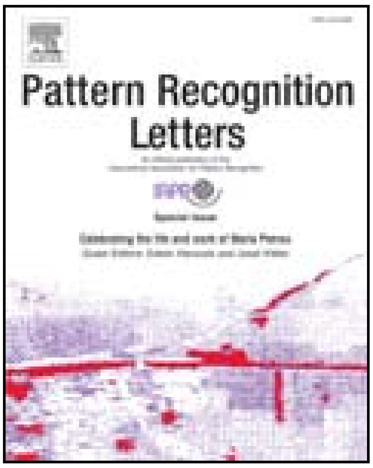
Journal Pre-proof



Long Short Term Memory based Patient- dependent Model for FOG Detection in Parkinson’s Disease

Amira S. Ashour , Amira El-Attar , Nilanjan Dey ,
Hatem Abd El-Kader , Mostafa M. Abd El-Naby

PII: S0167-8655(19)30356-3
DOI: https://doi.org/10.1016/j.patrec.2019.11.036
Reference: PATREC 7720

To appear in: *Pattern Recognition Letters*

Received date: 21 September 2019
Revised date: 20 November 2019
Accepted date: 26 November 2019

Please cite this article as: Amira S. Ashour , Amira El-Attar , Nilanjan Dey , Hatem Abd El-Kader , Mostafa M. Abd El-Naby , Long Short Term Memory based Patient- dependent Model for FOG Detection in Parkinson’s Disease, *Pattern Recognition Letters* (2019), doi: https://doi.org/10.1016/j.patrec.2019.11.036

Highlights

- Monitoring Parkinson's disease (PD) using a recorded signals' dataset from on-body wearable sensors is a vital requirement
- Freezing of gait (FOG) in PD patients can be detected from the acceleration signals
- A deep learning using LSTM network-based patient-dependent model was adopted for FOG detection
- A comparison between the proposed model and support vector machine with linear kernel was reported
- The LSTM achieved superior performance of 83.38% accuracy, while the SVM achieved 79.48% accuracy

Long Short Term Memory based Patient- dependent Model for FOG Detection in Parkinson's Disease

Amira S. Ashour[a,*], Amira El-Attar [a], Nilanjan Dey[b], Hatem Abd El-Kader[c], and Mostafa M. Abd El-Naby [a]

[a]*Department of Electronics and Electrical Communications Engineering, Faculty of Engineering, Tanta University, Tanta,*

[b]*Department of Information Technology, Techno India College of Technology, West Bengal, India*

[c]*Faculty of Computers and Information, Minufiya University, Egypt*

Corresponding author's email: amirasashour@yahoo.com, amira.salah@f-eng.tanta.edu.eg

ABSTRACT

Deep learning has a great impact on healthcare for discovering hidden patterns in the clinical data to detect or predict the different diseases. This work proposed a monitoring procedure for Parkinson's disease (PD) using a recorded signals' dataset from multiple wearable on body sensors placed at different positions on the leg, namely on knee, hip and ankle. Different symptoms of PD patients can be detected from the acceleration signals, where the Freezing of Gait (FOG) is considered the main sign. Typically, FOG is patient-dependent that varies in severity and incidence from patient to another. In this work, a deep learning model, namely the Long Short Term Memory (LSTM) network-based patient-dependent model was adopted for FOG detection. A comparison between the proposed model and the traditional machine learning methods, including the linear support vector machine (SVM) was conducted using the signals of the three sensors. The results established the superiority of the LSTM model, which achieved 83.38% in terms of the average accuracy in comparison with the SVM which achieved 79.48%. For example, in patient 2, the maximum accuracy achieved using the LSTM is 98.89%, while the corresponding maximum accuracy is 80% using the linear SVM.

Keywords: Parkinson's disease; wearable sensors; accelerometer sensor; freezing of gait; classification; support vector machine; long short term memory deep learning model.

1. Introduction

Parkinson's disease has a great influence on a widespread category of the population worldwide. Several studies were conducted to develop automated systems for PD detection and classification [1, 2]. The FOG is considered a popular symptom of PD patients that may cause falling. Monitoring PD patients is very imperative by using a suitable compatible type and positions of sensors. Since the FOG is the major symptom in PD, the accelerometer sensor becomes the most suitable type of sensors to measure the acceleration of the human movement. In PD patients, three accelerometer sensors are placed on knee, hip and on the ankle for monitoring [3]. The FOG can be detected using machine learning (ML) or deep learning (DL) approaches that deal directly with the raw data. The FOG detection is considered a challenging task due to the occurrence of irrelevant, redundant and noisy features that may affect the learning process during the detection process. In addition, the acquired signal is affected by the position of the wearable sensors, which in sequence affects the diagnostic decision [4, 5].

