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Convolutional neural network for the detection of Parkinson disease based on hand-draw spiral images

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ABSTRACT

Parkinson’s disease (PD) is a chronic and increasing sickness that hits hundreds-thousands of people globally. Patients who are infected by PD have been proven to show some common symptoms such as slowness of movement, tremors, and freezing of gait. One of the most popular exams to detect the PD is to use the handwritten assessment tool, where the individuals are asked to draw spirals on a template paper. Therefore, this study proposes a convolutional neural network algorithm for detecting the PD by utilizing the hand-draw spiral images. In the present study, balanced spiral images dataset has been utilized for both categories (i.e., Parkinson and healthy). The dataset contains 102 samples as a total number of spiral images (i.e., 51 Parkinson and 51 healthy). Moreover, numerous evaluation measurements were utilized in order to assess the proposed approach such as recall, precision, accuracy, F-measure, specificity, Matthew's correlation coefficient (MCC), and G-mean. Based on the outcomes of the experiments, the proposed approach achieves 93.33% accuracy, 86.67% specificity, 88.24% precision, 100.00% recall, 93.75% F-measure, 93.93% G-mean, and 87.45% MCC. The proposed approach demonstrates promising outcomes in the detection of PD. As well as the proposed convolutional neural network (CNN) approach was outperformed all its comparatives regarding the classification accuracy rate.

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1. INTRODUCTION

Parkinson's disease (PD) is well known as one of the utmost common neurodegenerative illnesses that hits the elderly people who are over 65 years old [1]. Since this illness is increasing in its nature, the careless in diagnosing it in the early phase and observing it at different phases could cause a heavy passive impact on the patients regarding to costs of the healthcare and the sharp health related disorders. Some of the motion disorders' symptoms such as tremor, bradykinesia, hardness, and instability in posture are mostly noticed on the patients with PD at different phases. In order to prevent the great passive impact on the PD patients, the detection of the PD at its early phase is quite necessary [2]. One of the utmost common effects which are easily observable among the patients of PD and most commonly utilized at the early diagnosing phase is finding the dissimilarity in sketching abilities and handwriting [3]. The non-invasive measures like drawing shapes such as waves, spirals, and other texts of the handwritten can be easily distinguished from one to another as well as a person with/without PD [4].

Recent decades, the efficiency and effectiveness of the machine leaning (ML) and deep learning (DL) approaches have been proven in many fields such as language identification (LID) [5], emotion speech recognition [6], detection of COVID-19 [7]. Therefore, recently, extensive researches have been conducted by utilizing ML and DL algorithms in the detection of PD based on hand-draw spiral images [8]-[10]. For instance, the research in [11] has proposed a hyper-sinh-convolutional neural network (CNN) algorithm for the detection of PD based on hand-draw spiral images. The proposed algorithm was evaluated based on two different datasets (i.e., Spiral HandPD and NewHandPD) which have been collected by the Botucatu Medical School at São Paulo State University in Brazil. The first dataset contains 92 spiral image's samples (74 samples of the PD patients and 18 samples of healthy). While the second dataset contains 66 spiral image's samples (31 samples of the PD patients and 35 samples of healthy). The experiments outcomes have shown that the proposed algorithm has achieved the highest performance with an accuracy rate of 81.00% and 91.00% for Spiral HandPD and NewHandPD datasets, respectively. Despite the superiority of proposed algorithm has been proven over its comparatives, the outcomes are still not encouraging and need more enhancement. Besides, the proposed algorithm has been evaluated based on F-measure, precision, accuracy, and recall only, while the other evaluation measurements are required such as G-mean, Matthew's correlation coefficient (MCC), and receiver operating characteristic (ROC). Moreover, Chakraborty *et al.* [12], have proposed a multistage classification technique for detecting the PD using hand-draw spiral images. The proposed technique has been evaluated based on a dataset that is contain a total number of spiral images equal to 102 (i.e., 51 samples of the PD and 51 samples of the healthy). The proposed technique has achieved the highest accuracy rate reached up to 93.30%. Even though, the proposed technique was outperformed all its comparatives, the results are still not that encouraging and need more improvement. In addition, the proposed technique was evaluated based on F-measure, precision, accuracy, and recall only, while other measurements of evaluation are still required such as G-mean, MCC, and ROC.

