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Deep feature learning for FoG episodes prediction In patients with PD

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Abstract

A common symptom of Parkinson's Disease is Freezing of Gait (FoG) that causes an interrupt of the forward progression of the patient’s feet while walking. Therefore, Freezing of Gait episodes is always engaged to the patient's falls. This paper proposes a model for Freezing of Gait episodes detection and prediction in patients with Parkinson's disease. Predicting Freezing of Gait in this paper considers as a multi-class classification problem with 3 classes namely, FoG, pre-FoG, and walking episodes. In this paper, the extracted feature scheme applied for the detection and the prediction of FoG is Convolutional Neural Network (CNN) spectrogram time-frequency features. The dataset is collected from three tri-axial accelerometer sensors for PD patients with FoG.
The performance of the suggested approach has been distinguished by different machine learning classifiers and accelerometer axes.

Keywords: Freezing of Gait (FoG), Parkinson's disease (PD), Machin Learning, Angular-axes feature Spectrogram, Convolutional neural network (CNN)

1. Introduction

Patients with Parkinson’s disease (PD) are affected with an inability to control their movements because PD is a brain nervous system symptom. Furthermore, Freezing of Gait (FoG) is the most occurring symptom for patients with PD that featured by a discontinuous walking of the feet's forward progression while walking. In most cases, FoG patients with PD lasts up to one minute and it could happen for a few seconds. Unexpectedly during walking, patients could enter into the FoG episodes by feeling that their feet are associated with the ground like magnetics. Therefore, FoG is classified as a momentary symptom, and patients are exposed to falling which makes them more likely for injuries [1].

In this topic, authors have proposed many research studies using various and different approaches for increasing the accuracy of detecting FoG episodes in patients with Parkinson's Disease. Nevertheless, for enhancing the prediction of FoG episodes, the proposed experiments not as much as the detection experiments, and a few have achieved notable accuracies. The author's studies for Freezing of Gait episodes prediction proposed different machine learning algorithms, and various features extracted from signals or spectrograms. Pre-that make authors in [2] during the episodes try to distinguish and recognize those characteristics. The authors also aim to compare the previously extracted characteristics with those episodes that do not present Freezing of gait. The proposed model adopted a technique relying on using thresholding for FoG detection. CuPiD dataset with a linear discriminant analysis classifier was used, the achieved results were 83% and 67% for sensitivity and specificity, respectively.

Authors in [3] aim to differentiate between patients with FoG and non-FoG, authors depend on using extracted spatiotemporal gait parameters along with convolutional statistical features. The proposed model was tested on 51 patients with Parkinson's Disease while using tri-axial accelerometers, the achieved accuracy was 88% using the Support Vector Machine classifier. The aim in [4] was to predict the Freezing of Gait episodes depending on the use of lower-limp accelerometers. For classification, the Freeze Index algorithm was used along with Discrete Wavelet Transform, sample entropy features, and ground truth was used with 2 seconds windowing. The author's proposed model reaches an average accuracy of 87.6%, 87.6% for sensitivity, and 87.5% F-measure.

On the other hand, the FoG detection domain has been adopted in many research studies using various algorithms and features. Inertial Measurement Unit (IMU) sensors, such as accelerometers and gyroscopes [5] have also been used to increase the detection performance. Daphnet dataset was adopted along with different time-domain and frequency-domain features were extracted and have been input to the decision tree classifier. Different time-domain features were extracted for detecting FoG episodes in [6] with the use of C4.5 classifier with CuPiD dataset [7], 90% hit rate and specificity starts from 66% to 80% was achieved. Authors aim in [8] for detecting FoG episodes with the use of an Artificial Neural Network (ANN) classifier with improved subsequence Dynamic Time Wrapping (isDTW) method. Daphnet dataset was adopted with the use of time-frequency features that achieved an accuracy of 92%. The author's aim in [10] is to detect patient-dependent FoG, Daphnet accelerometer readings were to apply them to several ML classifiers. The detected FoG episodes achieved a specificity of 82%, sensitivity of 85.1%, and F1-Score of 58.9%.

