A Hybrid CNN-LSTM Deep Learning Model for Classification of the Parkinson Disease

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Abstract— **Parkinson disease (PD) is a degenerative disorder of neurological disorders that affects movements, balance problems and more. Early prediction of PD means enhancing the productive life of patients. In this research work, three machine learning approaches are adopted, applied and tested for the diagnosis and classification of the PD. The first approach involves some supervised machine learning algorithms namely: the support vector machine (SVM), k-nearest neighbors (KNN), and naïve bayes (NB). The second approach involves the ensemble learning algorithms namely: XGBoost and random forest (RF) classifiers. The third approach is concerned with presenting a proposed model based on amalgamating deep learning algorithms such as convolutional neural network (CNN) and recurrent neural network (RNN). The proposed model has four layers. The first layer involves the histogram oriented gradients (HOG) descriptor after the preprocessing stage. The second layer is the CNN, which has four convolution and maxpooling layers. The third layer is the long-short term memory (LSTM). Finally, the fourth layer involves the SoftMax classifier. The proposed model is implemented and operated on two datasets as test-beds. A modification is done on the feature extraction layer by adding the HOG before CNN to select the most significant image features, and adding the LSTM before the classifier. From the experimental work it is easy to say that our proposed model is effective in classifying PD as it achieved the best average accuracy after comparing our results with some other related ones.**

Index Terms—**Convolution Neural Network (CNN), Long Short Term Memory (LSTM), Histogram of Oriented Gradients (HOG), Parkinson Disease (PD), Performance Evaluations.**

I. INTRODUCTION

Parkinson disease (PD) is a cumulative disorder that affects the nervous system with motor symptoms such as imbalance, tremor, slow movement, and rigidity. The progression of these symptoms has bad effects, as people may have some difficulties talking and walking. They may also have sleep problems, behavioral and mental changes, memory difficulties, depression, and fatigue. Early disease detection is important for treatment, making it an important point for research especially after the development of new diagnostic tools [1].

Several research efforts were presented for the early detection of PD. Mohamad Alissa, et al. [2] presented PD diagnosis using CNN and figure-copying tasks to discover variation in patients movements with the use of drawing tasks.

Himanish Shekhar Das et al. [3] used the features of HOG and the coefficients of the discrete wavelet transform (DWT) as two feature extraction techniques for the early detection of PD. The authors tested their experiments on two datasets that included wave, spiral, cube, and triangle images.

Nabeel Seedat et al. [4] presented an automated machine vision which enabled detection of movement disorders from hand drawn spirals using CNN to perform classification between PD, control subjects and Essential tremor.

Arjun Shenoy et al. [5] presented an evaluation of the RNN models for PD classification using drawing data. The authors presented comparisons between recurrent network models (LSTM), and echo-state networks.

Anette Schrag et al. [6] introduced a risk algorithm using multivariate logistic regression analysis based on primary care presentations to predict the diagnosis of PD.

Ismail Canturk [7] proposed a model that tested PD patients using fuzzy recurrence plot-based that were used to convert time-series signals to grayscale texture images then to analyze the dynamic and static spiral.

Diba Ahmadi Rastegar et al. [8] proposed a model that predicted PD progression using machine learning and serum cytokines from a clinically well characterized longitudinally.

Pir Masoom Shah et al. [9] presented a model that accurately classified the PD using a CNN based automatic diagnosis system.

Mahima Sivakumar et al. [10] introduced an enhancement of machine learning based on deep learning, the authors demonstrated efficiency to analyze and diagnose unstructured datasets and, hence to provide the best care for patients. The authors' model presented an early PD diagnosis technique based on combining LeNet and LSTM.

Mehmet Bilal ER, et al. [11] presented a model for detecting PD from speech sounds consisting of four stages, one for removing noise by applying VMD to the signals. Second, Mel-spectrograms are extracted from the enhanced sound signals with VMD. Third, pre-trained using ResNet-18, ResNet-50 and ResNet-101 models. The last stage is concerned with the classification process that had been occurred with the LSTM model.

Wei Zeng, et al. [12] proposed a method to classify healthy control subjects and patients with PD using gait analysis via deterministic learning theory. The authors used gait characteristics that were derived by the gait dynamics from the vertical ground response forces under the natural and self-selected steps of the subjects.

Hadeel Abd El Aal, et al. [13] presented an enhanced

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model based on deep learning by adopting the RNN-LSTM for early detection of PD using voice features. Peter Drotár et al. [34] applied feature selection algorithms and SVM learning methods to classify PD and HC. Shaban M. [36] studied the use of a fine-tuned pre-trained VGG-19for distinguishing between PD and controls.

De Souza et al. [39] composed of features extracted from hand-drawn images using Restricted Boltzmann Machines, and subsequently compared with baseline models such as SVM and KNN. Table I presents comparative studies of the deep learning and machine learning techniques used with handwriting dataset for PD diagnosis.

The organization of the remaining part of this paper will be as follows: Section II, presents the architecture of the main building blocks of the proposed model. In section III, some preprocessing operations are applied. Section IV introduces some feature extraction approaches. Section V presents the implementation and practical work of the paper. Finally, Section VI concludes the whole work.

II. Architecture of the proposed model

The proposed model for recognizing and classifying PD is presented. The model is illustrated in Figure 1. First of all, an input image goes through some preprocessing operations. The feature extraction can be developed by combining the deep learning layers CNN [14-15] and RNN (LSTM) based on the HOG descriptor which extracts the orientation and edge gradients. After that, the classification process is applied to identify and predict PD. The pre-processing operations and feature extraction are briefly presented and discussed as shown in the following sections.