Akter [13], have investigated the performance of several classification techniques in the detection of PD based on hand-draw spiral images. These classification techniques are random forest (RF), gradient boosting (GB), decision tree (DT), and K-nearest neighbor (KNN). Further, the authors have used histogram of oriented gradients (HOG) algorithm in order to extract the needed features and feed into the classification techniques one by one. In this study, the evaluation has been conducted based on a dataset that contains 102 spiral image's samples (i.e., 51 PD samples and 51 healthy samples). The experimental results have shown that the KNN technique has achieved the highest results with an accuracy of 89.33%. Although, the KNN technique was outperformed all its comparatives, the outcomes are still not encouraging and need more enhancement. Moreover, the evaluation of the proposed work was based on specificity, sensitivity, and accuracy only, while other evaluation measurements are still required such as F-measure, precision, recall, G-mean, MCC, and ROC. Further, Sivakumar *et al.* [14], has proposed a combination of long short term memory (LSTM) and LeNet methods for the detection of PD using hand-draw spiral images. The proposed approach has been assessed based on a dataset that consists of 102 spiral image's samples (i.e., 51 PD samples and 51 healthy samples). According to the authors, the performance of the proposed approach was good and outperformed all its comparatives. However, the authors did not report the experiments results and which evaluation measurements they have used. Furthermore, Kamble *et al.* [15], have proposed a PD detection system by using features engineering technique and four different classifiers (i.e., C-support vector classification (SVC), logistic regression (LR), KNN, and RF) based on hand-draw spiral images. The proposed system has been evaluated based on a dataset that consists of 40 spiral image's samples (i.e., 25 PD samples and 15 healthy samples). The experimental results have shown that the LR classifier has obtained the highest results with an accuracy of 91.60%. Although, the LR classifier was outperformed all its comparatives, the results are still not encouraging and need more improvement. Additionally, the evaluation of the proposed work was based on F-measure, recall, accuracy, and precision only, while other evaluation measurements are still required such as specificity, G-mean, MCC, and ROC.

Moetesum *et al.* [16] has proposed an automatic PD detection system using hand-draw spiral images. The proposed system was using the CNN for features extraction purpose and SVM for the classification purpose. The proposed system was evaluated based on a dataset that was collected from 75 subjects (i.e., 37 PD patients and 38 healthy). The experiments results have shown that the proposed system has achieved the best performance with an accuracy reached up to 83%. Despite, the proposed system was outperformed all its comparatives, the outcomes are still not that encouraging and need more enhancement. As well as, the proposed system was evaluated based on accuracy, precision, and recall only, while other measurements of evaluation are still required such as specificity, F-measure, G-mean, MCC, and ROC. Moreover, Impedovo *et al.* [17] has proposed a new system for PD detection utilizing hand-draw spiral images. The proposed system is based on dynamic features and a Naive Bayes (NB) classifier. The evaluation of the proposed system was conducted on a dataset that has been collected from 75 subjects (i.e., 37 PD patients and 38 healthy). The experimental outcomes have demonstrated that the proposed system achieved the highest performance with an accuracy reached up to 54.67%. However, the results are still not encouraging and need more improvement. Also, the proposed system was assessed based on accuracy, ROC, recall, and specificity only, while other evaluation measurements are still required such as F-measure, precision, G-mean, and MCC. Besides, Gupta and Chanda [18] have proposed a system for the detection of PD by using combined distance features and the SVM classifier. The proposed system was assessed based on a dataset of hand-draw spiral images that has been collected from

75 subjects (i.e., 37 PD patients and 38 healthy). The outcomes of the experiments have shown that the highest accomplished performance of the proposed system was with an accuracy of 81.66%. Even though, the proposed system was outperformed all its comparatives, the results are still not that encouraging and need more improvement. In addition, the proposed system was assessed based on accuracy, precision, recall, and F-measure only, while other evaluation measurements are still required such as specificity, G-mean, MCC, and ROC. Table 1 provides the illustration of the previous work.