Frequency domain features were adopted in [11] to measure the impact of using those features for detecting the FoG episodes. The SVM classifier was used for the FoG detection, the achieved accuracy result was above 90%. The authors' aim in [12] is to detect FoG episodes using time-frequency features applied to a Gaussian Neural Network (GNN) algorithm. The proposed approach achieved an accuracy rate of 87% with the use of a goniometer clinical data.

The importance of this paper is to determine the effectiveness of using CNN spectrogram learned time-frequency features, different machine learning algorithms, and the impact of using the extracted features on the detecting and predicting FoG episodes accuracy. Wherefore, the major contributions of the proposed work are detailed as follows:

- A new label is added in the dataset for pre-FoG episodes that featured all pre-FoG episodes that come exactly before FoG episodes.
- Convolutional Neural Network is used to extract spectrogram-based time-frequency analysis features.
- Trying the use of different sensor axes such as angular-axes for determining the effectiveness of using it and comparing it with principle-axes.

A baseline model including the use of time-domain features is implemented besides the proposed time-frequency spectrogram-based CNN features. The paper in the next proposed sections is organized starting with section 2 that presents an overview of the proposed model structure. In section 3 the experimental results have been discussed and illustrated. Section 4 presented the conclusions and future work.

2. The Proposed Model

The proposed model phases are described in this section. *Data Preparation*, *Feature Extraction*, and *Classification*, as shown in Figure 1 are the phases implemented for the proposed model. But first, a summarized description of the dataset used in this paper is presented, before start describing the first phase.

2.1 Dataset

The proposed benchmark Daphnet dataset [9] is available publicly and it is used in this paper for validating the proposed approach. The dataset contains continuous (time-series) data from ten FoG subjects with Parkinson's Disease while performing the requested walking tasks by the physiotherapists in a lab. Three wearable tri-axel accelerometer sensors were used to build the data of the benchmark Daphnet dataset, sensors were attached to the patient's body in different places, namely, the ankle (shank), above the knee (thigh), and lower back (trunk). The data takes over eight hours to be recorded, during the study, 237 FoG events have been identified by professional physiotherapists. In the original dataset, the data samples contain three events, namely, no-FoG, out of the experiment, and FoG events which in turn correspond to the labels 0, 1, and 2, respectively.

2.2 Data Preparation

For the Daphnet benchmark dataset description, the authors clarifying that samples didn't have pre-FoG episodes labels. For discriminating pre-FoG episodes with a new label, all consolidated labels for a specific window time before label 2 turns into label 3 in the data preparation phase. Figure 2 shows a signal that contains walking, pre-FoG, and FoG patterns.

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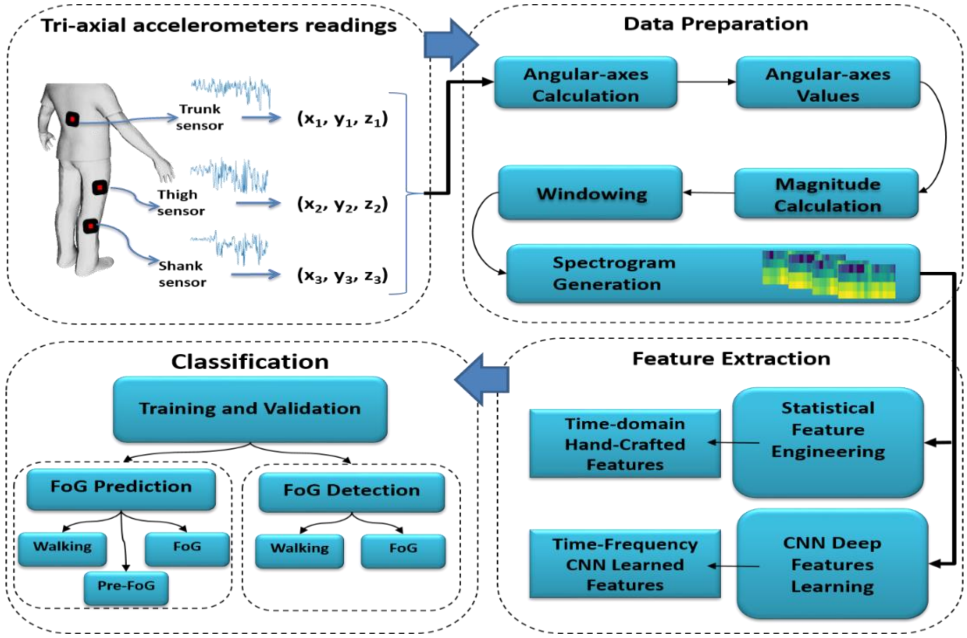

