n_t.
Ensure: Feature vector V_{SFTA}.
1: T $\longleftarrow$ **Multi-Level Otsu** $(\boldsymbol{I}, \boldsymbol{n_t})$
2: $T_A \longleftarrow \{\{t_i, t_{i+1}\}: t_i, t_{i+1} \in T, i \in [1..|T|-1]\}$
3: $T_B \longleftarrow \{\{t_i, n_t\}: t_i \in T, i \in [1..|T|]\}$
4: $i \longleftarrow 0$
5: **for** $\{\{t_l, t_u\}: \{t_l, t_u\} \in T_A \cup T_B\}$ **do**
6: $I_b \longleftarrow$ **Two Threshold Segmentation** (I, t_l, t_u)
7: $\Delta(x,y) \longleftarrow$ **Find Borders** (I_b)
8: $V_{SFTA}\ [i] \longleftarrow$ **Box Counting** (Δ)
9: $V_{SFTA}[i+1] \longleftarrow$ **Mean Gray Level** (I, I_b)
10: $V_{SFTA}[i+2] \longleftarrow$ **Pixel Count** (I_b)
11: $i \longleftarrow i+3$
12: **end for**
13: **return** V_{SFTA}

Fig. 6. SFTA Extraction Algorithm [22].

their total number of pixels is counted. The edge pixel coordinates will be used to calculate the average gray-level values in the gray-level images. The Fractal dimension information is obtained by applying the box-counting technique for each binary sub-image, after which the feature vector is created [22-24]. The *SFTA* algorithm is shown in Figure 6 to aid with comprehension.

3.4. Classification Algorithm

3.4.1. *Decision Tree (DT)*

The Decision Tree is a supervised learning method that may be applied to classification and regression issues; however, it works best when dealing with the first type. It is a tree-structured classifier, where internal nodes stand in for the dataset's features, branches for the decision-making processes, and each leaf node for the result [25, 26].

3.4.2. *Support Vector Machine (SVM)*

An effective supervised machine learning technique for classification and regression problems is the *SVM*. The imposition detection system, protein structure prediction, handwriting recognition, and detecting steganography in digital photos are a few examples of common applications of the *SVM* method. The *SVM* algorithm's goal is to develop the optimal mark or decision borderline that can classify an n-dimensional space, making it easier in the future to assign fresh data points to the appropriate category. A hyperplane is referred to as the optimal choice boundary in this situation [25, 26].

3.4.3. *k-Nearest Neighbor (kNN)*

One of the simplest machine learning algorithms, the k-Nearest Neighbor is based on the supervised learning method. The *kNN* method places the new case in the category that is most similar to the extant categories based on the assumption that the new case/data and the existing cases are comparable. The *kNN* algorithm saves all the information that is available and categorizes new data points based on similarity. This means that using the *kNN* method, fresh data can be quickly and accurately sorted into a suitable category [25, 26].

4. EXPERIMENTAL RESULT

4.1. Evaluation of Meander Test Result

k-Nearest Neighbor, *Decision Tree* (*DT*), and *Support Vector Machine* (*SVM*) classifier approaches have all used the extracted features from *SFTA* over the meander images as an input.

Table 1 shows the results of applying the aforementioned classification techniques to the features that were taken from meander images utilizing such classifiers. The findings demonstrate that although applying various classifiers to the *SFTA* output yields a range of values, depending on the classifier type, we can achieve high values for accuracy, sensitivity, specificity, and precision. The Validation *ROC Curve* is another significant measured parameter. When distinguishing between patients and healthy people, diagnostic tests' abilities can be assessed using the area under the curve (*AUC*) and the *Receiver Operating Characteristic* (*ROC*), which stands for *Receiver Operating Characteristic*[27]. Therefore, and due to the importance of the related *ROC* of each used classifier, figure 7 is a compressed picture including all *Validation ROC* curves plotted during the experimental try. With the accuracy of *Coarse kNN* (the lowest measure and equal to 50%) it was predictable that the worse state would be for its validation *ROC* as well.

4.2. Evaluation of Spiral Test Result

k- Nearest Neighbor, Decision Tree (*DT*), and *Support Vector Machine* (*SVM*) classification approaches have all used the extracted features from *SFTA* over the spiral images as input.

Similar to the previous section, table 2 shows the results of applying the earlier classification techniques to features that were derived from spiral pictures using such classifiers. The findings show that although applying a different classifier to the *SFTA* output produces varied values, depending on the classifier type, we can reach high values for accuracy, sensitivity, specificity, and precision.

The same as Meander's result, figure 8 is a compressed picture including all *Validation ROC* curves plotted during the experimental try. Again, the lowest and worst state would be for *Coarse kNN* validation *ROC* as well.

Table 1. The measured values over Different Classifiers- Meander Handwritten.