TABLE I.
COMPARISON OF MACHINE AND DEEP LEARNING APPROACHES APPLIED ON HANDWRITING DATASETS FOR PD DIAGNOSIS

Approach	Objective	Dataset	Model (ML/DL)	Performance	Limitation
Mohamad Alissa, et al. [2]	PD Diagnosis	Cube:82 original image (56 control,26 PD) Augmented 1214(598 control,616 PD) Pentagon :163(51 control, 112PD) Augmented 2405 (1173 control, 1232 PD)	CNN (19 layer)	Accuracy :93:53%	Complex training process
Himanish Shekhar Das et al. [3]	PD Detection	Dataset 1:spiral 51,wave 51 Dataset2:spiral 54,cube 54, triangle 58	DWT+HOG+KNN, SVM, RF, MLP, NB	Dataset1:accuracy % spiral: (73.3, 76.7, 81.3, 73.3, 56.7) Wave(80.0, 70.0, 80.3, 66.7, 43.3) Dataset2:accuracy % spiral: (79.2, 95.8, 87.5, 95.8, 87.5) cube(100, 100, 100, 100, 100) triangle(94.8, 94.7 , 91.7, 91.7, 91.6)	Limited performance, Small dataset
Nabeel Seedat et al. [4]	PD Detection	The dataset consists of spirals of the following categories: 370 PD. 669 Essential tremor subjects 357 control	ResNet32+CNN	Accuracy 98.2%	Complex training process
Arjun Shenoy et al. [5]	PD Diagnosis	87 subjects Only Spiral pentagon	ESN and LSTM	93.7% (ESN) (Pentagon)	Small dataset
Talitckii et al. [33]	PD Versus Neurological Disorders	Sensory Data (56 Patients)	Random Forest, Logistic Regression, SVM, Light GBM, Stacked Ensemble Model	Accuracy (Tremor and Bradykinesia Features): 85%	Limited performance, small dataset
Drotar et al. [34]	PD Detection	Handwriting Movements (37 PD, 38 Controls)	SVM	Accuracy :84%	Small dataset
Muniz et al. [35]	PD Detection	Gait Features (15 PD, 30 Controls)	Logistic Regression, PNN, SVM	Accuracy : (SVM): 94.6%	Small dataset
Shaban M. [36]	PD Detection	102 Spiral/Wave Handwriting Data (55 PD, 55 Controls)	VGG-19	Accuracy (Wave)88% S	Small dataset
Kamran et al. [37]	PD Detection	Handwriting Data (PaHaw: 37 PD, 38 Controls), (HandPD: 74 PD, 18 Controls), (NewHandPD: 31 PD, 35 Controls)	AlexNet, GoogleNet, VGG-16, VGG-19, ResNet-50, ResNet-101	Accuracy (AlexNet): 99.2%	Model training complexity
Afonso et al. [38]	PD Diagnosis	HandPD, 35 subjects (Meander, Spiral)	Deep optimum-path forest classifier	Accuracy 83:79%	Small dataset
De Souza et al. [39]	PD Diagnosis	Merged HandPD and NewHandPD, only final number of samples, Meander, Spiral	A restricted Boltzmann machine for feature extractor to a fuzzy optimum-path forest	Accuracy 79:57 % (Meander, 128 x 128)	Limited performance,

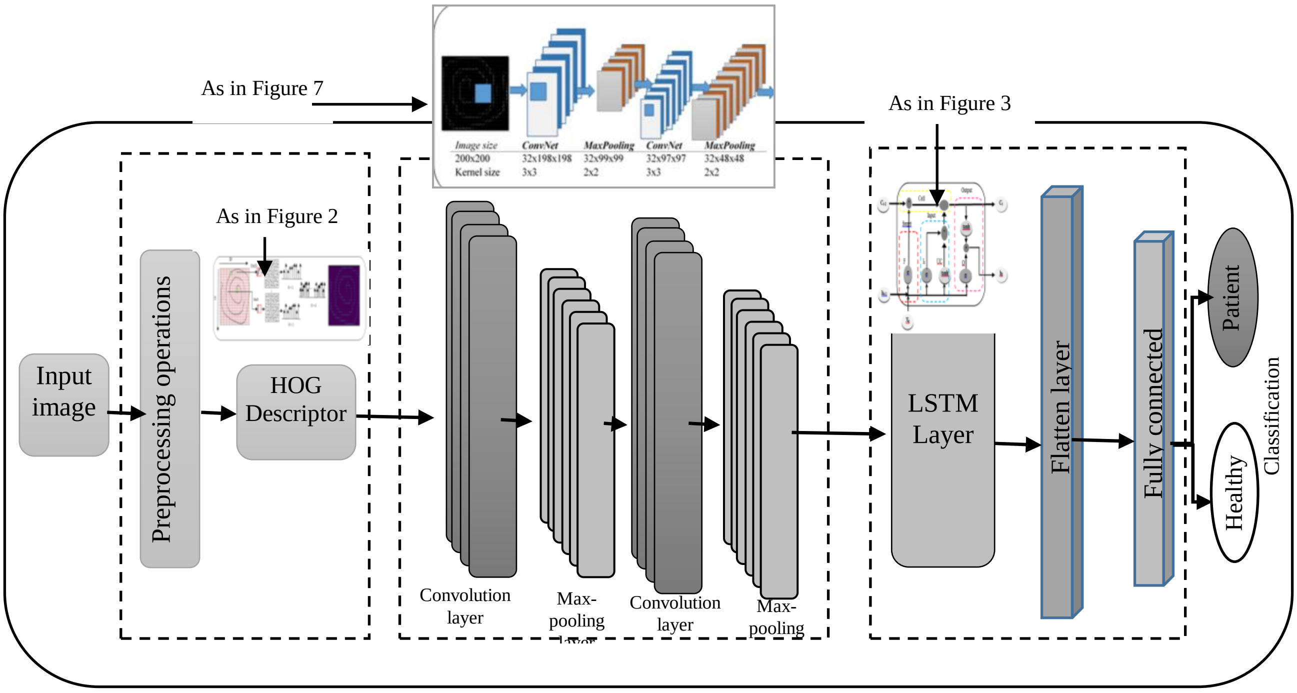


Fig. 1. Architecture of the proposed model for classifying the Parkinson diseases