Figure 1. The FoG detection/prediction general proposed model

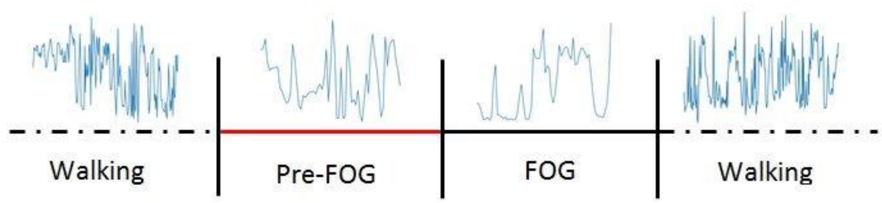

Figure 2. A sample of the categories of the FoG signal data

Wherefore, the four steps in the data preparation phase are angular-axes calculation, magnitude calculation, windowing, and spectrogram generation.

2.2.1 Angular-axes calculation

The reason of used the angular-axes [13] in this paper because of the need to gain data about the orientation in the three dimensions of an object, angular-axes also use a set of three rotations about different axes. In the angular-axes calculation step, the values of each accelerometer's principle-axes, namely, *x*, *y*, and *z* have been used to calculate new values of the angular-axes. Roll (*r*), Pitch (*p*), and Yaw (*y*) are the new calculated axes as presented in equations (1), (2), and (3), respectively, with constant $\Pi = 3.14$.

$$Roll = 180 * \arctan(y/\sqrt{x^2+z^2})/\pi \quad (1)$$

$$Pitch = 180 * \arctan(x/\sqrt{y^2+z^2})/\pi \quad (2)$$

$$Yaw = 180 * \arctan(z/\sqrt{x^2+y^2})/\pi \quad (3)$$

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2.2.2 Magnitude calculation

From the previous phase, the output of the angular-axes calculation has been used to calculate the magnitude for each of the three axes from each sensor, as shown in equation (4). Where s refers to each accelerometer sensor, namely, ankle, knee, and trunk.

$$Magnitude = \sqrt{(r_s^2 + p_s^2 + y_s^2)} \quad (4)$$

2.2.3 Windowing

The calculated magnitudes from each sensor from the previous step, have fixed size and the slicing technique is relying on using overlapping windows based on the sample's target. One sec. windowing scheme is used to be sure of having equal spectrogram sizes for the next phase. The 1 second (67 samples) windowing scheme is implemented with overlapping in case of having remaining samples below 67 with the same label. Data samples have been neglected if those samples have a size less than 67 samples (1 second) as shown in Figure 3.

2.2.4 Spectrogram Generation

Non-stationary or non-periodic signals cannot be clarified using time or frequency domain analysis, whose frequency content differs with time [14]. Wherefore, it is recommended to use time-frequency analysis to gain frequency-domain information from signals. The use of spectrograms will help in reach this objective because it can display the information of the time-frequency analysis.

For generating the corresponding spectrograms the Short-Time Fourier Transform (STFT) has been used as the time-frequency analysis algorithm of windowed sensors readings [15] as shown in Figure 4.

2.3 Feature Extraction

The investigated schemes in this section are time-domain and time-frequency extracted features. The hand-crafted time-domain statistical features are *Variance*, *Standard deviation*, *Median*, *Mean*, *Maxima*, *Minima*, and *Range*. The time-frequency features are based on the generated spectrogram images from the previous spectrogram generation phase. Deep learned features are used for time-frequency analysis of spectrogram images. The extracted CNN feature vectors reflecting the time and frequency analysis of spectrogram images. Lately, in the domain of image processing and deep learned features, the Convolutional Neural Network (CNN) is widely used with deep learning models [16]. Different CNN models can automatically learn features to capture complex visual variations. CNN structure contains different convolutional layers, fully-connected layers, and pooling layers. CNNs can automatically learn useful spatial hierarchies of the features from low-level to high-level patterns.

