Diagnostic Study for Parkinson'S Disease Based on Handwriting Analysis Using Computational Intelligence Techniques

Yomna M. Elbarawy, Wafaa A. Ghonaim, and Abeer S. Desuky

***Abstract*—Parkinson's disease (PD) is a long-term disease that mainly influences the central nervous system and thus affects movement, such as inability to move rigidity, and tremors. So, analysis of patients' movements under control, especially handwriting, is a helpful way to diagnose Parkinson's disease. Diagnosis, as the first step in medical practice, is critical to clinical decision-making. This paper uses multiple computational intelligence classification techniques such as Decision Tree, Naive Bayes, Support Vector Machine, and Random Forest to investigate the existence of the PD. Also, Convolutional Neural Network (CNN) and the Best First (BF) strategy are used as feature extractors. These techniques are applied over both Meander and Spiral data and some selected traits derived from the patient's handwriting during the handwritten exam. The available HandPD dataset has been used with both its images and selected attributes. The CNN is used for the feature extraction process across the images of the used dataset. Whereas, the BF search strategy is used to extract features based on the changes between the handwritten trace and the exam template features combined with instances resampling. Compared with other well-known diagnostic systems, the proposed one has the highest recognition rate.**

***Index Terms*—Parkinson's disease, Random forests, Handwritten trace, Best first search, Convolutional neural networks, Data resampling.**

I. Introduction

MEDICAL diseases diagnosis takes an important consideration in recent years specially the nervous system infection such as Alzheimer [1], Parkinson's disease, and epilepsy that are mainly affect the human brain [2]. Normally, the infection causes of Parkinson's disease are anonymous, but assumed to include mutually genetic and environmental factors. Parkinson's disease can affect person's speech, movement, cognition, and dexterity. Naturally, the people of age more than 60 and about 1% are affected. When PD shows up on individuals of age less than fifty, it is called young onset PD. Males are more frequently affected than females at a ratio of around three to two [3]. Parkinson's disease patients are suffering from exhibit disabilities of previously learned motor skills, such as handwriting, so handwriting can be considered as a main pointer for developing an automatized diagnostic tools [4]. Handwritten trace is considered as drawing which done by the patient during handwritten exam performing. Handwriting exams can be done by using paper or using other advanced tools as a smartphone or even digitizers. All these exams types have some benefits for feature extraction. However, the extraction of the paper features is convoluted, and has some errors in the printing process and also suffers from lack of clarity in the information [5]. Diagnosis and treatment in some cases are reported wrong due to clinical diagnosis being done mostly by a doctor's expertise, so the use of classification systems in medical diagnosis is increasing gradually [6].

This study investigates an approach for distinguishing between people with and without Parkinson's disease; it compares the patient's handwriting trace and handwriting templates to calculate the features or directly process the scanned images of the handwritten trace. Since feature extraction aims to extract the important features in order to increase the classification accuracy [7], this investigation uses two different methods. The first method is the CNN and the second is the Best First (BF) search strategy. Both methods were used to select the best subset of features to apply multiple classification algorithms to them. Various classifiers have been applied to predict the PD based on the earlier two methods of feature extraction. As a result of this investigation, the RF classifier gives the highest accuracy for diagnosing Parkinson's disease using the BF feature extraction method combined with instance resampling.

The rest of this paper is organised as follows. Section II has preliminaries including related work and some details about the RF classifier as it gives the highest accuracy. Section III explains the work methodology, including the used dataset, its features, the proposed approach, and the used performance measures. The experimental results and comparison with other existing methods are illustrated in Section IV. Finally, the conclusion is introduced in section V.

II. Preliminaries

This section briefly illustrates other authors related work and some literature about the Random Forest (RF) classifier.

A. Related work

Millions of people around the world are affected by Parkinson's disease, and various approaches have been proposed to predict the existence of the disease at an early stage. In 2013, Artificial Neural Networks (ANNs) were used to classify Parkinson's disease patients' data using different types of feed-forward networks, Radial Basis Function (RBF) and Multi-Layer Perceptron (MLP) [8]. The results

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concluded that RBF displays less accuracy than MLP, so neurologists and medical centres can use ANNs in automatic disease diagnosis systems. In 2018, De Souza, et al. [5] proposed an approach to diagnose Parkinson's disease by determining the similarity relationship between the exam template and the patient's handwritten trace using the Structural Cooccurrence Matrix (SCM). Various exam templates were used to evaluate this approach and the patient's handwritten traces. Each of the variations was used collectively with the Naïve Bayes (NB), Optimum-Path Forest (OPF) and Support Vector Machine (SVM) classifiers. The results deduce that this approach is capable of helping in the diagnosis of PD achieving high accuracy with the SVM (85.54% for spiral data and 82.23% for meander).