Table 1. The illustration of the previous work

Ref	Dataset	Method	Results	Disadvantages
[11]	Two Datasets (first dataset contains 92 samples and second dataset contains 66 samples).	hyper-sinh-CNN	Accuracy of 81.00% and 91.00% for the first and second datasets, respectively	1. The outcomes are still not encouraging and need more enhancement. 2. The proposed algorithm has been evaluated based on F-measure, precision, accuracy, and recall only, while the other evaluation measurements are required such as G-mean, MCC, and ROC.
[12]	Dataset that contains 102 spiral images.	multistage classification technique	93.30% accuracy	1. The results are still not that encouraging and need more improvement. 2. The proposed technique was evaluated based on F-measure, precision, accuracy, and recall only, while other measurements of evaluation are still required such as G-mean, MCC, and ROC.
[13]	Dataset that contains 102 spiral images.	KNN	89.33% accuracy	1. The outcomes are still not encouraging and need more enhancement. 2. The evaluation of the proposed work was based on specificity, sensitivity, and accuracy only, while other evaluation measurements are still required such as F-measure, precision, recall, G-mean, MCC, and ROC.
[14]	Dataset that contains 102 spiral images.	Combination of LSTM and LeNet methods	-	1. The authors did not report the experiments results and which evaluation measurements they have used.
[15],	Dataset that contains 40 spiral images.	LR	91.60% accuracy	1. The results are still not encouraging and need more improvement. 2. The evaluation of the proposed work was based on F-measure, recall, accuracy, and precision only, while other evaluation measurements are still required such as specificity, G-mean, MCC, and ROC.
[16]	75 subjects (i.e., 37 PD patients and 38 healthy)	SVM	83% accuracy	1. The outcomes are still not that encouraging and need more enhancement. 2. The proposed system was assessed based on accuracy, ROC, recall, and specificity only, while other evaluation measurements are still required such as F-measure, precision, G-mean, and MCC.
[17]	75 subjects (i.e., 37 PD patients and 38 healthy)	NB	54.67% accuracy	1. The outcomes are still not that encouraging and need more enhancement. 2. The proposed system was evaluated based on accuracy, precision, and recall only, while other measurements of evaluation are still required such as specificity, F-measure, G-mean, MCC, and ROC.
[18]	75 subjects (i.e., 37 PD patients and 38 healthy)	SVM	81.66% accuracy	1. The outcomes are still not that encouraging and need more enhancement. 2. The proposed system was assessed based on accuracy, precision, recall, and F-measure only, while other evaluation measurements are still required such as specificity, G-mean, MCC, and ROC.

Based on the above-mentioned previous works and its limitations, the major aims of this study are listed as follow:

- Propose a new CNN algorithm with sixteen layers for the detection of PD using hand-draw spiral images.
- Evaluate the proposed CNN algorithm based on various evaluation measurements such as recall, accuracy, F-measure, precision, G-Mean, specificity, Matthew's correlation coefficient (MCC), and ROC (receiver operating characteristic).

– Compare the performance of the proposed CNN algorithm against some recent studies in terms of accuracy.

The reminder of this paper as follow: section 2 presents a deep description of the proposed method. While section 3 provides the experiments results and discussion. Section 4 illustrates the conclusion of this study.

2. METHOD

CNN algorithm was extensively utilized and demonstrated its effectiveness and efficiency in the operation of classification. Thus, the current research proposes a CNN algorithm for the detection of Parkinson disease based on the hand-draw spiral images. In addition, numerous evaluation measurements were utilized to assess the proposed approach performance in the regards of effectiveness. Further, the proposed approach was generated based on 3 major stages. The 1st stage denotes the hand-draw spiral images dataset that has been utilized in the present study. The 2nd stage denotes the preprocessing operation of the hand-draw spiral images for the healthy and Parkinson classes. The 3rd stage denotes to both processes (i.e., process of extracting features and process of classification), where the CNN model is utilized to differentiate the hand-draw spiral images regarding their class. Figure 1 depicts the proposed approach diagram for the detection of Parkinson disease. Moreover, the following sub-sections will provide a deep description of the three stages of the proposed approach separately.