2. Literature review

Various methods used to control and manage the collected data from the sensors, which have a great impact on the performance of classification models. The research trends on the FOG detection of PD can be categorized into ML-based techniques and freezing threshold based techniques [6, 7, 8]. Mazilu *et al*. [9] suggested a wearable assistant system which,

consisting of a smartphone and a wearable accelerometer to detect FOG. The system relies on ML methods for detecting the FOG episodes automatically. The system relies on ML methods for detecting the FOG episodes automatically. The system's performance was evaluated in terms of the window size various models (e.g. Independent/ dependent experiments) and different ML algorithms (e.g. Decision Trees (DT), and Random Forests (RF) etc.). The results reported average sensitivity and specificity of about 95% in patient-dependent model for FOG detection. In PD patients, Saad *et al*. [10] used a Gaussian neural network classifier for identifying the FOG during walking, which achieved an average accuracy of 75%. On the other hand, the patient-independent methods were employed to train the machine learning classifier [7, 11-15]. El-Attar et al. [14] implemented a patient- independent method using the recorded signals from the vertical acceleration sensor only. The discrete wavelet transform (DWT) was applied for extracting the intrinsic motion features in the acquired signals. Then, the SVM was applied to detect the FOG with an accuracy of 87.50%. Rodríguez-Martín *et al*. [16] compared a patient-dependent personalized model to a patient-independent generic model. The results established the super accuracy of the patient-dependent model compared to the patient-independent model. Lipton *et al*. [17] assessed the LSTM capability to identify dissimilar patterns in clinical measurements. Eskofier *et al*. [18] compared standard ML as SVM and with DL which employed a convolutional neural network model proving the superiority of the DL by 4.6% accuracy improvement in the classification rate.

Consequently, the present work proposed a detection method of the FOG in PD patients using a robust classification model to distinguish between freezing and nonfreezing events based on patient-dependent models using LSTM on a public dataset. This dataset includes signals from the three accelerometer sensors positioned on the patient's hip, knee, and ankle. Then, the DL using the LSTM network was designed and applied directly without feature extraction. Finally, a study was carried out to compare the LSTM without prior SVM and ANN (artificial neural network) after feature extraction using different transform domains.

The following sections are structured as follows. Section 2 presents the proposed DL model using LSTM network for FOG detection and then extracting features from the acceleration signals for further classification using the SVM for FOG detection. Section 3 describes the used dataset with reporting the performance of using the proposed LSTM network-based patient-dependent model compared to using linear SVM. Finally, the conclusion was included in section 4.

3. Methodology of FOG Detection

FOG is the main symptom of the PD patients that occurs in a form of episodes, were the captured signals from the acceleration sensors consist of a sequence of freezing and nonfreezing in different time durations [6]. Accordingly, the proposed model handled the acquired signals from each patient separately using a patient-dependent LSTM model, where all freezing and non-freezing episodes were determined.

3.1. FOG detection using deep learning

The LSTM network is one of the efficient DL models for signal classification using time-series training set to build the detection model [19]. In PD, the symptoms vary in incidence, severity and timing from person to person and FOG occurred in a form of episodes with different durations of time, thus, the LSTM network is suitable to deal with such disease for classification.

3.1.1. LSTM network

The LSTM is a special kind of the Recurrent Neural Network (RNN) architecture that designed for signals. It is capable to perform long-term learning dependences between the time periods in a sequential data using a memory cell. The memory cell consists of multiplicative gate that controls the entree to the error flow. Furthermore, LSTM has a layer state which consists of the hidden state and cell state. This layer state eliminates or adds information at each time step to control any updates using gates. Any memory cell encloses 4 elements that deal with the cell state, namely i) the input gate i representing the control level of the updates, ii) the forget gate f representing the control level of the reset, iii) the cell candidate g representing the addition of information, and iv) the output gate o representing the control level added to hidden state. The weights of the LSTM network are input weight *W*, recurrent weight *R*, and the bias *b*, which are illustrated for each gate. These weights can be expressed as follows [20, 21]:

$$W=\begin{bmatrix} W_i \\ W_f \\ W_g \\ W_o \end{bmatrix}, R=\begin{bmatrix} R_i \\ R_f \\ R_g \\ R_o \end{bmatrix}, b=\begin{bmatrix} b_i \\ b_f \\ b_g \\ b_o \end{bmatrix} \tag{1}$$

So, at a time step t , the cell state can be stated as:

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{2}$$

where $\odot$ denotes the Hadamard product. At time step t , the hidden state is given by:

$$h_t = o_t \odot \sigma_c(c_t) \tag{3}$$

The four gates tolerate the accessibility and preservation of the information within the cells information along lengthy time periods using the following mathematical equations at a time step t :

$$i_t = \sigma_g(W_i x_t + R_i h_{t-1} + b_i) \tag{4}$$

$$f_t = \sigma_g(W_f x_t + R_f h_{t-1} + b_f) \tag{5}$$

$$g_t = \sigma_c(W_g x_t + R_g h_{t-1} + b_g) \tag{6}$$

$$o_t = \sigma_g(W_o x_t + R_o h_{t-1} + b_o) \tag{7}$$

Where σ_c and σ_g are the state and gate of activation function, respectively. In the current work, the sequence to sequence LSTM structure is used, where the output is the combination of the hidden states of all the layers. The layer's array contains of i) a sequence input layer, which has the input size at each time step, ii) LSTM layer, which includes number of hidden layers, the output mode ('sequence' or 'last'), activation function for updating the cell, and the hidden state, iii) a fully connected layer specifies the number of classes, iv) softmax layer for calculating the output of the layer, and v) output layer which computes the cross entropy loss for multi-class classification problem.