In [9] the identification of Parkinson's disease is based on the deep learning technique of Convolutional Neural Network (CNN) which is used for extracting the features from handwritten exams. CNN parameters are optimised using Particle Swarm Optimization (PSO), Bat Algorithm (BA) and the Firefly Algorithm (FA). The paper concluded that the best results are obtained for meanders images compared with spiral images. There is a vast range of factors that may influence an individual's health, so there is difficulty in predicting a person's disease status. Wearable sensors and smart devices help in capturing a few factors with a minimum burden on users by passively and continuously tracking behaviours and environmental factors [10]. In 2011, data mining algorithms were used to identify Parkinson's disease [11]. A survey of most current algorithms of knowledge discovery in databases using data mining algorithms is provided. It is aimed to find the classifier algorithm which has the best accuracy using the Tanagra data mining tool. An open-source project for data mining is used. Firstly, the feature relevance on the dataset is done, and then the classifiers are implemented on the dataset. In 2018 Wroge, et al. proposed a diagnosis system for Parkinson's disease based on machine learning and voice recognition [12]. This system studied the efficiency by using some supervised classification algorithms, such as deep neural networks, to perfectly diagnose people with the disease. It concluded that the disease diagnosis prediction process is promising through using only some features as noninvasive voice biomarkers. Authors in [13] introduced a PD system prediction which based on the platform of the Internet of Things (IoT) in the environment of health. In 2021 Lamba R., et al. proposed a systematic approach to diagnose Parkinson's disease through Kinematic Features (KF) extracted from spiral handwritten drawings and classification through the AdaBoost classifier, achieving 96.02% accuracy [14].

B. Random forest classifier

The RF classifier aids the automatic identification of Parkinson's disease, and achieves high accuracy results compared with other applied classification algorithms. RF was initialized by Breiman as a powerful and new statistical classifier [15]. It has some advantages compared to other classifiers such as the classification accuracy is very high; can determine variable importance; capability for performing several functions including classification, regression, unsupervised learning, and survival analysis [16], [17], [18]. RF is a collection of tree predictors, each one of them related to a random vector values which are independent sampled and with the same spread for all forest trees [19]. Random forests are a kind of method which creates predictions by considering the average over the numerous independent base models predictions. The framework of the random forests has an advantage of being a common purpose of regression and classification. A random forest with m trees is considered as a classifier involving a group of randomized base tree classifiers $gn(x, Z1), ..., gn(x, Zm)$ where $Z1, ..., Zm$ are identically distributed random vectors, independent conditionally on X and Y. A random forest is also considered as a collection of tree structured classifiers $h(x, \theta k), k = 1, ...$ such that the θk are independent distributed random vectors [6].

III. Methodology

This section introduces the used dataset, in addition to the methodology that is used to design the general approach as well as the features-based classification.

A. HandPD Dataset

The writing of Parkinson's patients is frequently unclear and smaller than that of non-Parkinson's patients due to their slowness and minimised movement amplitudes. Pereira et al. in [20] recently built a dataset and are concerned with handwriting images that were acquired during handwriting exams that aim to describe individual skills. The concept of the exam is done by asking a person to do some drawing, such as drawing "meanders" as in Figure 1, and "spirals" as in Figure 2, performing the handwriting test. The HandPD dataset contains 736 images from handwriting exams which are split into two sets: The first set called Control Set (CS), contains 144 images where samples are shown in subfigures 1(a), 1(b), 2(a) and 2(b) and the second, called Patient Set (PS), contains 592 images where samples are shown in subfigures 1(c), 1(d), 2(c) and 2(d). The Parkinson's HandPD database used in this study was collected at Brazil, the Sao Paulo State University and Faculty of Medicine of Botucatu.