In this paper, a convolutional neural network has been adopted for the learned feature extraction. Principle Component Analysis (PCA) is adopted and applied to measure the impact of using it on the extracted feature vectors.

The CNN model is implemented for extracting the time-frequency features from spectrogram images. The model is structured as follows: relu activation function, adadelta optimizer, three convolutional, and max-pooling layers are used with a flatten layer. The use of a flatten layer for reshaping the output produced from the previous convolutional layers, one feature vector contains 128 features extracted from each image.

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Time-consuming and higher computation complexity problems could be raised because of the high dimensionality. PCA consists of some statistical steps to convert a set of correlated variables to a set of uncorrelated variables and to minimize columns of a dataset into fewer new column set as shown in Figure 5.

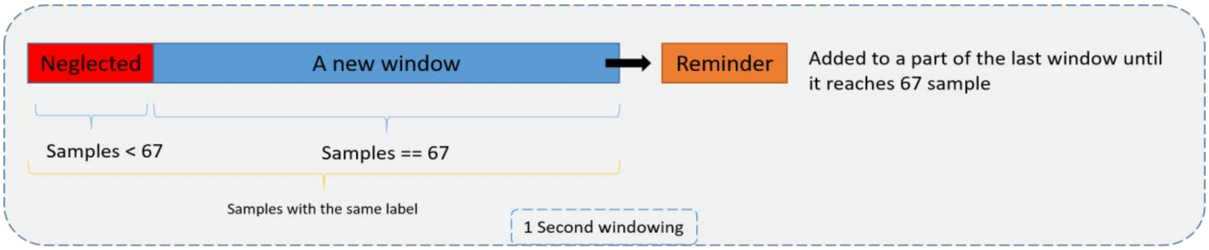

Figure 3. 1-second windowing scheme (67 samples)