3.2. Feature extraction for FOG detection using classical machine learning methods

To evaluate the proposed LSTM network, a comparison with classical ML methods, including the SVM and ANN was conducted using prior feature extraction process. Accordingly, transformation becomes essential to extract the information from the PD patients' signals in both the FOG and normal movement cases to distinguish between them and detect the patient's status. Two types of transformation are used, namely the DWT, which produce approximate and detail coefficients *CA* and *CD*, respectively [22], and Fast Fourier Transform (FFT) to obtain the FFT coefficient (*CF*). Then, the features were extracted from these coefficients. In this paper, a hybrid combination of the FFT and DWT features were performed for the analysis of acceleration sensor's signals to take advantages of both methods in the extracted features. The performance using hybrid DWT-FFT features in [15] is better than compared to using DWT or FFT only [14]. These features were used to discriminate the non-freezing and FOG events, which are as follows:

The variance is calculated for approximate coefficient *CA*, detail coefficient *CD*, and FFT coefficient *CF* using the following expression:

$$V_{CA} = \frac{1}{n-1}\sum_{i=1}^{n}(CA_i - \overline{CA})^2 \tag{8}$$

$$\overline{CA} = \frac{1}{n}\sum_{i=1}^{n} CA_i \tag{9}$$

Where V_{CA} and $\overline{CA}$ are the variance and mean of the approximate coefficients, which are expressed as:

$$V_{CD} = \frac{1}{n-1}\sum_{i=1}^{n}(CD_i - \overline{CD})^2 \tag{10}$$

$$\overline{CD} = \frac{1}{n}\sum_{i=1}^{n} CD_i \tag{11}$$

Where V_{CD} and $\overline{CD}$ are the variance and mean of the detail coefficients, which are given by:

$$V_{CF} = \frac{1}{n_f - 1}\sum_{i=1}^{n_f}(|CF_i| - \overline{CF})^2 \tag{12}$$

$$\overline{CF} = \frac{1}{n}\sum_{i=1}^{n}|CF_i| \tag{13}$$

Where V_{CF} and $\overline{CF}$ are variance and mean of the FFT coefficients where n and n_f are the number of the DWT and FFT coefficients, respectively.

The maximum amplitude of the coefficients is given by:

$$CA_{\max} = \max\left[CA_i\right]_{i=1}^{n} \tag{14}$$

$$CD_{\max} = \max\left[CD_i\right]_{i=1}^{n} \tag{15}$$

$$CF_{\max} = \max\left[|CF_i|\right]_{i=1}^{n_f} \tag{16}$$

The minimum amplitude of the coefficients is given by:

$$CA_{\min} = \min\left[CA_i\right]_{i=1}^{n} \quad (17)$$

$$CD_{\min} = \min\left[CD_i\right]_{i=1}^{n} \quad (18)$$

$$CF_{\min} = \min\left[\left|CF_i\right|\right]_{i=1}^{n_f} \quad (19)$$

The maximum energy from the coefficients' sequences is given by:

$$E_{CA\max} = \max\left[CA_i \bullet * CA_i\right]_{i=1}^{n} \quad (20)$$

$$E_{CD\max} = \max\left[CD_i \bullet * CD_i\right]_{i=1}^{n} \quad (21)$$

$$E_{CF\max} = \max\left[\left|CF_i\right| \bullet * \left|CF_i\right|\right]_{i=1}^{n_f} \quad (22)$$

Where $\bullet *$ denote the dot product.

The minimum energy from the coefficients' sequences is given by:

$$E_{CA\min} = \min\left[CA_i \bullet * CA_i\right]_{i=1}^{n} \quad (23)$$

$$E_{CD\min} = \min\left[CD_i \bullet * CD_i\right]_{i=1}^{n} \quad (24)$$

$$E_{CF\min} = \min\left[\left|CF_i\right| \bullet * \left|CF_i\right|\right]_{i=1}^{n_f} \quad (25)$$

Each feature is calculated for the freezing and nonfreezing events, for both the FFT and DWT detail and approximate coefficients to discriminate the two classes. These features concluded 15 features for each sample, where the feature vector FV can be expressed as:

$$FV = \left[V_{CA}; CA_{\max}; CA_{\min}; E_{CA\max}; E_{CA\min}; V_{CD}; CD_{\max}; CD_{\min}; E_{CD\max}; E_{CD\min}; V_{CF}; CF_{\max}; CF_{\min}; E_{CF\max}; E_{CF\min}\right] \quad (26)$$

In this work, these features are extracted from the 9 acceleration signals of the 3 sensors on the knee, ankle, and the hip concluded 135 total number of features. The extracted features from all sensors and the corresponding target were fed to different kernels of SVM to discriminate between the freezing and nonfreezing events. In addition, a two-layer feed-forward neural network with sigmoid hidden layer of 20 neurons was included in the comparative study, where a scaled conjugate gradient back-propagation model was used in the training phase to classify the data [23, 24].

3.3. Proposed FOG detection system

The 9 signals from the sensors were used in the FOG detection for a PD patient by distinguishing between the two classes of freezing and nonfreezing for each patient separately. The present study included two scenarios, namely applying the LSTM network directly to the acquisition data without any prior features extraction, and using the SVM or ANN after extracting and integrating the DWT and the FFT features. Figure 1 and Figure 2 illustrated the two scenarios, where the performance assessment of each classifier was calculated in terms of the classification accuracy.