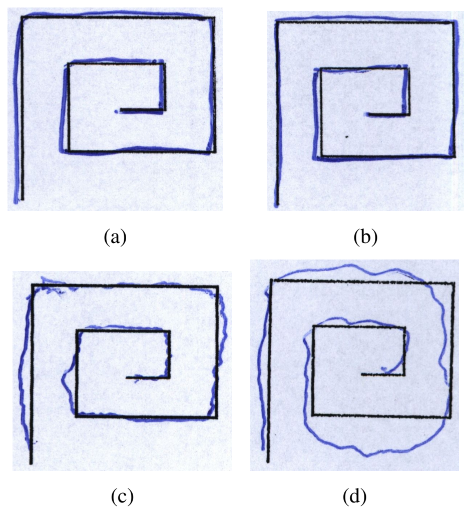
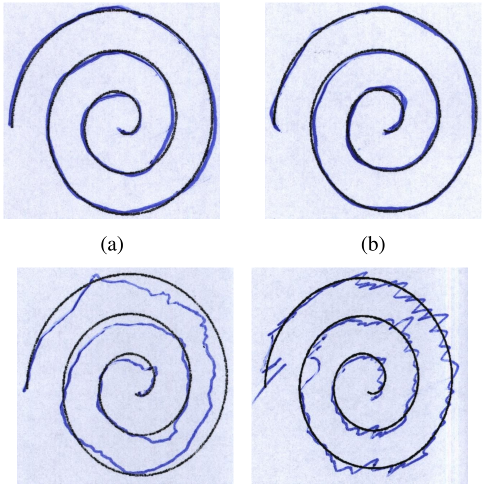


Fig. 1. Meander images samples.



(a) (b)

(c) (d)

Fig. 2. Spiral images samples.

B. The dataset features

The HandPD dataset contains 9 features which are based on the changes between the Handwritten Trace (HT) and the Exam Template (ET), which are listed below [20]:

1. RMS (Root Mean Square): The average square root of the sum of squares of the difference in HT and ET radius, calculated as in Equation 1.

$$RMS = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(r^i_{HT} - r^i_{ET})^2} \quad (1)$$

Where n denotes the number of drawn points for each HT and ET, and r^i_{HT} and r^i_{ET} represent the HT and ET radius, which is primarily the length of the straight line connecting the i^{th} point to the center of the spiral or meander.

2. The greatest change between ET and HT Equation 2.

$$\Delta max = argmax(\sum_{i=0}^{n}|(r^i_{HT} - r^i_{ET})|) \quad (2)$$

3. The smallest change between ET and HT radius Eq. 3.

$$\Delta min = argmin(\sum_{i=0}^{n}|(r^i_{HT} - r^i_{ET})|) \quad (3)$$

4. The standard deviation of the difference between ET and HT radius.
5. Mean Relative Tremor (MRT) calculated as in Equation 4

$$MRT = \frac{1}{n-d}\sum_{i=d}^{n}(r^i_{ET} - r^{i-d+1}_{ET}) \quad (4)$$

6. Greatest HT radius MAX_HT.
7. Smallest HT radius MIN_HT.
8. Standard deviation of HT radius (STD_HT).
9. The number of times the difference between ET and HT radius changes from negative to positive, or vice-versa.

C. Proposed approach

This subsection presents the general approaches used to solve the issue under investigation. The scope of work has two directions depending on the input data type. The first direction has images for the input data (spiral and meander), then the CNN is used as a feature extractor [21], [22]. The used network architecture is illustrated in **Table** II which contains the CNN architecture layers. The second column of the table has names for the operations in each layer generated using the Matlab platform. It consists of 12 layers including one imageinput layer having images of size 600x600, two convolutional layers with a number of convolutions 12 and 36, respectively, two max pooling layers having a kernel size of 2x2 and one Fully Connected (FC) layer. The second direction has the extracted features by the authors in [20] during the handwritten exam (illustrated earlier in section 3.2) as input data, and some of the important features are selected based on the BF strategy. After that, the extracted features are resampled. This technique aims to reduce the gap between the two classes' instance numbers by generating new synthetic instances from the minority class (oversampling) while removing some instances from the majority class (undersampling). Finally, the patient's case (CS or PS) is classified based on multiple classification methods. The flow diagram of the proposed two approaches is shown in Figure 3. **Table** I shows the original number of HandPD dataset instances, which indicates the imbalance between the two classes CS and PS. The instance resample (oversampling) technique has been used to solve this misbalancing problem.