Classifier	Model	Accuracy	Sensitivity	Specificity	Precision
Decision Tree	Fine Tree	75.0%	76.6%	73.3%	74.1%
	Medium Tree	75.0%	76.6%	73.3%	74.1%
	Coarse Tree	78.3%	83.3%	73.3%	75.7%
	Optimizable Tree	84.2%	85.0%	83.3%	83.6%
Support Vector Machine	Fine Gaussian SVM	75.0%	92.5%	56.6%	65.7%
	Linear SVM	82.5%	86.6%	78.3%	80.0%
	Quadratic SVM	85.0%	85.0%	85.0%	85.0%
	Qubic SVM	85.0%	86.6%	83.3%	83.8%
	Qoarse Gaussian SVM	81.7%	85.0%	78.3%	79.6%
	Optimizable SVM	89.2%	88.3%	90.0%	89.8%
k Nearest Neighbor	Fine kNN	85.8%	85.0%	86.6%	86.4%
	Cosine kNN	83.3%	86.6%	80.0%	81.2%
	Coarse kNN	50.0%	97%	97%	50.0%
	Weighted kNN	83.3%	85.0%	81.6%	82.2%
	Optimizable kNN	89.2%	90.0%	88.3%	88.5%

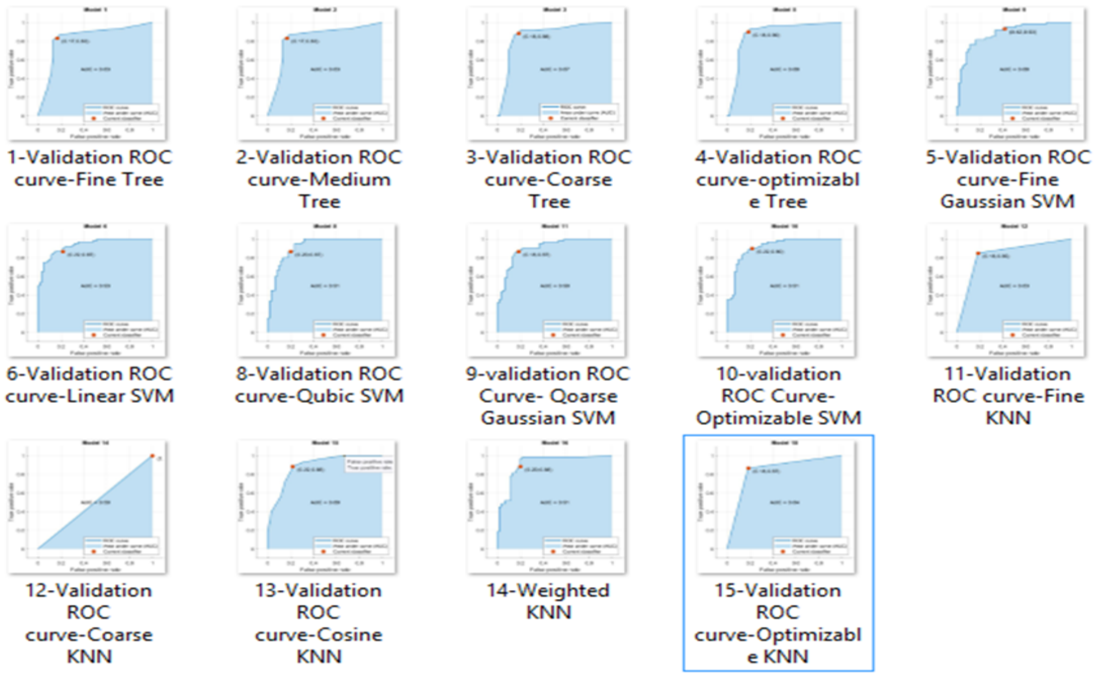

Fig. 7. Meander Handwritten- Validation ROC Curve.

Table2. Measured Values over Different Classifiers- Spiral Handwritten.

Classifier	Model	Accuracy	Sensitivity	Specificity	Precision
Decision Tree	Fine Tree	72.5%	73.3%	71.6%	72.1%
	Medium Tree	72.5%	73.3%	71.6%	72.1%
	Coarse Tree	75.8%	76.6%	75.0%	75.4%
	Optimizable Tree	77.5%	78.3%	76.6%	77.0%
Support Vector Machine	Fine Gaussian SVM	75.0%	81.6%	68.3%	72.0%
	Linear SVM	80. 0%	86.6%	75.8%	76.4%
	Quadratic SVM	86.7%	91.6%	81.6%	83.3%
	Qubic SVM	82.5%	86.6%	78.3%	80.0%
	Qoarse Gaussian SVM	80.8%	85.0%	76.6%	78.4%
	Optimizable SVM	81.7%	86.6%	76.6%	78.7%
K Nearest Neighbor	Fine kNN	80.8%	83.3%	78.3%	79.3%
	Coarse kNN	50.00%	98%	98%	50.0%
	Cosine kNN	80.8%	93.3%	68.3%	74.6%
	Weighted kNN	83.3%	93.3%	73.3%	77.7%
	Optimizable kNN	86.7%	90.0%	83.3%	84.3%