Figure 1 illustrated the steps of FOG detection-based patient dependent approach using classical machine learning methods, namely SVM and ANN. The acquired data from each patient is used separately to train the classifier using the following steps. Firstly, the freezing and nonfreezing episodes in the raw data are separated, then two types of transformation (DWT and FFT) are applied. The main significant features that affect the acceleration signal are extracted from the transformed signal, including variance, maximum amplitude, minimum amplitude, maximum energy, and minimum energy. Afterward, a hybridization of the two kinds of features is performed for further classification of these combined features using the SVM and ANN classifiers separately for the final evaluation of their performance. The performance of the proposed model-I (using the traditional classifiers) is compared with the second proposed model (model—II) (using deep learning network, namely LSTM) and is illustrated in Figure 2.

<u>Algorithm 1 :PD feature extraction for classical classification</u>

Start
- ***Input*** acceleration signal of sensor S and their annotations
- ***Compute*** coefficients of DWT and FFT of input signals
- ***Form*** feature vector from all coefficients
- ***Classify*** input signal to freezing or nonfreezing using the extracted feature vector

End

In Figure 2, the LSTM network based deep learning classifier is used for distinguishing the freezing and nonfreezing cases in PD patients using the raw data directly without any further steps of transformation and feature extraction.

Algorithm 2 : LSTM network for PD detection

Start
Input acceleration signal of sensor S and their annotations
Start training phase
Set LSTM network structure
Adapt LSTM number of layers and configuration to realize best performance
Start test phase
Detect freezing cases
End

In each patient's recorded signal over a long period of time, a case study of patient number 1 is shown in Figure 3 displaying the first 6 episodes of p1.

Figure 3 depicted that for patient 1 (P1) has 18 episodes of freezing (F) and 18 episodes of nonfreezing (NF) concluded a total of 36 recorded episodes (samples). Thus, P1 has 9 signals, 15 extracted features (hybrid DWT-FFT features) from each signal concluded a total of 135 features per sample. Hence, 135 features for 36 samples are obtained to form an input matrix of size 135×36 and target matrix of size 1×36. These features are used with the linear SVM or the ANN classifiers to evaluate the performance of FOG detection in PD patients [23].

4. Results and discussions

The dataset of the experiment was recorded over a period of time to monitor and detect the FOG of ten PD patients wearing acceleration sensors. The acquired 9 signals from the wearable sensors consist of 3-dimensional accelerometers positioned on the knee, hip, and on the ankle. Each sensor measured 3 signals, namely lateral, vertical and horizontal acceleration signals [6]. The sampling rates of the movement were 64Hz as the data was transmitted through a Bluetooth link. The signals for the sensors were recorded over eight hours for ten individuals, where only eight patients had FOG and the remaining 2 patients had no-freezing event during the experiment [6].

In this work, MATLAB R2018b software was employed to carry out the experimental part using Intel-Core i5-2410M 2.3 GHz processor. The proposed patient-dependent model was evaluated using these signals. Furthermore, the FOG detection performance using the linear SVM and ANN classifiers and the LSTM based DL network were finally compared.

4.1. Performance of FOG detection using deep learning based patient-dependent

The recorded data of eight patients suffering from FOG are separated to freezing and nonfreezing sequences and applied directly to the LSTM network. The LSTM network is characterized by 9 dimensions input sequences, 100 hidden units, 2 fully connected layers, where the sequence has 2 labels, namely '1' for nonfreezing, and '2' for freezing event as well as softmax and output layers. The data of each patient divided into 70% of each data for training, and 30% for test. Figure 3 demonstrated the performance of the FOG detection of P1. The numbers of iterations are displayed in the *x*- axis.

Figure 4 illustrated the relation between the number of iterations against the discrimination ability of the diseased cases and the healthy ones correctly in terms of accuracy and loss, respectively. The results showed that the maximum accuracy is about 100% after 17 iterations and the minimum accuracy after 27 iterations, while the corresponding loss has its minimum value at iteration 17 and its maximum value at iteration 27. Moreover, Table 1 showed the accuracy of FOG detection for each patient and the corresponding computational time.

Table 1 demonstrated that the accuracy and the computational time varied from patient to another depending on the number and duration of samples of each patient. The FOG detection in the case of Patient 6 achieved maximum accuracy of 98.89%.

4.2. Performance of FOG detection using SVM-based patient-dependent

In this section, the fifteen hybrid features from each signal from each sensor were extracted and combined for each patient concluded a total of 135 features with different number of samples *N* related to each patient. All features were applied to different SVM kernels to determine the best type of SVM as reported in Table 2.

Table 2 reported that the linear SVM achieved the best accuracy for all patients; the performance of some selected patients is shown in Figure 5 as the accuracy in *y*-axis and patient number in *x*-axis.

In addition, Table 3 reported a comparison between using features from each signal separately and combined for each patient using linear SVM.