TABLE I
NUMBER OF HANDPD DATASET INSTANCES.

Dataset		**#CS**	**#PS**
Meander	Original	72	296
	Resampled	156	212
Spiral	Original	72	296
	Resampled	156	212

D. Performance measures

Since classification accuracy in Equation 5 alone is typically not enough information to validate algorithms' performance, three other metrics (Precision Equation 6, Recall Equation 7, and F1-score Equation 8) were used to test the performance of the proposed approaches. Where, TP represents the True Positive rate, TN represents the True Negative rate, FP is the False Positive rate, and FN is the False Negative rate of classified examples by the considered learning technique.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$Percision = \frac{TP}{TP + FP} \quad (6)$$

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

$$F1 - score = \frac{2TP}{2TP + FP + FN} \quad (8)$$

IV. EXPERIMENTAL SETUP AND RESULTS

All experiments were conducted using Matlab R2015a on a computer equipped with 6GB RAM and 2.20

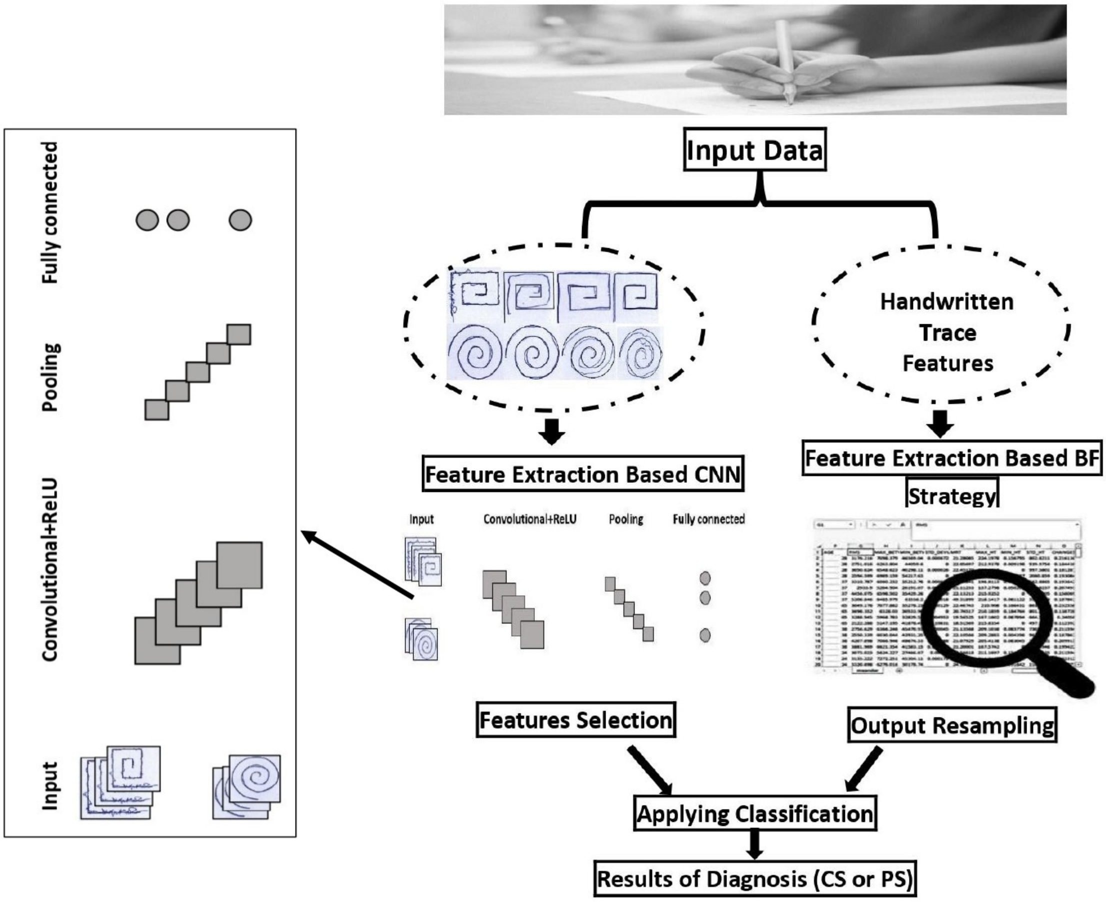


Fig. 3. The system architecture.