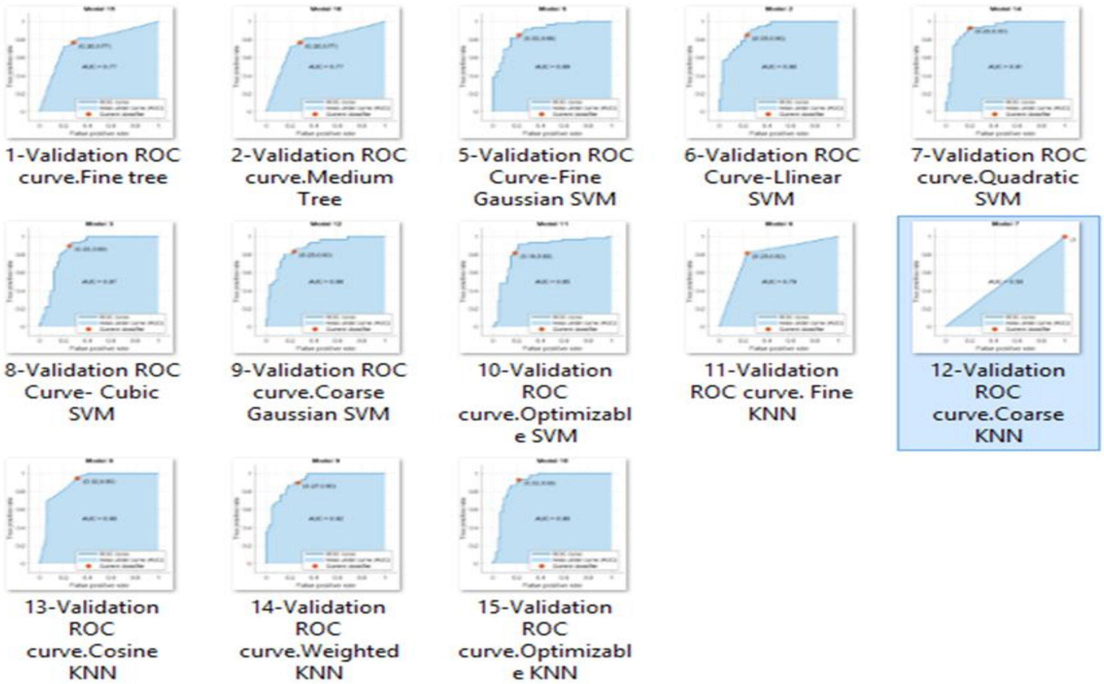

Fig. 8. The Spiral Handwritten- Validation ROC Curve.

Table3.Comparison of Different Classifications and Data Set.

Classifiers		Meander Accuracy	Spiral Accuracy
Decision Tree	Fine Tree	75.0%	72.5%
	Medium Tree	75.0%	72.5%
	Coarse Tree	78.3%	75.8%
	Optimizable Tree	84.2%	77.5%
Support Vector Machine	Fine Gaussian SVM	75.0%	75.0%
	Linear SVM	82.5%	80.0%
	Quadratic SVM	85.0%	86.7%
	Qubic SVM	85.0%	82.5%
	Qoarse Gaussian SVM	81.7%	80.8%
	Optimizable SVM	89.2%	81.7%
k Nearest Neighbor	Fine kNN	85.8%	80.8%
	Coarse kNN	50.00%	50.00%
	Cosine kNN	83.3%	80.8%
	Weighted kNN	83.3%	83.3%
	Optimizable kNN	89.2%	86.7%

5. CONCLUSION AND FUTURE WORK

Solving the problem of neurodegenerative disease recognition by more noninvasive and less expensive way was the main purpose of this paper. Using new methods such as machine learning and computer vision techniques has been the second important aim that we were able to achieve. The main challenge in this sort of study is related to access to a valid dataset. By utilizing a genuine dataset that includes handwriting exam photos from both the spirals and meanders tests, we can resolve this issue. They were removed from digitally preserved handwriting tests. A pipeline was suggested to address the issue of learning from unregistered photos. The suggested method was able to automatically extract the handwritten trace and the template from each exam for subsequent feature extraction and categorization. The results of the experiment lead us to believe that meandering exams are more informative than spiral exams (a comparison of their correctness is provided in Table 3) and that the posture of the latter is more difficult because of the curves in its design. Additionally, the results did not seem to be improved by combining the two strategies. The dataset's high degree of changeability, which includes people with the disease in its very early stages and makes it challenging to diagnose, has been the main issue. Future research should aim to add additional samples to the dataset and develop new features that can more effectively distinguish between patients and controls.

Future research will focus on gathering more information from various neurodegenerative patients and using different categorization approaches to automatically diagnose the condition based on the suggested criteria. More research will be done to determine whether training on entirely novel, straightforward handwriting tasks improves accuracy percentage and other crucial metrics. In a similar vein, further research will assess if extended training on complex form tasks is beneficial as well as deploy such electronic equipment to enable dynamic and online analysis of the results.

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