Table 3 depicted that the accuracy differs from patient to another in an irregular and unspecified manner. For example, P1 with 18 episodes of freezing and 18 for nonfreezing has the best accuracy using the horizontal signal from the sensor at the ankle. However, both P2 with 9 episodes of freezing and 9 for nonfreezing, and P7 with 16 episodes of freezing and 16 for nonfreezing have the best accuracy using all sensors' signals. In addition, P3 with 43 episodes of freezing and 43 for nonfreezing, has the best result using the horizontal signal from the sensor at the ankle, P5 with 40 episodes of freezing and 40 for nonfreezing have the best accuracy using the vertical signal from the knee sensor, P6 with 10 episodes of freezing and 10 for nonfreezing has the best accuracy using the horizontal signal from the sensor at the hip or using the lateral signal from the hip sensor or using the all sensor signals. P8 with 14 episodes of freezing and 14 for nonfreezing has the best accuracy using the horizontal signal of ankle sensor or using the all sensor signals, and P9 with 27 episodes of freezing and 27 for nonfreezing has the best accuracy using the vertical signal from the ankle sensor or using the all sensor signal. Moreover, the performance of the ANN is stated in Table 4.

Table 4 illustrated that the ANN has poor performance with the patient-dependent model, where the maximum achieved accuracy was 66.7% using all sensor signals with P2. However, Tables 3 and 4 established that the linear SVM is the best for the proposed patient-dependent model as it achieved maximum accuracy of 93.8% with P7. In addition, the maximum achieved accuracy was 66.7% using the ANN in the case of P2, while the corresponding maximum accuracy was 83.3% for the same P2 using the linear SVM.

4.3. Comparative study

The performance of FOG detection was assessed using the dataset of 8 patients by implementing two methods namely the , the classical machine learning using SVM and ANN for FOG detection using the hybrid extracted DWT-FFT features and LSTM network as a type of deep learning without feature extraction. Consequently, a comparison between the proposed LSTM method and the machine learning based methods for classification-based FOG detection using patient-dependent procedure is conducted. Table 5 illustrated the comparison between these two methods.

Table 5 showed that the performance of FOG detection has been improved using the LSTM network for all patients except patient 7 and 9 compared to classical machine learning. Patient 7 and 9 are considered fail samples owing to the short duration of freezing and nonfreezing that enabled the classifier to discriminate the two events. The results illustrated that there is 2.01% increase in the classification accuracy of patient 1, 12.5% increase in the classification accuracy of patient 2, 26.4% increase in the classification accuracy of patient 3, 1.9% increase in the classification accuracy of patient 5, 18.8% increase in the classification accuracy of patient 6, 21.9% decrease in the classification accuracy of patient 7, 0.54 % increase in the classification accuracy of patient 8, 5.54% decrease in the classification accuracy of patient 9 compared to SVM. So, the average accuracy of FOG detection using LSTM is about 83.38% while the average accuracy using linear SVM is 79.48%. In addition, the average accuracy of classification-based FOG detection is illustrated in Figure 7.

Figure 6 established the superiority of the LSTM for FOG detection with average accuracy of 83.83% and standard deviation (SD) of 0.10, while the classification accuracy using the ANN and SVM are 54% and 79.48%, respectively with SD of 0.06 and 0.12.

5. Conclusions

This work is interested to detect FOG in PD patients who suffer from many symptoms that decrease their quality of life, where FOG may cause patient to fall. An improved system using all sensors' signals based on patient-dependent model was presented, which supported by the DL approach using LSTM network for FOG detection of PD patients. Comparing between using SVM and LSTM in the case of each patient demonstrated that the accuracy of detecting FOG events differ from patient to another based on the number of episodes of freezing and nonfreezing of each patient. Moreover, the LSTM achieved the superior performance in most all the cases. Additionally, in this work, the hybrid DWT-FFT features was used to feed the SVM classifier, while using the LSTM directly to the network without any feature extraction reduced the computational time, which achieved average accuracy about 83.38% compared to the average accuracy of linear SVM which achieved 79.48%.

<u>Conflict of Interest</u>

We are the authors of the manuscript titled "**Long Short Term Memory based Patient- dependent Model for Freezing of Gait Detection in Parkinson's Disease**" confirm that no conflict of interest exist.

References

[1] Sharma, P., Sundaram, S., Sharma, M., Sharma, A. and Gupta, D., 2019. Diagnosis of Parkinson's disease using modified grey wolf optimization. *Cognitive Systems Research*, *54*, 100-115.

[2] Mostafa, S.A., Mustapha, A., Mohammed, M.A., Hamed, R.I., Arunkumar, N., Ghani, M.K.A., Jaber, M.M. and Khaleefah, S.H., 2019. Examining multiple feature evaluation and classification methods for improving the diagnosis of Parkinson's disease. *Cognitive Systems Research*, *54*, 90-99.

[3] Mazilu, S., Blanke, U., Dorfman, M., Gazit, E., Mirelman, A., M Hausdorff, J. and Tröster, G., 2015. A wearable assistant for gait training for Parkinson's disease with freezing of gait in out-of-the-lab environments. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, *5*(1), 1-5.

[4] Dey N, Ashour AS, Shi F, Fong SJ, Sherratt RS. Developing residential wireless sensor networks for ECG healthcare monitoring. IEEE Transactions on Consumer Electronics. 2017 Nov;63(4):442-9.

[5] Dey N, Hassanien AE, Bhatt C, Ashour AS, Satapathy SC, editors. Internet of things and big data analytics toward next-generation intelligence. Berlin: Springer; 2018.

[6] Bachlin, M., Plotnik, M., Roggen, D., Maidan, I., Hausdorff, J.M., Giladi, N. and Troster, G., 2009. Wearable assistant for Parkinson's disease patients with the freezing of gait symptom. *IEEE Transactions on Information Technology in Biomedicine*, *14*(2), 436-446.