TABLE II
THE USED CNN ARCHITECTURE.

Layer No.	Name	Type	Description
1	'imageinput'	Image input	600x600x3 images with zero center normalization
2	'conv_1'	Convolutional	Convolutions numbers 12 7x7x3 with stride [1 1] and padding [1 1 1 1]
3	'batchnorm_1'	Batch Normalization	Batch normalization with 12 channels
4	'relu_1'	ReLU	Replaces every negative pixel values in the feature map by zero value
5	'maxpool_1'	Max pooling	max pooling with kernel size 2x2, stride [2 2] and padding [0 0 0 0]
6	'conv_2'	Convolutional	Convolutions numbers 36 7x7x12 with stride [1 1] and padding [1 1 1 1]
7	'batchnorm_2'	Batch Normalization	Batch normalization with 36 channels
8	'relu_2'	ReLU	Replaces every negative pixel values in the feature map by zero value
9	'maxpool_2'	Max pooling	max pooling with kernel size 2x2, stride [2 2] and padding [0 0 0 0]
10	'fc'	Fully connected	The output unit activation of the network is made
11	'softmax'	Softmax	The Softmax function calculates the probability distribution of the two different possible outcomes
12	'classoutput'	Classification output	cross entropy execution with classes 'CS' and 'PS' to indicate the distance between the experimental output and the expected one

GHZ processor speed. Instances resample (oversampling) technique has been applied using the WEKA tool.

This research investigates the diagnosis of Parkinson's disease with two approaches. The first one applies the CNN architecture in **Table** II directly over 120 selected images from the HandPD dataset. 60 images of the spiral and 60 for meander handwriting exams. Each set has 10 images for training and testing the Control Set (CS) and 20 images for training and testing the Patient Set (PS). All executions were carried out under 30 epochs. The extracted features from the FC layer are imported as an input to different classifiers, including the Softmax, Decision Tree (DT), Naïve Bayes (NB), Support Vector Machine (SVM), and RF. **Table** III illustrates the performance measures values of applying the earlier classification methods over extracted features from the spiral images using the CNN. The results indicate that using the SVM classifier over the output of the FC layer gives the highest values, 95% for accuracy, 96.5% for precision, 92.5% for recall and 94.5% for F1-score measure. **Table** IV illustrates the performance measures values of applying the earlier classification methods over extracted features from the meander images using the CNN. The results indicate that using the SVM classifier over the output of the FC layer gives the highest values, 93.3% for accuracy, 95% for precision, 95% for recall and 95% for F1-score measure.

Since CNNs achieve better results at the cost of higher computing and memory requirements [23], a second approach is presented, uses the selected features from [20] as input data and uses the BF technique for feature extraction. The earlier classification methods are applied once over the full data without applying the feature extractor and the other over the reduced data after applying the feature extractor. All training and validation subsampling were done using the 10 fold cross validation technique.

Table V shows the accuracy of applying DT, NB, SVM, and RF classifiers over reduced data after using the BF technique and over full data without using the BF technique for both datasets (meander and spiral). All classifiers give better accuracy over the reduced data than over the full data, except in the case of applying the SVM. The RF gives the highest accuracy over the reduced data, 95.4% for both meander and spiral data. The DT gives the highest accuracy over the full data, 94.8% for both meander and spiral data. **Table** VI displays the precision values obtained by applying DT, NB, SVM, and RF classifiers over reduced data and full data for both datasets (meander and spiral). All classifiers give better accuracy over the reduced data than over the full data, except in the case of applying the SVM and RF. The RF gives the highest precision value over the reduced data, 96.6% for meander and 95.9% for spiral data. Also, the RF gives the highest precision value over the full data, 95.3% for meander and 96.8% for spiral data. **Table** VII shows the recall measure values of applying DT, NB, SVM, and RF classifiers over reduced and full data for both datasets (meander and spiral). All classifiers give a better recall value over the reduced data than over the full data except in the case of applying the SVM over spiral data. The RF gives the highest recall value over the reduced and full data, 89.2% for meander and 88.7% for spiral data. But the DT gives the highest precision value over the full data, 88.4% for meander and 86.1% for spiral data.**Table** VIII displays the F1-score measure values obtained by applying DT, NB, SVM, and RF classifiers over reduced and full data for both datasets (meander and spiral). All classifiers give better values over the reduced data than over the full data, except in the case of applying the SVM over spiral data. The RF gives the highest recall value over the reduced and full data, 92.5% for meander and 92.4% for spiral data.