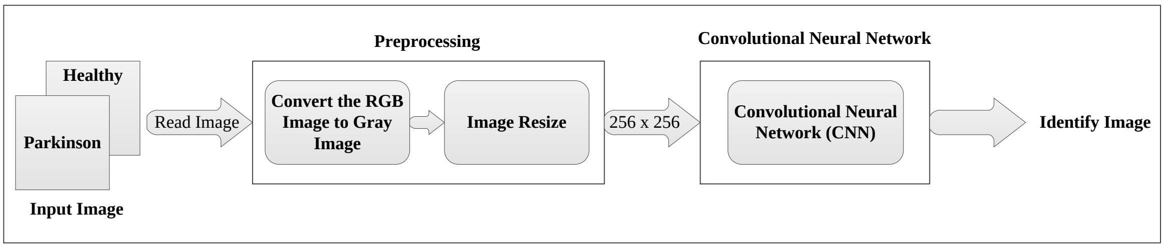
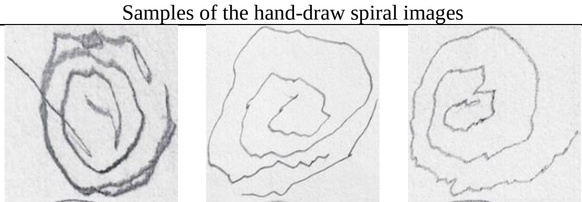
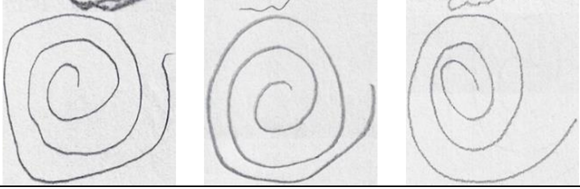


Figure 1. The proposed approach diagram for the detection of Parkinson disease

2.1. Spiral images dataset

In this research, the dataset of the hand-draw spiral images was taken from [19]. The dataset consists of two main categories, the first category refers to the samples of the patients who were diagnosed with Parkinson disease. While the second category refers to the samples of the healthy people (i.e., uninfected people with Parkinson disease). In the present research, the overall number of the hand-draw spiral images is 102 samples. The Parkinson category contains 51 samples of the hand-draw spiral images, and the healthy category contains 51 samples of hand-draw spiral images as well. Moreover, the dataset in the proposed research was divided into a 70% for the purpose of training (i.e., the total is equal to 72 samples; each category contains 36 samples). While the remaining 30% of the dataset was for the purpose of testing (i.e., the total is equal to 30 samples; each category contains 15 samples). Furthermore, a deep detail of the dataset that has been used in this research is provided in Table 2.

Table 2. Dataset depiction

Category	No of Samples	Samples of the hand-draw spiral images	Category label
Parkinson	51		1
Healthy	51		2

2.2. Image preprocessing

In this research, the preprocessing stage of the hand-draw spiral images contains two main steps. These two main steps are image conversion, and image resize. The role of image conversion step is to read and check the dimensionality for each image. Meaning that, the RGB image with three dimensions will be transformed into a gray image with two dimensions. Whilst the role of image resize step is to resize the dimensionality of all images into (256×256) dimensions. Following that, the outcomes of the preprocessing step will be inputs for the CNN algorithm.