[7] Zabaleta, H., Keller, T. and Masso, J.M., 2009. Power spectral distribution analysis for detection of freezing of gait in patients with Parkinson's disease. In *4th European conference of the international federation for medical and biological engineering* (pp. 2089-2092). Springer, Berlin, Heidelberg.

[8] Moore, S.T., MacDougall, H.G. and Ondo, W.G., 2008. Ambulatory monitoring of freezing of gait in Parkinson's disease. *Journal of neuroscience methods*, *167*(2), 340-348.

[9] Mazilu, S., Hardegger, M., Zhu, Z., Roggen, D., Tröster, G., Plotnik, M. and Hausdorff, J.M., 2012, May. Online detection of freezing of gait with smartphones and machine learning techniques. In *2012 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops* (pp. 123-130). IEEE.

[10] Saad, A., Zaarour, I., Guerin, F., Bejjani, P., Ayache, M. and Lefebvre, D., 2017. Detection of freezing of gait for Parkinson's disease patients with multi-sensor device and Gaussian neural networks. *International Journal of Machine Learning and Cybernetics*, *8*(3), 941-954.

[11] Jovanov, E., Wang, E., Verhagen, L., Fredrickson, M. and Fratangelo, R., 2009, September. deFOG—A real time system for detection and unfreezing of gait of Parkinson's patients. In *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 5151-5154). IEEE.

[12] Moore, S.T., Yungher, D.A., Morris, T.R., Dilda, V., MacDougall, H.G., Shine, J.M., Naismith, S.L. and Lewis, S.J., 2013. Autonomous identification of freezing of gait in Parkinson's disease from lower-body segmental accelerometry. *Journal of neuroengineering and rehabilitation*, *10*(1), 1-19.

[13] Zhao, Y., Tonn, K., Niazmand, K., Fietzek, U.M., D'Angelo, L.T., Ceballos-Baumann, A. and Lueth, T.C., 2012, January. Online FOG identification in Parkinson's disease with a time-frequency combined algorithm. In *Proceedings of 2012 IEEE-EMBS International Conference on Biomedical and Health Informatics* (pp. 192-195). IEEE.

[14] El-Attar, A., Ashour, A.S., Dey, N., Abdelkader, H., Abd El-Naby, M.M. and Sherratt, R.S., 2018. Discrete wavelet transform-based freezing of gait detection in Parkinson's disease. *Journal of Experimental & Theoretical Artificial Intelligence*, 1-17.

[15] El-Attar, A., Ashour, A.S., Dey, N., Abdelkader, H., Abd El-Naby, M.M. and Shi,F., 2018. Hybrid DWT-FFT Features for Detecting Freezing of Gait in Parkinson's Disease, *in the international conference on Information Technology and Intelligence Transportation Systems (ITITS 2018),* Augaste, pp. 117-126.

[16] Rodríguez-Martín, D., Samà, A., Pérez-López, C., Català, A., Arostegui, J.M.M., Cabestany, J., Bayés, À., Alcaine, S., Mestre, B., Prats, A. and Crespo, M.C., 2017. Home detection of freezing of gait using support vector machines through a single waist-worn triaxial accelerometer. *PloS one*, *12*(2), p.e0171764.

[17] Lipton, Z.C., Kale, D.C., Elkan, C. and Wetzel, R., 2015. Learning to diagnose with LSTM recurrent neural networks. *arXiv preprint arXiv:1511.03677*.

[18] Eskofier, B.M., Lee, S.I., Daneault, J.F., Golabchi, F.N., Ferreira-Carvalho, G., Vergara-Diaz, G., Sapienza, S., Costante, G., Klucken, J., Kautz, T. and Bonato, P., 2016, August. Recent machine learning advancements in sensor-based mobility analysis: Deep learning for Parkinson's disease assessment. In *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 655-658). IEEE.

[19] Chollet, F., 2017. Deep Learning with python" *Manning Publications Co.*,

[20] Hochreiter, S. and Schmidhuber, J., 1997. Long short-term memory. *Neural computation*, *9*(8), 1735-1780.

[21] Li Z, Dey N, Ashour AS, Cao L, Wang Y, Wang D, McCauley P, Balas VE, Shi K, Shi F. Convolutional neural network based clustering and manifold learning method for diabetic plantar pressure imaging dataset. Journal of Medical Imaging and Health Informatics. 2017 Jun 1;7(3):639-52.

[22] Han, J., Pei, J. and Kamber, M., 2011. Data mining: concepts and techniques, Elsevier.

[23] Abe, S., 2005. *Support vector machines for pattern classification* (Vol. 2, p. 44). London: Springer.