Table IX shows the accuracy, precision, recall, and F1-score for applying DT, NB, SVM, and RF classifiers over meander and spiral datasets after using the BF technique combined with the instances resample technique. The overall results indicate that applying the resampling technique enhances the results more than it was, especially with applying the RF classifier, since it achieves the highest measures values. While using meander dataset, the RF gives 98.65%, 98.68% and 97.41% for accuracy, precision, and recall, respectively. also achieves 99.19%, 99.04% and 98.62% for accuracy, precision and recall respectively, while using the spiral dataset.

Random Forest algorithm uses many classification trees to analyse a dataset and then combines the predictions from all the trees. The algorithm begins with the selection of many. Figure 4 and Figure 5 show the variation of random decision forest performance accuracy with the number of trees in the forest from 1 to 100 trees applied to the full, selected features and the resampled features of the spiral and mender data sets , respectively. It is clear that the performance accuracy increases with the number of trees for the first 60 trees, after which it tends to be stable. Also, the figures show that RF gives better performance accuracy with the resampled features from both datasets than with the full datasets.

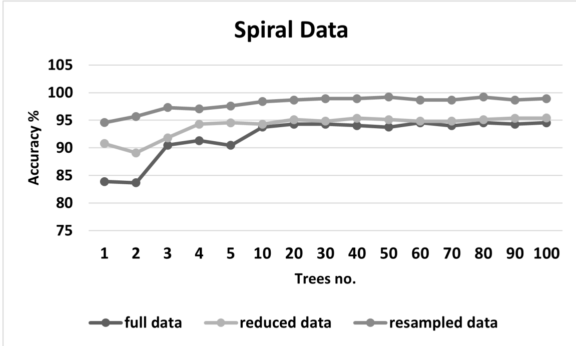


Fig. 4. The variation of random decision forest performance accuracy with the number of trees in the forest in case spiral data.

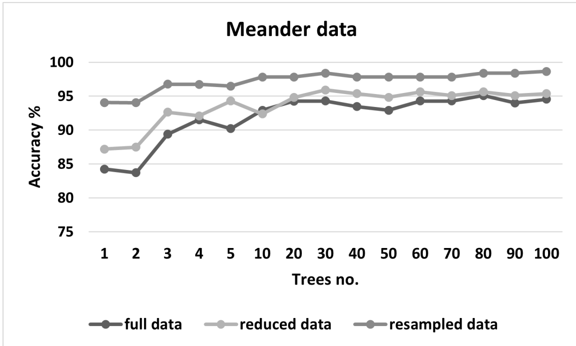


Fig. 5. The variation of random decision forest performance accuracy with the number of trees in the forest in case meander data.

A. Comparative analysis

To evaluate the performance, this section provides a comparison between the proposed approaches and other systems that provide a solution for Parkinson's disease diagnosis. **Table** X shows the proposed system, as well as other existing ones, demonstrating performance accuracy. Authors in [20] collect features depending on the changes between HT and ET, then apply multiple classifiers. SVM gave an accuracy of 66.36% for meander data and NB gave 65.88% for spiral. In [24] the authors collected the data and extracted the features using a biometric sensor. The SVM achieves accuracy of 95.4% for meander data and 96.7% for spiral. The study in [5] achieved accuracy of 82.23% and 85.54 for meander and spiral data respectively, using the Structural Cooccurance Matrix (SCM) and the SVM. Authors in [9] use the CNN with the Bat Algorithm (BA) and achieve an accuracy of 83.11% for meander and 90.38% for spiral data. In [25] the authors reached an accuracy of 87.36% with meander data using the PSO with the RF classifier and reached 84.73% with spiral data using the PSO with the SVM classifier. Authors in [14] extracted the Kinematic Features (KF) from a spiral handwritten drawing and used the AdaBoost classifier to achieve a 96.02% accuracy. On the other hand, Figure 6 summarizes the classification accuracy of various Parkinson's disease diagnostic systems sorted based on the publication years. As illustrated, the proposed approaches give a high prediction quality in both data cases meander / spiral where they have the higher accuracy values, 98.65% and 99.19% respectively.