III. Preprocessing Operations

Before the feature extraction phase, some preprocessing operations are applied on the input image. Step 1, read the input image in RGB scale. Step 2, create four images from each original image using an augmentation process to train more images. Two different data augmentation techniques have been used. The first is the augmentation technique which is based on geometric transformations, namely flipping and cropping. We flipped the image horizontally and vertically, and cropped the image with a random fraction from the continuous interval [0.0, 0.3]. The second augmentation technique is that based on color transformations where a Gaussian noise is added to the input image. Step 3, rebuild a database containing the original and augmented images. Step 4, convert the color scale image to gray scale by using equation (1) [16]:

$$G_g(i,j)= 0.299I_{R(i,j)}+ 0.587I_{G(i,j)}+0.114I_{B(i,j)} \qquad (1)$$

Where I is the image and i and j are representing the pixel coordinates. Step 5, resize the image to an optimal size (200x200) because it can be of several sizes. Step 6, apply a threshold value on an image to facilitate image analysis.

IV. Feature Extraction

In this section, we briefly describe some well-known feature extraction approaches that can be used for classifying PD.

A. *Histogram of Oriented Gradients (HOG)*

HOG is a feature descriptor often used to extract features from an input image. HOG [3],[16] is able to provide the edge orientation and shape of the object. HOG is distinguished by focusing on the shape or structure of an object. The magnitude M and direction θ of the edges are calculated using equations (2) and (3) respectively.

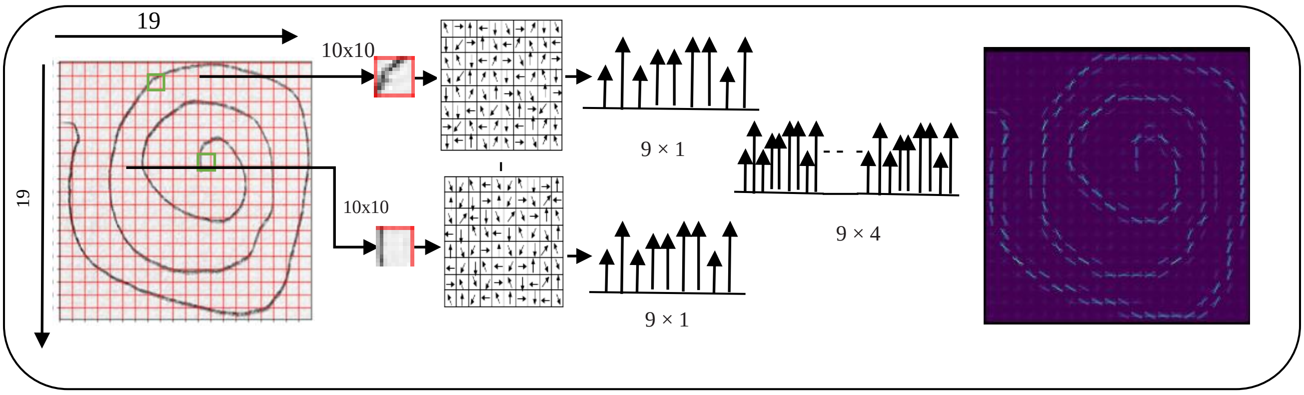


Fig. 2 Process of HOG features extraction

$$M_{i,j} = \sqrt{(L(i+1,j)-L(i-1,j))^2 + (L(i,j+1)-L(i,j-1))^2} \quad (2)$$

$$\theta_{i,j} = \tan^{-1}\frac{L(i,j+1)-L(i,j-1)}{L(i+1,j)-L(i-1,j)} \quad (3)$$

Where L is the intensity (grayscale) and i, j are the gradients of each cell in both the horizontal and vertical directions respectively. The amplitude of the gradient and the orientation of each pixel in the cell are voted in 9 bins. Each image as shown in figure 2 is divided into cells of size 10x10 pixels and the number of cells in each block is 2x2. The orientation of all pixels is calculated and represented in a 9-bins histogram of orientations corresponding to angles 0, 20, 40, 60 … 160. All cell histograms are concatenated in order to construct the final feature vector.

B. *Long-Short Term Memory (LSTM)*

LSTM is a particular kind of RNN eligible of handling long-term dependencies. LSTM was introduced by Hochreiter & Schmidhuber [17][18]. The logical structure of LSTM includes three gates namely; the input gate, the output gate, and the forget gate. Those gates can arrange the flow of information. The architecture of the LSTM is shown in Figure 3 (redrawing from [19] with clarification the three gates that are explained below).