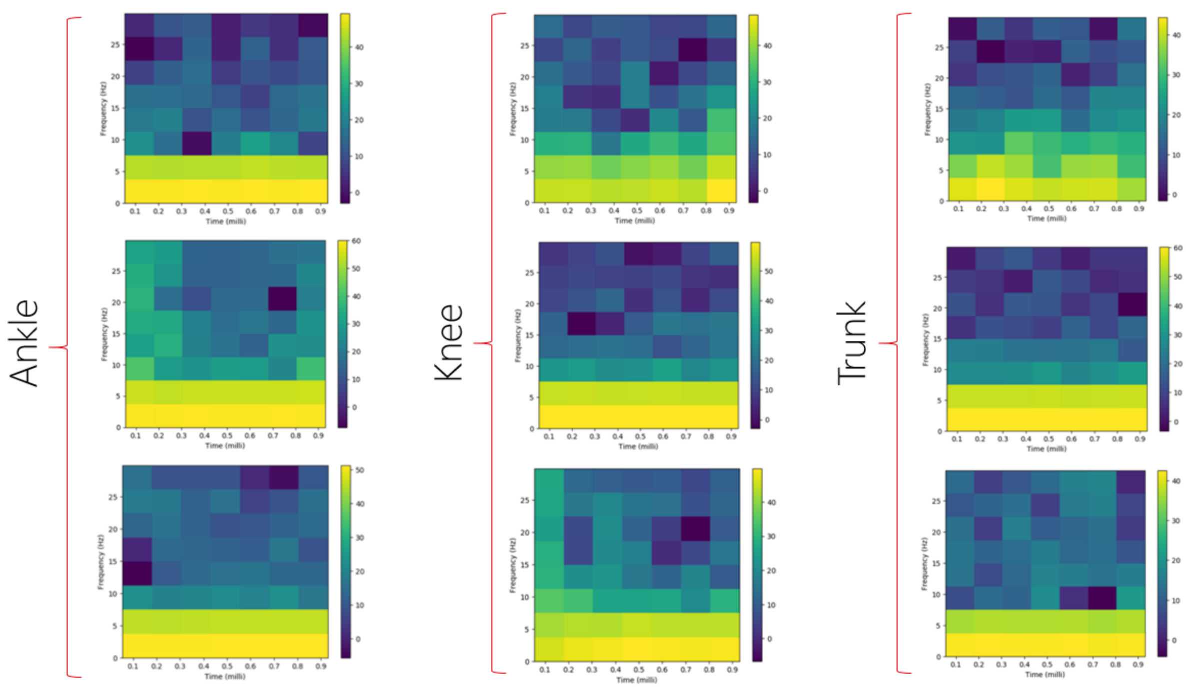

Figure 4. Spectrogram samples from ankle, knee, and trunk sensors

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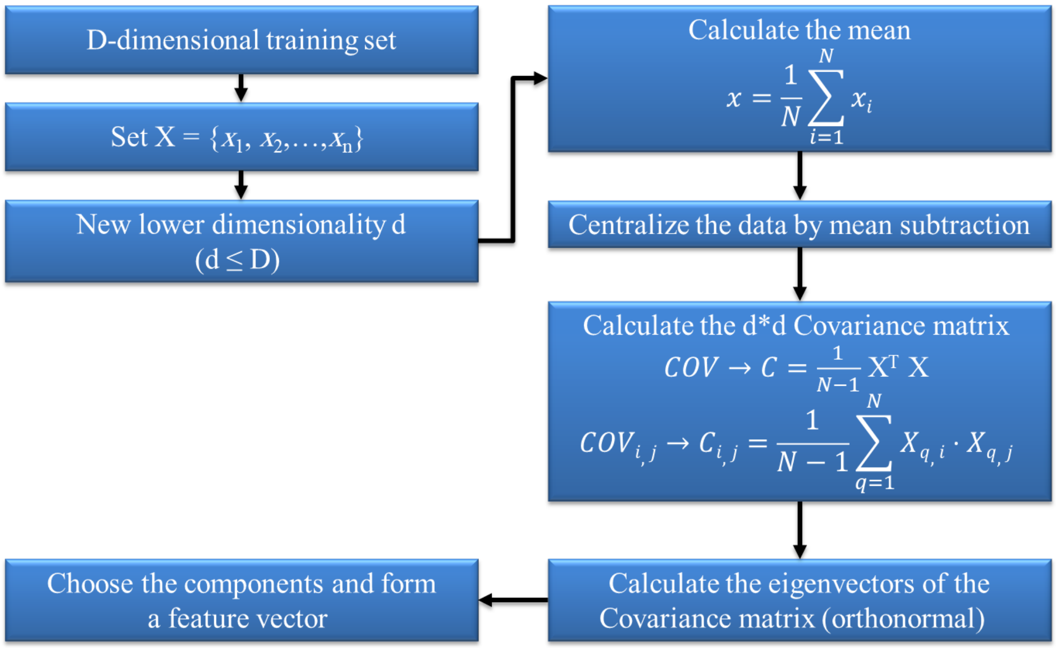

Figure 5. PCA for dimensionality reduction calculation steps

2.4 Classification

From the previous feature extraction phase, feature vectors have been implemented, k-fold cross-validation is applied to the extracted features. For training and validating the work, different machine learning algorithms have been adopted. Different trained machine learning models are adopted for measuring the performance of the proposed Freezing of Gait detection and prediction approaches.

In this paper, the adopted machine learning classifiers [17, 18] are:

- Random Forest
- Bagging
- Logistic Regression
- Adaptive boosting (Adaboost)
- K-Nearest Neighbor (KNN)
- Decision tree
- Support Vector Machine (SVM) with different kernel functions, namely linear, RBF, polynomial, and sigmoid.

3. Results and Discussion

The experimental outcomes are presented in this section, also an illustration is proposed about the effectiveness of using the extracted spectrogram CNN learned time-frequency features for FoG episodes detection and prediction. For implementing the proposed experiments, Google Colab and 15GB memory are used. The proposed approach has been conducted under the use of python Tensorflow and Keras environments. The performance measurements used are Accuracy, Recall, Precision, and F−measure as shown in Table 1, which have been calculated according to equations (5), (6), (7), and (8), respectively.

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Where, the terms TP, FP, TN, and FN are True Positive, False Positive, True Negative, and False Negative, respectively.

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

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

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

$$F - score = 2\frac{precision*recall}{precision+recall} \quad (8)$$

The dataset has been sliced into 80% and 20% for training and testing, respectively for each of the resulted feature sets. The proposed model is trained and validated with k-fold cross-validation with k=5.