TABLE III
PERFORMANCE EVALUATION MEASURES OF APPLYING DIFFERENT CLASSIFICATION METHODS OVER EXTRACTED FEATURES FROM SPIRAL IMAGES USING CNN

		CNN+Softmax	CNN+NB	CNN+DT	CNN+SVM	CNN+RF
Measures	**Accuracy**	90	93.3	91.6	95	90
	Precision	85.7	92.5	91.07	96.5	88.7
	Recall	70	92.5	90	92.5	88.7
	F1-score	82.4	92.5	90.5	94.5	88.7

TABLE IV
PERFORMANCE EVALUATION MEASURES OF APPLYING DIFFERENT CLASSIFICATION METHODS OVER EXTRACTED FEATURES FROM MEANDER IMAGES USING CNN

		CNN+Softmax	CNN+NB	CNN+DT	CNN+SVM	CNN+RF
Measures	**Accuracy**	86.6	85	88.3	93.3	83.3
	Precision	80	94.3	90.42	95	85.7
	Recall	80	82.5	92.5	95	90
	F1-score	80	88	91.4	95	87.8

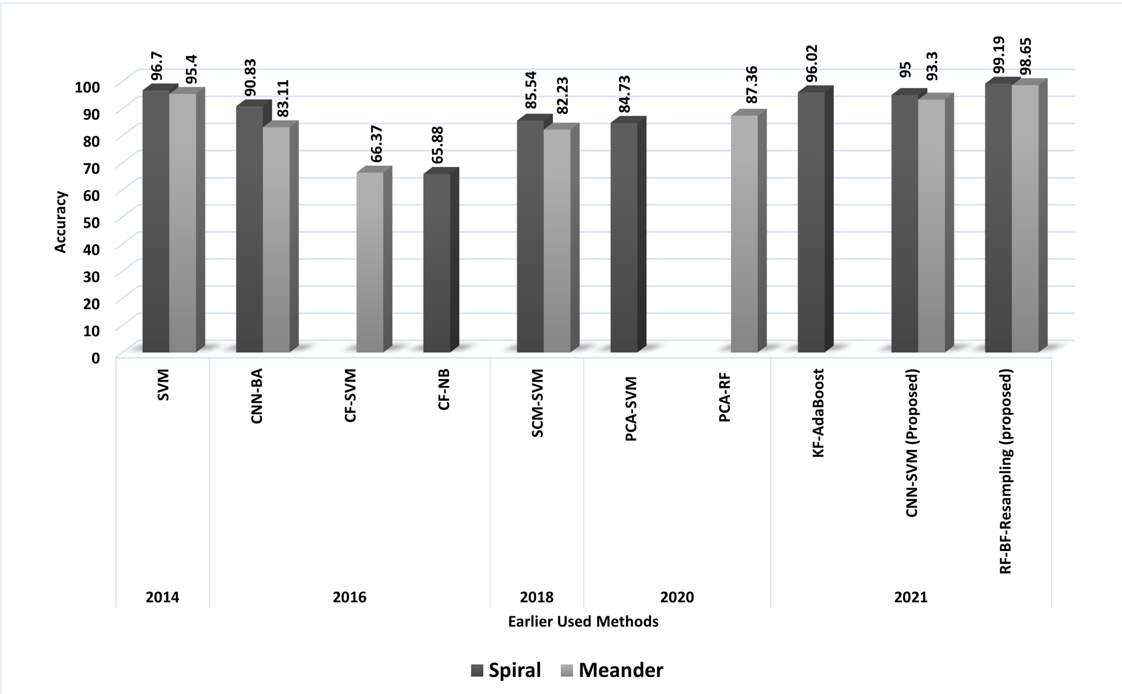


Fig. 6. Comparison between proposed approach based accuracy and different systems sorted by publishing year.

TABLE V
DIFFERENT CLASSIFICATION METHODS ACCURACIES FOR MEANDER/SPIRAL DATA FEATURES.