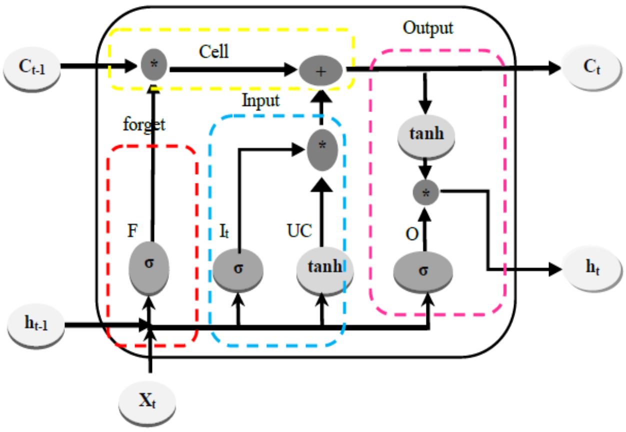


Fig. 3. Main architecture of LSTM (redrawing from [19])

The forget gate determines which information requires attention and which can be neglected by calculating F_t using (4):

$$F_t = \sigma(W_f * [h_{t-1}, X_t] + b_f) \quad (4)$$

Where F_t is the forget gate at time steps t which generates values between 0 and 1, X_t is the input at t, h_{t-1} is the previous hidden state, b_f is the connection bias at t, and W_f is the weight between forget and output gates.

The input gate updates the cell status using equations (5) and (6):

$$I_t = \sigma(W_I * [h_{t-1}, X_t] + b_I) \quad (5)$$

$$UC_t = \tanh(W_c * [h_{t-1}, X_t] + b_c) \quad (6)$$

Where UC_t is the output vector of tanh operator which can create a vector with all the possible values between -1 and 1. I_t is the input gate at t, W_I is the weight between input and output gates, and W_c is the weight of tanh operator between the cell state and output [20].

The output gate decides the value of the next hidden state based on cell state Ct using (7) and (8):

$$O_t = \sigma(W_O * [h_{t-1}, X_t] + b_O) \quad (7)$$

$$h_t = O_t * \tanh(C_t) \quad (8)$$

Where O_t is the output gate at t and h_t LSTM output [21].

V. IMPLEMENTATION WORK

We have used an Intel(R) Core(TM) i7-8565U CPU @ 1.80GHz 1.99 GHz with 12 GB of RAM to perform and execute all our experiments. The PD classification is implemented using Jupyter (anaconda3) Python3 on a 64-bit Microsoft Windows 10 O.S.

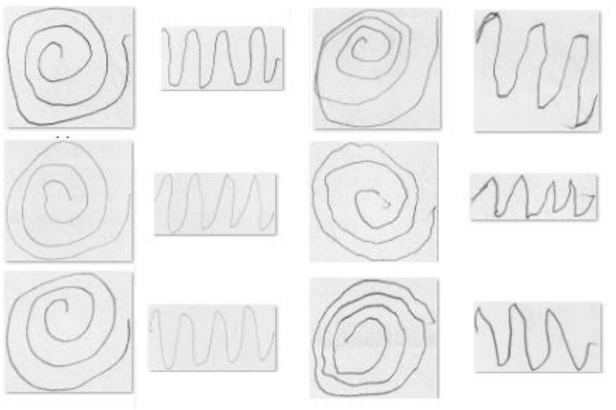
A. *Datasets description*

All the experimental work was carried out on two datasets as test beds. The first dataset was created by Adriano de Oliveira Andrade and Joao Paulo Folado from the NIATS of Federal University of Uberlândia [22][23]. The dataset includes 204 images of different image sizes. This dataset is divided into two types of drawing spiral and wave. The number of images in each type is 102. Moreover, data augmentation was adopted using a set of scaled images.

After applying data augmentation [24] with different conditions four times on each original image, the dataset contains 4*204=816 images. The dataset is splitted into a training set and a testing set. The dataset now is decomposed into two subsets: 408 spiral images and 408 wave images. The spiral images are decomposed into 288 images for training (144 images for each class) and 120 images for testing (60 images for each class). The spiral images may be healthy or parkinson. The wave images are splitted into 288 and 120 for training and testing respectively. Figure 4 represents samples of the healthy group as in (a) and the parkinson group as in (b) for spiral and wave drawing. Table II shows the initial and final numbers for each type (spiral-wave and healthy-patients).

TABLE II.
IMAGES CREATED OVER THE ORIGINAL DATASETS (NUMBER OF SAMPLES IN BRACKETS) BY APPLYING AUGMENTATION TECHNIQUES

Dataset	Training		Testing	
	Healthy	Patient	Healthy	Patient
Spiral	36 (144)	36 (144)	15 (60)	15 (60)
Wave	36 (144)	36 (144)	15 (60)	15 (60)



(a) Healthy (b) Parkinson

Fig. 4. Examples of the chosen Spiral and Wave datasets

The proposed model was also tested on another dataset, namely the NewHandPD dataset [25]. This dataset consists of 594 images is divided into three types of drawings: spiral, meander, and circle drawings. The dataset is composed of 264 images (160 male and 104 female) for each spiral and meander drawings, and 66 images for circle drawings. Each type was divided into two groups: the healthy and patient groups: The healthy group as shown in figure 5; contains 140, 140 and 35 for spiral images, meander images and circle images respectively. The patient group on the other hand as shown in figure 6; has 124 spiral images, 124 meander images and 31 circle images. Table III shows the numbers of images for the training and testing for the two groups after discarding some noisy images.