The results show that the Random Forest classifier outperforms the other implemented classifiers. Figures 6 and 7 present the classification accuracy for FoG prediction and detection using time-domain statistical features on the previously stated machine learning classifiers. From Figure 6 it can be observed that angular-axes outperform using principle-axes with an enhancement of 1.9% without using PCA and 3.8% using PCA. Also, it can be observed from Figure 6 (a) and (b) that not using PCA achieves better results than using PCA by 5.2% on the Random Forest classifier. Figure 7 also ensures that using angular-axes over principle-axes achieves the best results by 5% without using PCA and 6% using PCA. Moreover, Figure 7 (a) and (b) show that not using PCA achieves better results than using it by 9.1%.

Figures 8 and 9 present the classification accuracy achieved when implementing the previously stated machine learning classifiers for the prediction and the detection of Freezing of Gait under the use of the extracted feature scheme. Besides, the Stacked Ensemble of classifiers algorithm has been also adopted for two tasks, firstly, for combining the SVM kernels, secondly for adding all the applied machine learning classifiers. As shown in Figure 8 (a), and (b), it has been observed that using time-frequency CNN features without using PCA outperforms using it with PCA for FoG prediction.

It also can be observed the enhancement using angular-axes over principle-axes, the increase in the prediction accuracy is 3.7% without using PCA against using PCA with Random Forest classifier. Furthermore, the best implementation of FoG episodes prediction is through the Random Forest classifier with adopting the proposed time-frequency CNN features, using angular-axes data without applying PCA dimensionality reduction with an accuracy of 82.5%.

A model's performance can't always depend on the accuracy, therefore, the following additional performance measures have been used namely, precision, recall, and F-measure, as shown in Table 1, to measure the performance of the implemented machine learning algorithms taking into consideration the extracted features and the calculated angular-axes values with and without applying the PCA algorithm.

Moreover for FoG detection, as shown in Figure 9 (a) and (b) the Random Forest and Bagging ensemble learning classifiers achieves better results than the other tested machine learning classifiers with an accuracy of 87.6% using the spectrogram CNN learned features sets. An enhancement of using angular-axes over the principle-axes could be seen in the accuracy that achieved 2.1% when using PCA and 4.1% without using PCA.

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From Table 1 and Table 2, it can be observed the positive impact of not applied PCA on the extracted CNN time-frequency features and time-domain features. It also shows the result's convergence between detection and prediction, which in terms insure that despite the difficulty of the prediction mechanism but using the proposed extracted features for pre-FoG prediction achieves a good enhancement.

Results from Figures 8 and 9 matches the results from Table 1 in which not using PCA on the extracted CNN learned time-frequency features from spectrogram images is better than applying PCA on the extracted features. Figure 10 presents a comparison between the proposed model, baseline model, and the related work, it can be observed that the proposed time-frequency detection model outperforms other related work models with an F-measure of 88.8%.