2.3. CNN algorithm

The classifier and convolutional are the major 2 bases for the CNN architectures. The convolutional base comprises 3 main kinds of layers which are pooling, convolutional, and activation layers. These 3 layers are utilized to extract the critical features from the input images that is called maps of features. While the classifier base includes the dense layers which transforms the maps of features into vectors with 1Ds to speed up the task of classification using number of neurons [20]. This research offers a CNN algorithm with sixteen layers for diagnosing the Parkinson disease using hand-draw spiral images. The diagram with a full detail of the proposed CNN algorithm is depicted in Figure 2. The proposed CNN has a single fully connected layer, 3 max-pooling layers, and 3 convolutional layers. The 1st convolutional layer contains 8 filters of (3×3) size, with 1 stride and same padding followed by both batch normalization (batchnorm) layer and rectified linear units (ReLU) layer. The 2nd and 3rd convolutional layers are containing sixteen and thirty-two filters of (3×3) size; respectively. Besides, both of the layers are containing 1 stride and a same padding, also both of them are followed by the ReLU and batchnorm layers. The 3 layers of max-pooling are coming with the size of 2 and the stride of 2, they are followed the 1st, 2nd, and 3rd convolutional layers. These layers' output will be flattened and used as an input into a totally connected layer which is followed by a layer of softmax. The last layer (i.e., layer of output) denotes to the binary-classification. The demonstration of the values of the parameters for the trained CNN algorithm that has been used for detecting Parkinson disease is provided in Table 3.

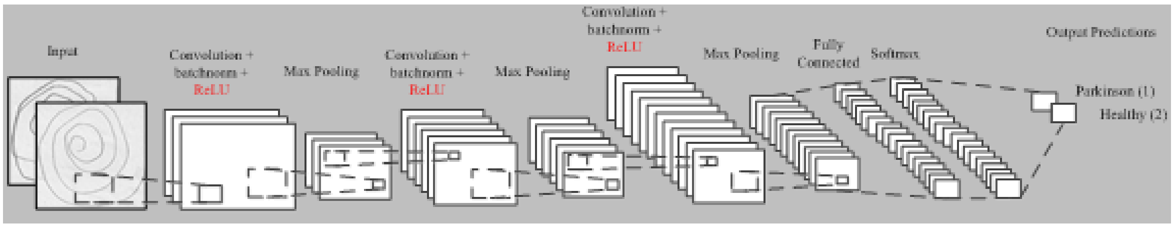


Figure 2. The proposed CNN algorithm diagram

Table 3. The values of the parameters for the trained CNN algorithm that has been used for detecting Parkinson disease

Parameter	Value
Optimisation Method	sgdm
Rate of Learning	0.0100
Shuffle	Once
Max Epochs	20
Mini Batch Size	100
Momentum	0.9000

3. RESULTS AND DISCUSSION

The goal of the proposed approach is to detect the Parkinson disease via utilizing CCN based on hand-draw spiral images for differentiating the patients (i.e., people who were diagnosed with Parkinson disease) from the healthy people. In the current work, the dataset was divided into a 70% for the purpose of training and 30% for the purpose of testing. Additionally, the proposed approach was implemented via utilizing the MATLAB R2019a as a tool of simulation over a laptop utilizing Windows 10, 8 GB RAM, and Intel Core-i5, 3.00 GHz CPU. Besides, numerous measurements of evaluation were utilized in order to assess the proposed CNN performance with respect to the efficacy in detecting the Parkinson disease. These measurements of evaluation are recall, accuracy, F-measure, precision, G-mean, specificity, and MCC. Furthermore, these measurements of evaluation were calculated as depicted in equations (1-7).

$$\text{Recall} = \frac{TP}{TP + FN} \tag{1}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$\text{F} - \text{measure} = \frac{2 \times Precision \times Recall}{Recall + Precision} \tag{3}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

$$\text{G} - \text{Mean} = \sqrt[2]{\text{Specificity} \times \text{Recall}} \tag{5}$$

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

$$\text{MCC} = \frac{(\text{TP}\times \text{TN} - \text{FP}\times \text{FN})}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{7}$$

Where: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). Table 4 presents the accomplished outcomes of the proposed CNN in detecting the Parkinson disease. Based on the experimental outcomes which have depicted in Table 4, the proposed approach has offered promising outcomes for the detection of the Parkinson disease; where the proposed model has accomplished a highest rate of accuracy reached up to 93.33%. Moreover, the proposed CNN model has achieved a 100.00% for the recall measurement. Whilst the achieved outcomes for the F-measure 93.75%, precision 88.24%, G-mean 93.93%, specificity 86.67%, and MCC 87.45%. Based on the accomplished outcomes, the proposed approach utilizing the CNN model has the ability to perform effectively in detecting the Parkinson disease based on hand-draw spiral images. In addition, the confusion matrix of the proposed CNN is presented in Figure 3. Moreover, the proposed CNN was assessed in terms of ROC; where the proposed CNN has accomplished 0.93333 of ROC as depicted in Figure 4.