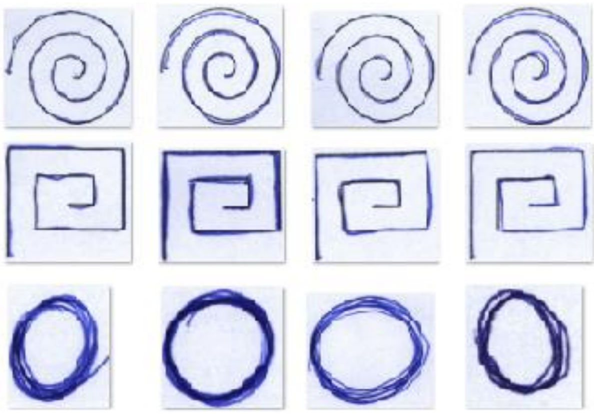


Fig. 5 Healthy samples (spiral, meander and circle)

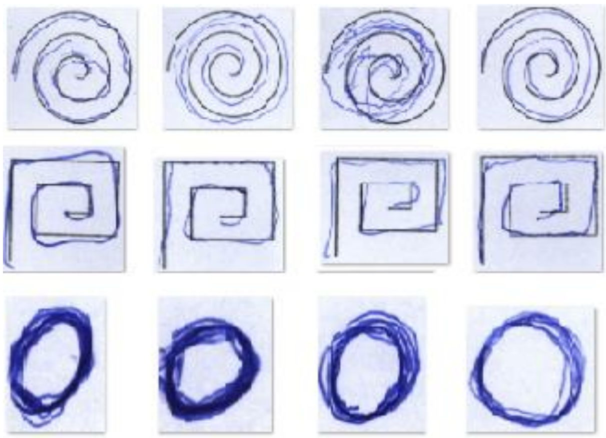


Fig. 6 Patient samples (spiral, meander and circle)

TABLE III.
THE NUMBER OF SAMPLES IN EACH DRAWING IN DATASET

Dataset	Training		Testing	
	Healthy	Patient	Healthy	Patient
Spiral	91	39	40	20
Meander	91	39	40	20
Circle	21	14	13	9

B. *Experimental results for classifying PD*

In this section, five classification methods are adopted and classified. First, the XGBoost is an ensemble learning algorithm with default parameter learning_rate=0.1 and base_score=0.5. Secondly, the K-NN classifier is applied using equation of the Euclidean distance where the number of neighbors K=3. Thirdly, the random forest classifier (RF) is applied based on creating subsets randomly of training data using the bag ensemble method with random subsampling of training features to build the decision trees [26] with random_state=1. Fourth, the SVM has been applied using one-vs.-one [27] based on linear kernel function [28]. Fifth, the NB has been applied based on Gaussian distribution as likelihood of the features. The experimental results of the adopted classifies for spiral and wave datasets are shown respectively in Tables IV and V.

TABLE IV.
CLASSIFICATION ACCURACIES FOR THE DIFFERENT CLASSIFIERS USING PD-SPIRAL DATASET

Classifier	Average accuracy	Sensitivity	Specificity
XGBoost	70%	60%	80%
K-NN	63.33%	60%	66.66%
RF	73.33 %	53.33%	93.33%
SVM	76.67%	73.33%	80%
NB	60%	100%	20%

TABLE V.
CLASSIFICATION ACCURACIES FOR THE DIFFERENT CLASSIFIERS USING PD-WAVE DATASET

Classifier	Average accuracy	Sensitivity	Specificity
XGBoost	53.33%	33.33%	73.33%
K-NN	50%	0%	100%
RF	66.67 %	53.33%	80%
SVM	56.67%	60%	53.33%
NB	50%	80%	20%

C. *Improving the classification performance using HOG*

In this section, we aim to improve the classification performance. The feature extraction methods that represent an image are more suitable for the recognition model. These features are the best for representing an object in the image. The HOG descriptor has been used to extract a feature vector for each image after the preprocessing operations. The HOG descriptor has been used for feature extraction with settings as shown in Table VI. The values of classification accuracy for the five adopted classifiers using the HOG descriptor for extracting features are shown in Tables VII and VIII for the spiral and wave datasets respectively.

TABLE VI
THE PARAMETER SETTING FOR HOG

parameter	Value
Image size	200x200
cell size	10x10
block size	2×2
number of orientation histogram bins	9

TABLE VII
CLASSIFICATION ACCURACIES FOR THE DIFFERENT CLASSIFIERS USING PD-SPIRAL DATASET USING HOG FEATURE EXTRACTION

Feature Extraction	Classifier	Average accuracy	Sensitivity	Specificity
HOG	K-NN	73.33%	66.67%	80.00%
	XGBoost	73.33%	66.67%	80.00%
	RF	81.67%	77.00%	90.33%
	NB	53.33%	93.33%	13.33%
	SVM	76.67%	80.00%	73.33%

TABLE VIII
CLASSIFICATION ACCURACIES FOR THE DIFFERENT CLASSIFIERS USING PD-WAVE DATASET USING HOG FEATURE EXTRACTION

Feature Extraction	Classifier	Average accuracy	Sensitivity	Specificity
HOG	K-NN	63.33%	60%	66.67%
	XGBoost	73.33%	73.33%	73.33%
	RF	76.67%	73.33%	80.00%
	NB	53.33%	53.33%	53.33%
	SVM	73.33%	66.67%	80.00%

D. Improving the performance of classification using Deep CNN based on HOG

CNN is a popular deep learning architecture due to the tremendous publicity and effectiveness of convents. CNN is a powerful model that performs automatic feature extraction [29],[30],[31]. The CNN architecture based on HOG descriptor is adopted and discussed as shown in Figure 7.
Table IX shows the CNN model structure setting based on HOG descriptor with the ADAM optimizer, activation function is ReLU and classifier softmax [32]. Tables X and XI show the CNN model based on HOG descriptor performance with ADAM optimizer on the PD-Spiral dataset and the PD-wave dataset respectively.