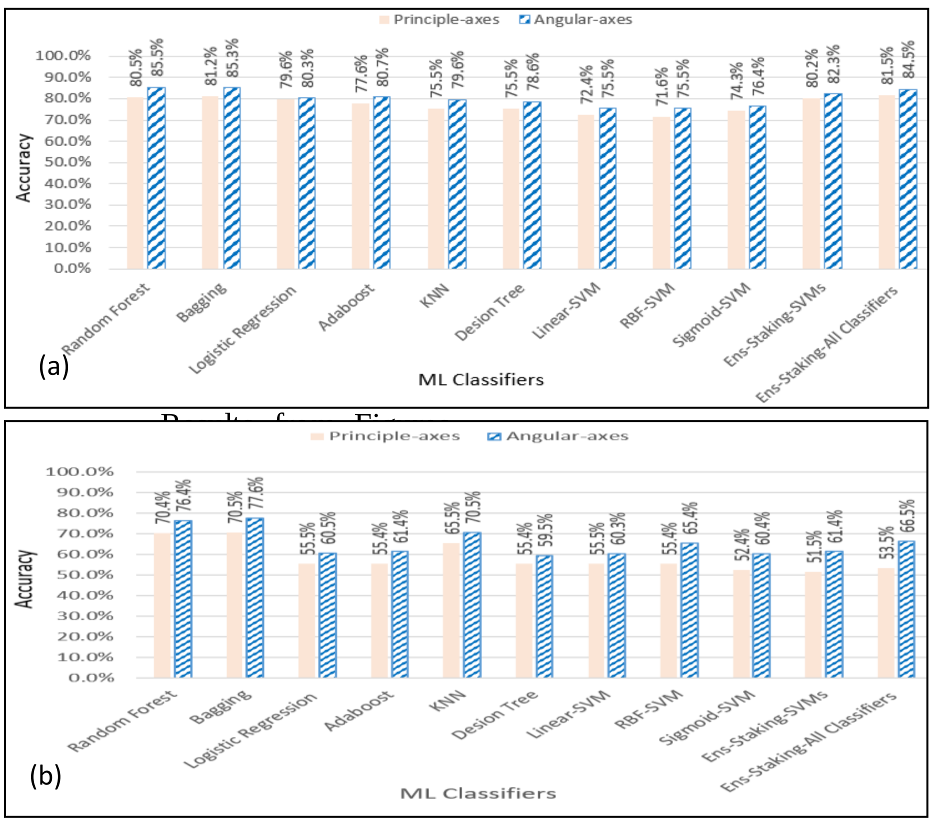

Figure 6. Classification accuracy measurement time-domain features for FoG prediction, (a) without using PCA and (b) using PCA

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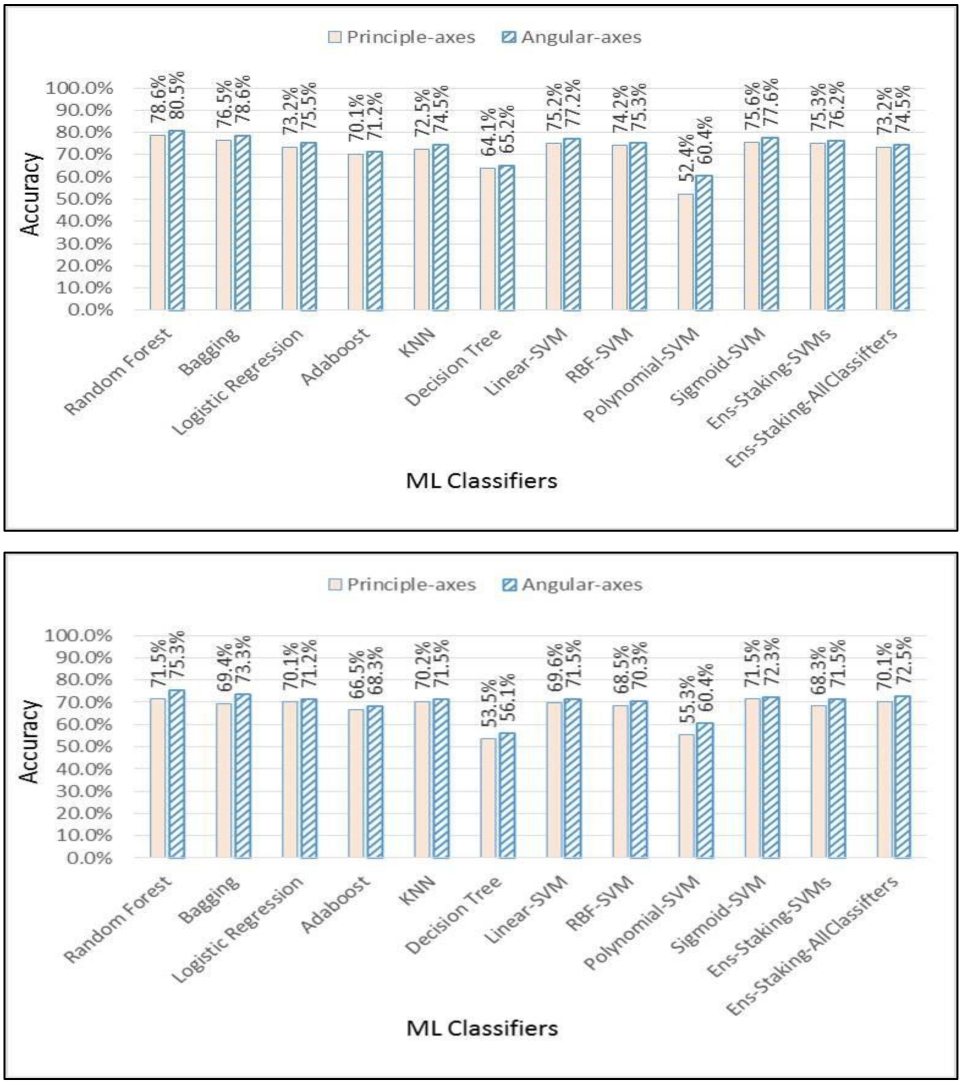