Table 4. The accomplished outcomes of the proposed CNN

Accuracy	Precision	Recall	F-measure	G-mean	Specificity	MCC
93.33	88.24	100.00	93.75	93.93	86.67	87.45

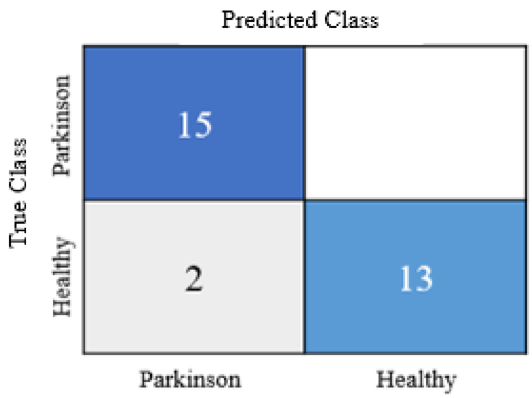


Figure 3. The proposed CNN confusion matrix using the hand-draw spiral images

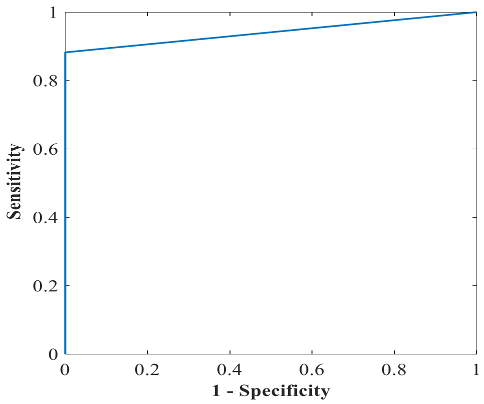


Figure 4. The proposed CNN ROC result using the hand-draw spiral images

Additionally, the proposed CNN algorithm underwent further experiments based on hand-draw wave images that been taken form [19]. The dataset contains two main classes, the first class denotes to the samples of the patients who were diagnosed with Parkinson disease. While the second class denotes to the samples of the healthy people (i.e., uninfected people with Parkinson disease). The dataset consistes of a total number of the hand-draw wave images is 102 samples. The Parkinson class contains 51 samples of the hand-draw wave images, and the healthy class contains 51 samples of hand-draw wave images as well. Moreover, the experiments were conducted based on dividing the dataset into 70% for the training purpose (i.e., the total is equal to 72 samples; each class contains 36 samples). Whilst the remaining 30% of the dataset was for the testing purpose (i.e., the total is equal to 30 samples; each class contains 15 samples). Table 5 depicts the highest achieved results of the proposed CNN in the Parkinson disease detection using hand-draw wave images. Figures 5 and 6 represent the confusion matrix and the ROC of the highest achieved results by the proposed CNN algorithm using the hand-draw wave images.

Table 5. The achieved results of the proposed CNN algorithm using the hand-draw wave images

Accuracy	Precision	Recall	F-Measure	G-Mean	Specificity	MCC
90.00	87.50	93.33	90.32	90.37	86.67	80.18

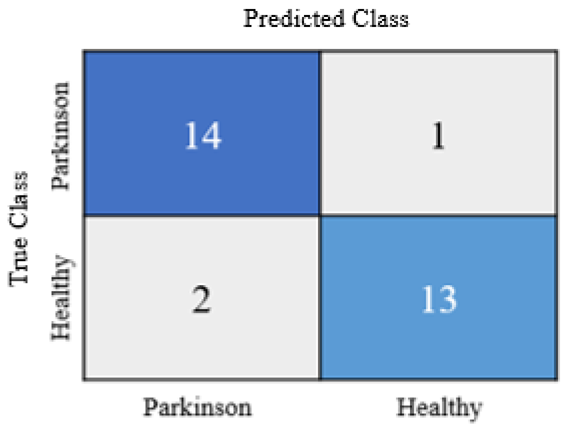


Figure 5. Confusion matrix of the proposed CNN algorithm using the hand-draw wave images