TABLE IX.
THE PARAMETER SETTING FOR CNN MODEL BASED HOG DESCRIPTOR

parameter	Value
Image size	200x200
Number of network layers	7
Number of hidden layers	5
Number of epochs	48
Loss function	sparse_categorical_crossentropy
Activation function	ReLU
Classifier	SoftMax
Optimization	ADAM optimizer
Number of training samples	288 (144 images for each class)
Number of testing samples	120 (60 images for each class)

TABLE X.
CLASSIFICATION ACCURACIES FOR CNN MODEL ON PD-SPIRAL DATASET USING HOG FEATURE EXTRACTION

Feature Extraction	Classifier	Average accuracy	Sensitivity	Specificity
HOG + CNN	Softmax	87.02%	81.4%	90.12%

TABLE XI.
CLASSIFICATION ACCURACIES FOR CNN MODEL ON PD-WAVE DATASET USING HOG FEATURE EXTRACTION

Feature Extraction	Classifier	Average accuracy	Sensitivity	Specificity
HOG + CNN	Softmax	81%	72.13%	87.57%

E. Improving feature extraction using Deep CNN-LSTM based on HOG

The prediction process of PD is enhanced and improved by adding an LSTM layer after the CNN based on the HOG descriptor after the preprocessing layer as shown in Figure 1. The proposed architectural model for PD recognition and classification is implemented, tested and evaluated.
Figure 8, Figure 9 present respectively the classification accuracy of the proposed model for the spiral and wave datasets. The accuracy values were different number of epochs.

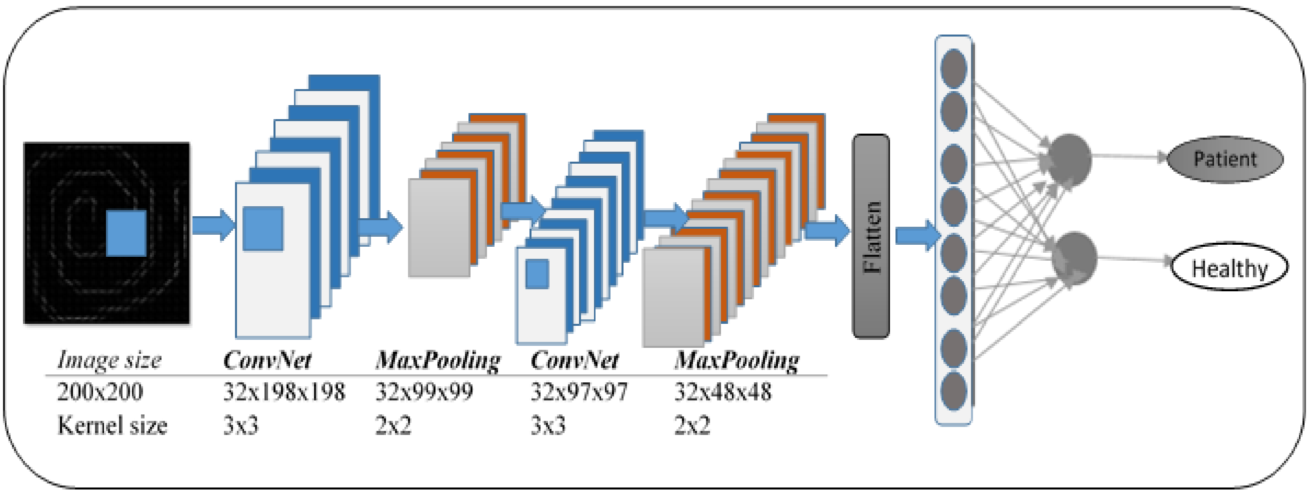


Fig.7. Architecture of the CNN model based on HOG descriptor

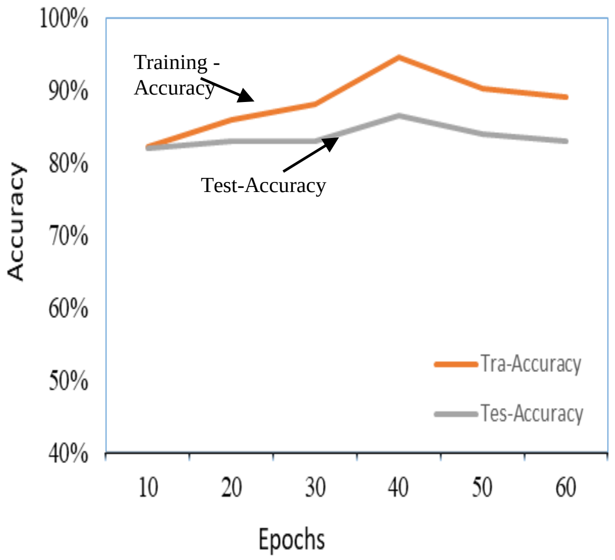


Fig.8. Classification accuracy for HOG-CNN-LSTM model on PD-spiral dataset with different no. of epochs

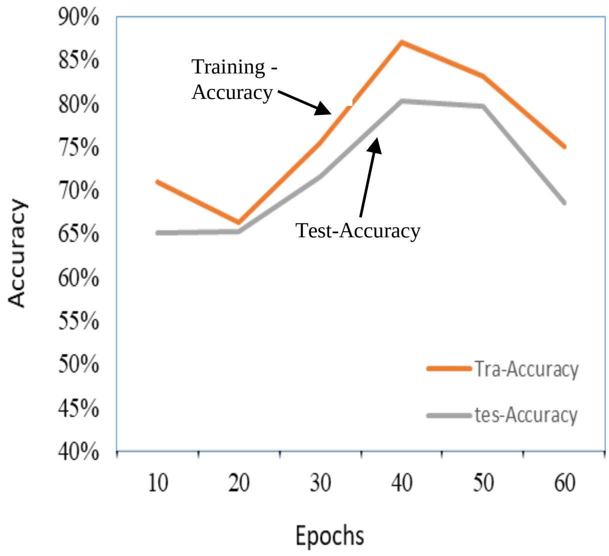


Fig.9. Classification accuracy for HOG-CNN-LSTM model on PD-wave dataset with different no. of epochs