[24] Chatterjee S, Hore S, Dey N, Chakraborty S, Ashour AS. Dengue fever classification using gene expression data: a PSO based artificial neural network approach. InProceedings of the 5th international conference on frontiers in intelligent computing: theory and applications 2017 (pp. 331-341). Springer, Singapore

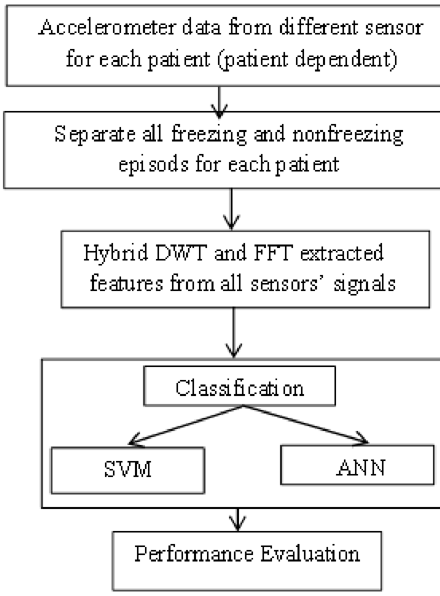


Fig. 1 Proposed model using traditional classifiers (Model – I)

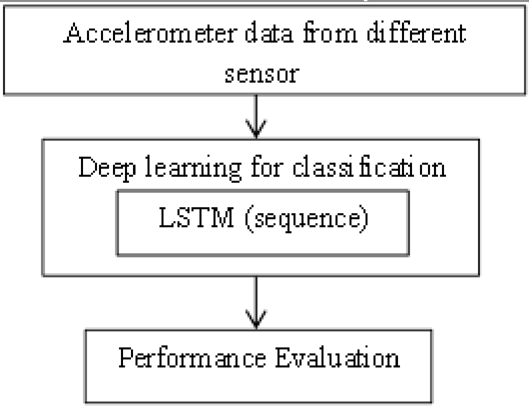


Fig. 2 **Proposed method using LSTM (Model –II)**

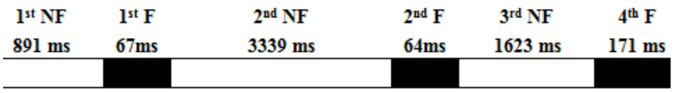


Fig.3. The first six episodes of patient # 1 (P1)

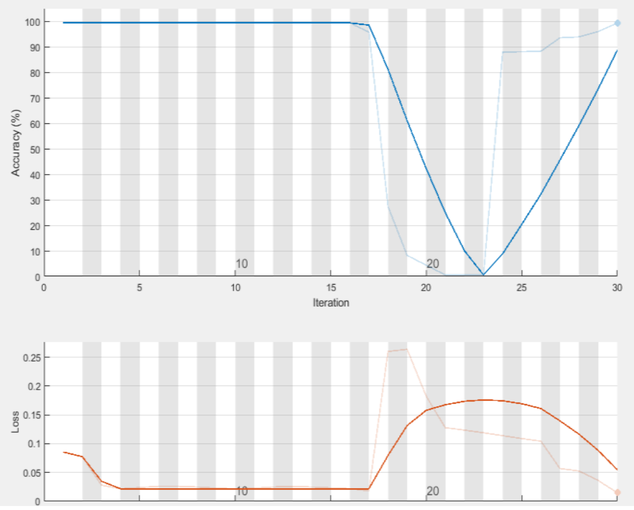


Fig .4. Performance of FOG detection using LSTM for patient 1

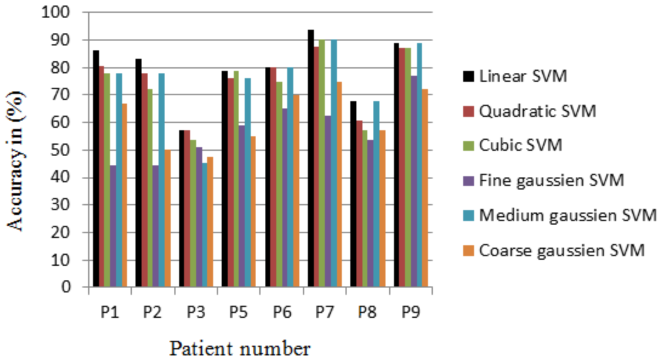


Fig.5. Performance of different SVM kernels (selected patients)

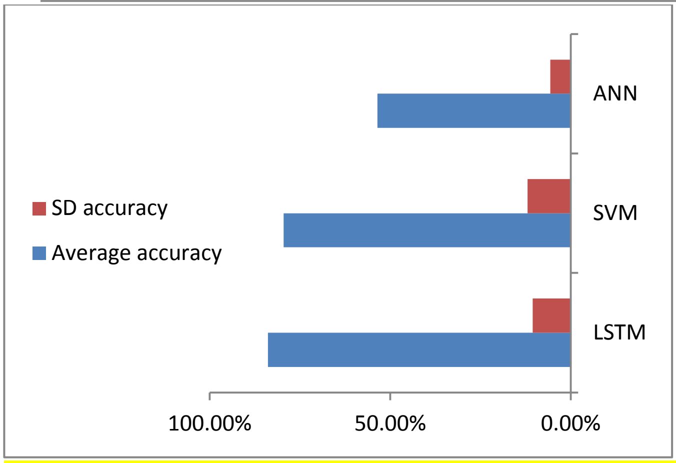


Fig.6. Average classification accuracy and standard deviation (SD) of LSTM, ANN, and SVM

Table 1. Individual patient's FOG detection accuracy using LSTM

Patient number	Accuracy	Computational time (Mins.)
Patient 1 (P1)	88.11%	33
Patient 2 (P2)	95.82%	1
Patient 3 (P3)	83.41%	41
Patient 5 (P5)	80.71%	24
Patient 6 (P6)	98.89%	20
Patient 7 (P7)	71.88%	42
Patient 8 (P8)	68.44%	9
Patient 9 (P9)	83.36%	97