Data	Classifier	Full Data	Reduced Data
Meander	**DT**	94.8	95.1
	NB	63.3	85.9
	SVM	80.2	82.1
	RF	94.5	95.4
Spiral	**DT**	94.8	94.8
	NB	61.4	87.2
	SVM	82.6	79.9
	RF	94.6	95.4

TABLE VI
DIFFERENT CLASSIFICATION METHODS PRECISIONS FOR MEANDER/SPIRAL DATA FEATURES.

Data	Classifier	Full Data	Reduced Data
Meander	**DT**	94.9	95.7
	NB	63.5	78.1
	SVM	64.4	77.0
	RF	95.3	96.6
Spiral	**DT**	95.5	95.5
	NB	63.1	79.9
	SVM	80.7	60.5
	RF	96.8	95.9

V. CONCLUSION

Early identification and detection of Parkinson's disease is quite a challenge in the medical domain. Analysis of handwriting plays an important role in supporting the diagnosis of Parkinson's disease at earlier stages. Many CI techniques are

TABLE VII
DIFFERENT CLASSIFICATION METHODS RECALL FOR MEANDER/SPIRAL DATA FEATURES.

Data	Classifier	Full Data	Reduced Data
Meander	**DT**	88.4	88.6
	NB	71.4	74.4
	SVM	54.0	56.3
	RF	87.2	88.7
Spiral	**DT**	87.9	87.9
	NB	70.8	78.9
	SVM	57.1	51.8
	RF	86.1	89.2

TABLE VIII
DIFFERENT CLASSIFICATION METHODS F1-SCORE FOR MEANDER/SPIRAL DATA FEATURES.

Data	Classifier	Full Data	Reduced Data
Meander	**DT**	91.5	92.0
	NB	67.2	76.2
	SVM	58.8	65.0
	RF	91.1	92.5
Spiral	**DT**	91.5	91.5
	NB	66.7	79.4
	SVM	66.9	55.8
	RF	91.2	92.4

TABLE IX
PERFORMANCE EVALUATION MEASURES OF THE RESAMPLED FEATURES DATASET.

Data	Classifier	Accuracy	Precision	Recall
Meander	**DT**	89.43	86.68	81.63
	NB	87.23	81.67	81.93
	SVM	86.97	85.85	74.50
	RF (100)	98.65	98.68	97.41
Spiral	**DT**	90.51	88.88	82.76
	NB	84.54	79.11	73.35
	SVM	82.89	76.93	69.31
	RF (50)	99.19	99.04	98.62

TABLE X
PERFORMANCE ACCURACY OF THE PROPOSED SYSTEM VS. OTHER PROPOSED SYSTEMS

Data	Method	accuracy
Meander	CF-SVM [20]	66.37
	SVM [24]	95.4
	SCM-SVM [5]	82.23
	CNN-BA [9]	83.11
	PCA-RF [25]	87.36
	CNN-SVM (Proposed)	93.3
	RF-BF-Resampling (proposed)	98.65
Spiral	CF-NB [20]	65.88
	SVM [24]	96.7
	SCM-SVM [5]	85.54
	CNN-BA [9]	90.38
	PCA-SVM [25]	84.73
	kF-AdaBoost [14]	96.02
	CNN-SVM (Proposed)	95
	RF-BF-Resampling (proposed)	99.19

used to increase diagnostic accuracy and minimize possible errors. In this study, two main approaches were applied. The first uses the datasets of spiral and meander images and convolutional neural networks for the feature extraction step, then different classifiers are applied. It concluded that the SVM gives higher performance than other classifiers over the same set of features, which achieved 95% recognition accuracy. The second approach uses a dataset of 9 features based on the change between the HT and the ET. The BF strategy is used for feature extraction. Data resampling is done and then multiple classifiers are applied. Based on experimental results, it was concluded that the RF classifier gives higher performance than other classifiers over either the full dataset or the resampled one with the same set of features. The BF based feature extraction helps in improving classification accuracy, achieving 95.4% accuracy based on the Random Forest classifier, while resampling the dataset instances improved it to reach 99.19%. Results show that the RF classifier gives better accuracy with the selected features for meander and spiral datasets than when using full datasets. Also, the results show that RF-based classifier accuracy increases with the number of trees for the first 60 trees, after which it tends to be stable.

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