Tables XII and XIII illustrate the performance of the proposed model and comparative results of the different architectures adopted on the PD-spiral dataset and the PD-wave dataset are presented separately. The proposed model achieved average accuracy about (89.67%) for PD classification for the spiral dataset. The authors in [3] used a HOG descriptor based on DWT for feature extraction and FR as a classifier. The best reported result was (83.3%). In [4] the ResNet-32 CNN architecture and softmax were used as classifiers. The reported result was (80.9%) when using this architecture for the PD-spiral dataset. The authors in [7] used five layers for convolution based on fuzzy recurrence plot-based. The reported result was (79.2%) when using this architecture for the PD-spiral dataset. The research [2] reported (82.4%) when the CNN model was applied. In [10] a model was suggested that contains LeNet and LSTM to predict PD but not tested on any Dataset. We tested the authors' model on the PD-spiral dataset with average accuracy (76.53%). In [11] the models ResNet and LSTM are combined together for feature extraction. The reported result was (86%) when using this architecture for the PD-spiral dataset. Therefore, our proposed model is effective in PD classification.

The proposed model was also tested using the NewHandPD dataset. The dataset contains three types of drawings: spiral, meander, and circle.

Figures 10, 11 and 12 present respectively the model accuracy (for different number of epochs) for spiral, meander, and circle drawings. Table XIV present the accuracy values for the proposed model compared with some other related ones for second dataset.

TABLE XII
CLASSIFICATION ACCURACIES FOR HOG-CNN-LSTM MODEL ON PD-SPIRAL DATASET

Method	Average accuracy
Himanish Shekhar Das, et. al. [3]	83.3%
Nabeel Seedat, et. al.[4]	80.9%
Arjun Shenoy et al. [5]	82.63%
Ismail Canturk [7]	79.2%
Mohamad Alissa, et. al. [2]	82.4%
Mahima Sivakumar, et. al. [10]	76.53%
Mehmet Bilal ER, et. al. [11]	86%
Our proposed model(HOG+CNN-LSTM)	**89.67%**

TABLE XIII
CLASSIFICATION ACCURACIES FOR HOG-CNN-LSTM MODEL ON PD- WAVE DATASET

Method	Average accuracy
Himanish Shekhar Das, et. al. [3]	75.1%
Nabeel Seedat, et. al.[4]	72%
Arjun Shenoy et al. [5]	71.01%
Mohamad Alissa, et. al. [2]	70.45%
Mehmet Bilal ER, et. al. [11]	76.8%
Our proposed model(HOG+CNN-LSTM)	**83.31%**

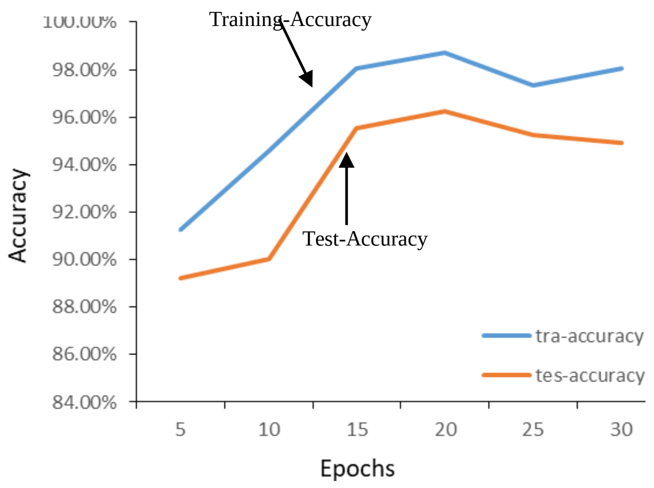


Fig. 10. Classification accuracy for HOG-CNN-LSTM model on spiral-NewHandPD dataset with different no. of epochs

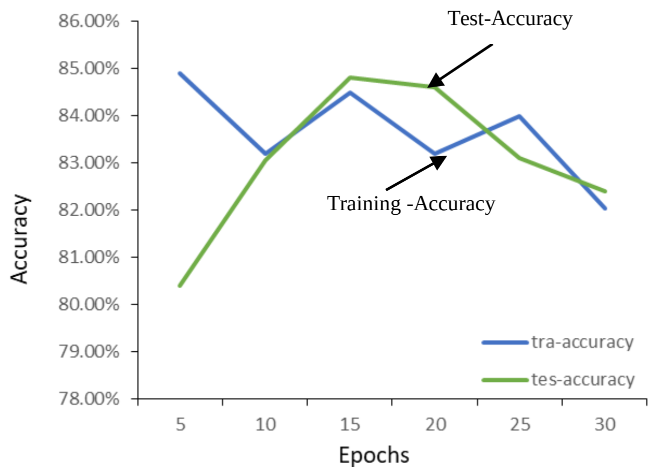


Fig. 11. Classification accuracy for HOG-CNN-LSTM model on meander- NewHandPD dataset with different no. of epochs