Table 2. Performance of all SVM kernels using all sensors' signals based patient dependent

All sensor signals (135*N)	Classification accuracy per patient							
	P1 (135*36)	P2 (135*18)	P3 (135*86)	P5 (135*80)	P6 (135*20)	P7 (135*32)	P8 (135*28)	P9 (135*54)
Linear SVM	86.1%	83.3%	57%	78.8%	80%	93.8%	67.9%	88.9%
Quadratic SVM	80.6%	77.8%	57%	76.3%	80%	87.5%	60.7%	87%
Cubic SVM	77.8%	72.2%	53.5%	78.8%	75%	90%	57.1%	87%
Fine Gaussian SVM	44.4%	44.4%	51.2%	58.8%	65%	62.5%	53.6	77%
Medium Gaussian SVM	77.8%	77.8%	45.3%	76.3%	80%	90.6%	67.9%	88.9%
Coarse Gaussian SVM	66.7%	50%	47.7%	55%	70%	75%	57.1%	72.2%

Table 3. Performance of linear SVM using all sensors' signals (patient-dependent

Sensor/ signal		Classification accuracy per patient							
		P1	P2	P3	P5	P6	P7	P8	P9
Sensor at ankle	Horizontal	88.9%	55.8%	60.5%	73.8%	75.0%	78.1%	67.9%	79.6%
	Vertical	80.6%	55.8%	59.3%	78.8%	65%	87.5%	60.7%	83.3%
	Lateral	80.6%	33.3%	54.7%	71.3%	75%	84.4%	50%	74.1%
Sensor at knee	Horizontal	66.7%	55.6%	48.8%	80.0%	70%	75.0%	50.%	81.5%
	Vertical	66.7%	50.0%	53.3%	85%	65%	87.5%	50%	75.9%
	Lateral	66.7%	38.9%	59.3%	71.3%	70%	81.3%	57.1%	63.0%
Sensor at hip	Horizontal	66.7%	72.2%	53.5%	50%	80%	78.1%	57.1%	72.2%
	Vertical	66.7%	50%	50.0%	77.5%	75%	87.5%	60.7%	81.5%
	Lateral	77.8%	55.6%	39.5%	55.0%	80%	81.3%	64.3%	68.5%
All sensor signals (135*N)		86.1%	83.3%	57%	78.8%	80%	93.8%	67.9%	88.9%

Table 4. Performance of ANN using all sensors' signals (patient-dependent)

Sensor/ signal		Classification accuracy per patient							
		P1	P2	P3	P5	P6	P7	P8	P9
Sensor at ankle	Horizontal	52.2%	55.6%	50%	50%	50%	50%	50%	50%
	Vertical	50%	55.6%	50%	50%	45%	50%	53.6%	50%
	Lateral	50%	50%	50%	50%	55%	50%	53.6%	50%
Sensor at knee	Horizontal	50%	50%	51.2%	50%	40%	53.1%	50%	50%
	Vertical	50%	50%	50%	50%	50%	50%	53.6%	50%
	Lateral	50%	50%	50%	50%	55%	53.1%	50%	50%
Sensor at hip	Horizontal	50%	55.6%	50%	50%	50%	46.9%	50%	50%
	Vertical	50%	50%	50%	50%	45%	53.1%	50%	50%
	Lateral	50%	50%	50%	50%	50%	50%	57.1	50%
All sensors signals (135*N)		50%	66.7%	50%	50%	55%	53.1%	53.6%	50%

Table 5. Performance of FOG detection using classical and deep learning

Patient number	Deep learning	Classical machine learning	
	LSTM	SVM	ANN
Patient 1	88.11%	86.1%	50%
Patient 2	95.82%	83.3%	66.7%
Patient 3	83.41%	57%	50%
Patient 5	80.71%	78.8%	50%
Patient 6	98.89%	80%	55%
Patient 7	71.88%	93.8%	53.1%
Patient 8	68.44%	67.9%	53.6%
Patient 9	83.36%	88.9%	50%

Graphical Abstract

Long Short Term Memory based Patient-dependent Model for FOG Detection in Parkinson's Disease

Amira S. Ashour, Amira El-Attar , Nilanjan Dey, Hatem Abd El-Kader, and Mostafa M. Abd El-Naby

Leave this area blank for abstract info.

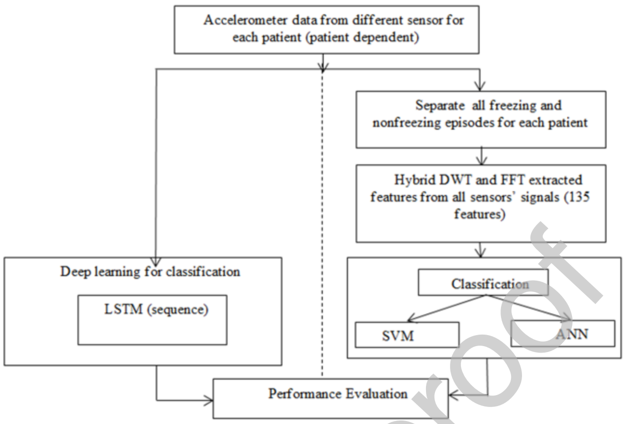


Fig. Proposed system for FOG detection