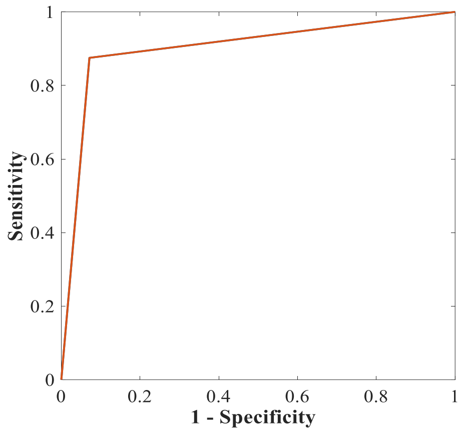


Figure 6. ROC of the proposed CNN algorithm using the hand-draw wave images

According to the experiments results in Table 6, Figures 5 and 6, the proposed CNN algorithm has also offered promising results for the Parkinson disease detection using hand-draw wave images; where the proposed approach has achieved a highest rate of accuracy reached up to 90.00%. Moreover, the proposed approach has achieved a 93.33% for the recall measurement. Whilst the achieved outcomes for the F-measure 90.32%, precision 87.50%, G-Mean 90.37%, specificity 86.67%, and MCC 80.18%. Thus, based on the achieved results, the proposed CNN algorithm has the ability to perform effectively in the Parkinson disease detection based on hand-draw wave images.

Moreover, the proposed approach performance utilizing CNN algorithm was compared against other recent studies [21]-[24] in terms of classification accuracy rate in detecting the Parkinson disease. These studies have presented diverse ML approaches and diverse DL approaches for detection of the patients who were infested by Parkinson disease using hand-draw spiral and wave images. The proposed CNN algorithm performance was more superior than all its comparatives regarding to the classification accuracy rate. Table 6 presents the comparison among approaches in terms of classification accuracy rate in detecting the Parkinson disease.

Table 6. The comparison accuracy among approaches in detecting the Parkinson disease

Hand-draw spiral images	
Method	Accuracy
AlexNet [21]	92.16%
fine-tuned VGG-19 in [22]	88.50%
HOG-CNN [23]	84.00%
VGG16 [24]	90.00%
Proposed Method	93.33%
Hand-Draw Wave Images	
RF in [25]	84.67%
fine-tuned VGG-19 [22]	88.00%
Resnet 34 [26]	83.33%
Proposed Method	90.00%

4. CONCLUSION

Recently, deep learning algorithms have been extensively utilized and demonstrated its effectiveness and efficiency in the operation of classification. Therefore, the present study has proposed a CNN approach for detecting the Parkinson disease based on hand-draw spiral images. In the current study, there were 51 image's samples for the category of healthy and 51 image's samples for the category of patients (i.e., people who suffer from Parkinson disease). According to the results of the experiments, the proposed CNN algorithm has achieved 93.33% accuracy, 100.00% recall, 93.75% F-measure, 88.24% precision, 93.93% G-Mean, 86.67% specificity, and 87.45% MCC. Based on the achieved outcomes, the proposed CNN algorithm can accomplish encouraging accuracy of detection for Parkinson disease utilizing hand-draw spiral images. In the future research, our aim is to implement the proposed model in detecting the Parkinson disease based on a bigger dataset with a large number of image's samples. Another future study can include utilizing the machine learning approaches in the detection of Parkinson disease.

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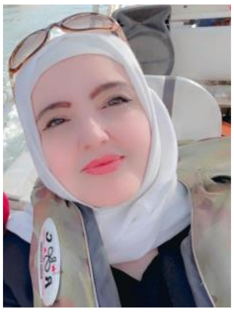

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