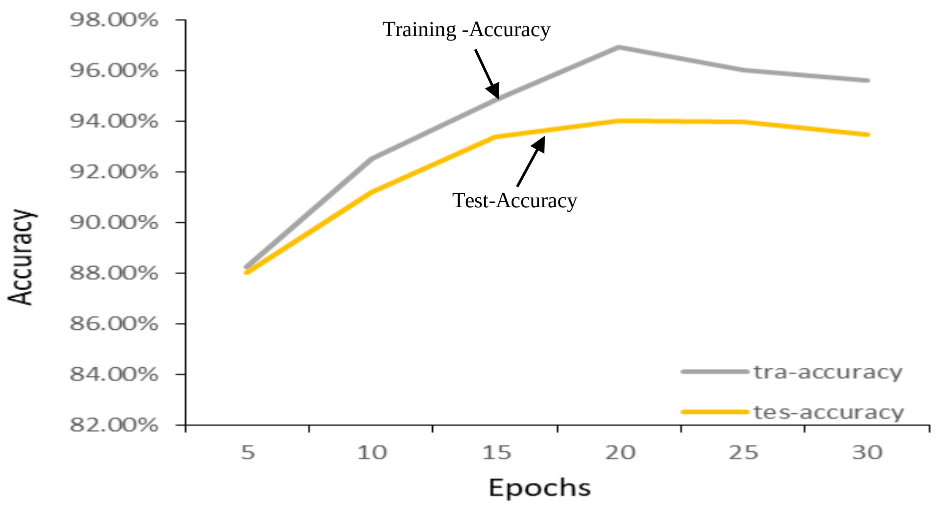


Fig. 12. Classification accuracy for HOG-CNN-LSTM model on circle - NewHandPD dataset with different no. of epochs

TABLE XIV
CLASSIFICATION ACCURACIES FOR THE PROPOSED MODEL ON THE NEWHANDPD SECOND DATASETS AND SOME RELATED ONES

Method	Spiral	Meander	Circle
	Average accuracy		
Himanish Shekhar Das, et al. [3]	86.04%	76.21%	84.92%
Nabeel Seedat, et al.[4]	84.1%	75%	83.02%
Mohamad Alissa, et al. [2]	85.6%	75.31%	83.9%
Mahima Sivakumar, et al. [10]	80%	71.52%	82.04%
Arjun Shenoy et al. [5]	83.52%	76.3%	80.25%
De Souza et al. [39]	82.63%	77.59%	84.65%
Mehmet Bilal ER, et al. [11]	90.77%	78.89%	89.23%
Our proposed model(HOG+CNN-LSTM)	**96.25%**	**84.60%**	**94.02%**

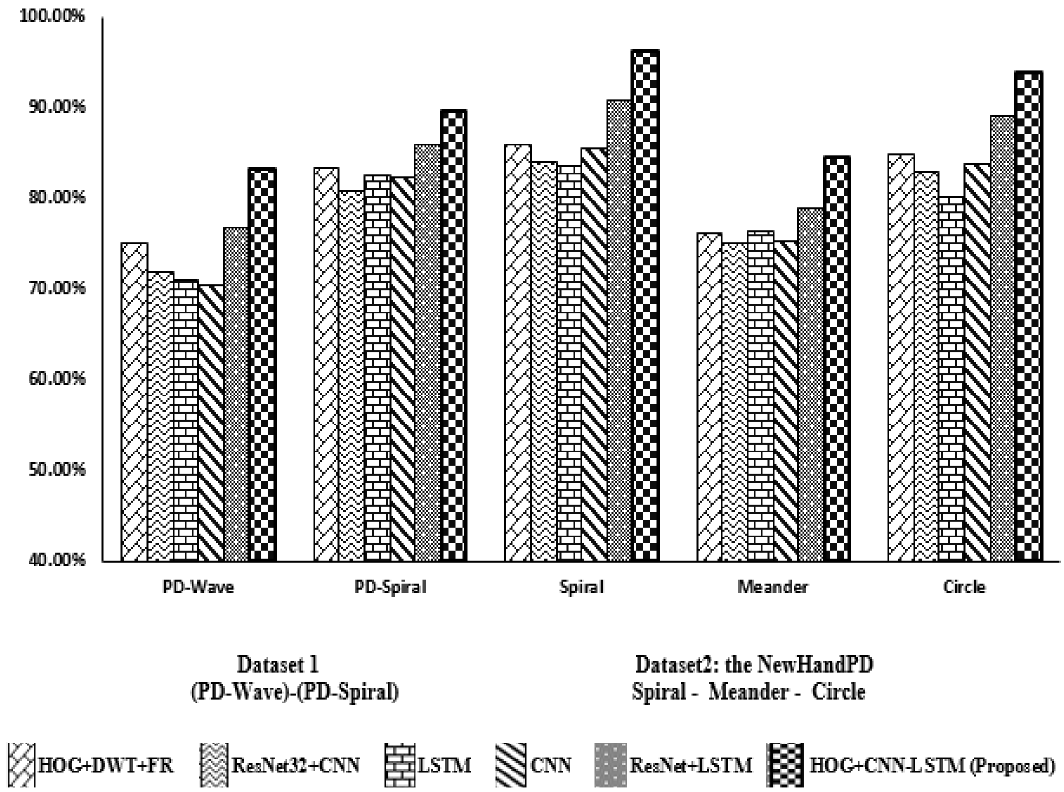


Fig. 13. Comparative results of different architectures for the proposed model on the two datasets and some related ones

VI. Conclusion

In this research work, a fusion approach combining both CNN and LSTM was adopted. The approach and/or model were based on the HOG descriptor to detect Parkinson disease. The proposed model was tested using two datasets as test-beds. The first dataset was used after applying data augmentation with different conditions such as image flipping, color transformations and image cropping. Using the HOG descriptor before the CNN-LSTM model to select the most significant image features. The values of classification accuracy were efficient and promising for the proposed CNN-LSTM model with the feature extraction HOG. The proposed model achieved an average accuracy of about 89.67% and 83.31% for classifying a PD for the spiral and wave datasets respectively. The accuracy values of the proposed model for the second dataset were respectively 96.25%, 84.60, and 94.02% for spiral, meander, and circle drawings. The model is also expected to be efficient for other datasets. Figure 13 represents a comparison of different architectures for the proposed model on the two datasets and some related ones.

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