Figure 7. Classification accuracy measurement time-domain features for FoG detection, (a) without using PCA and (b) using PCA

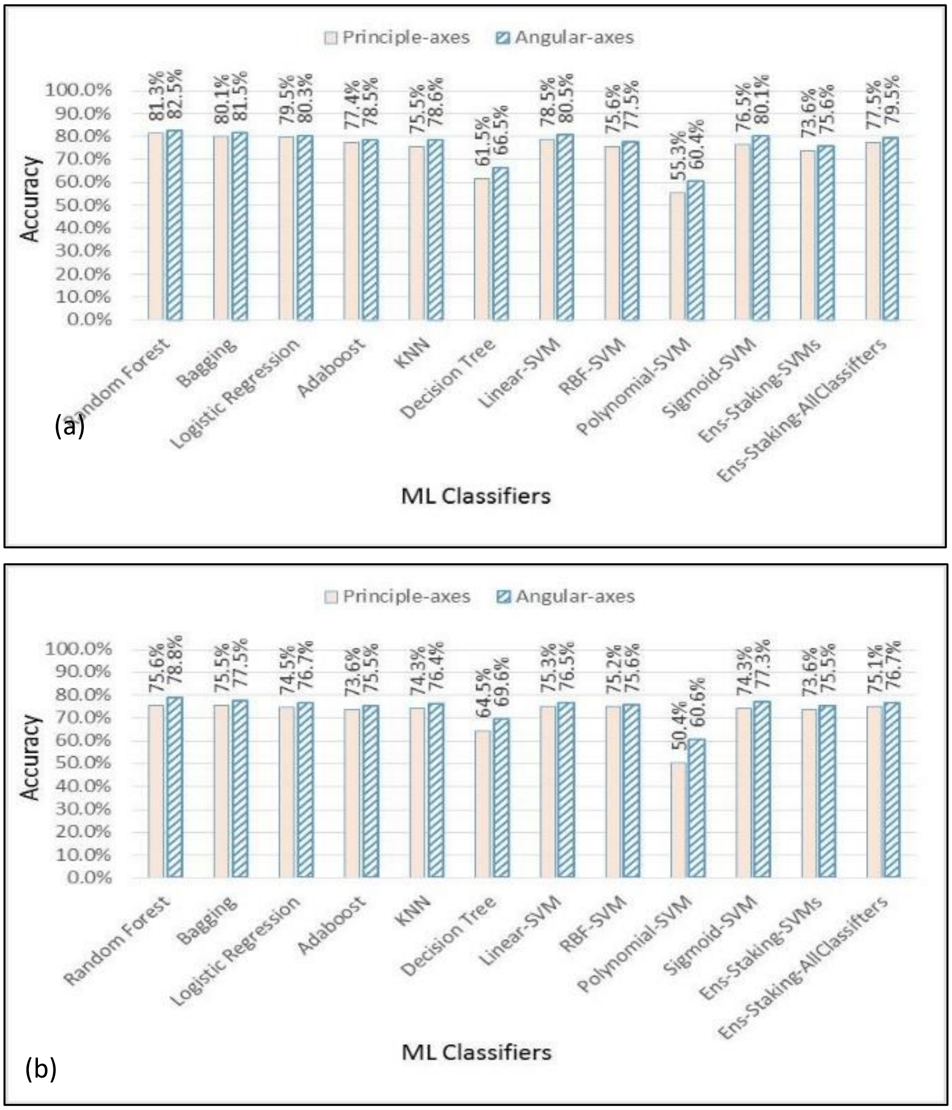

Figure 8. Classification accuracy measurement using spectrogram-based CNN learned features for FoG prediction, (a) without using PCA and (b) using PCA

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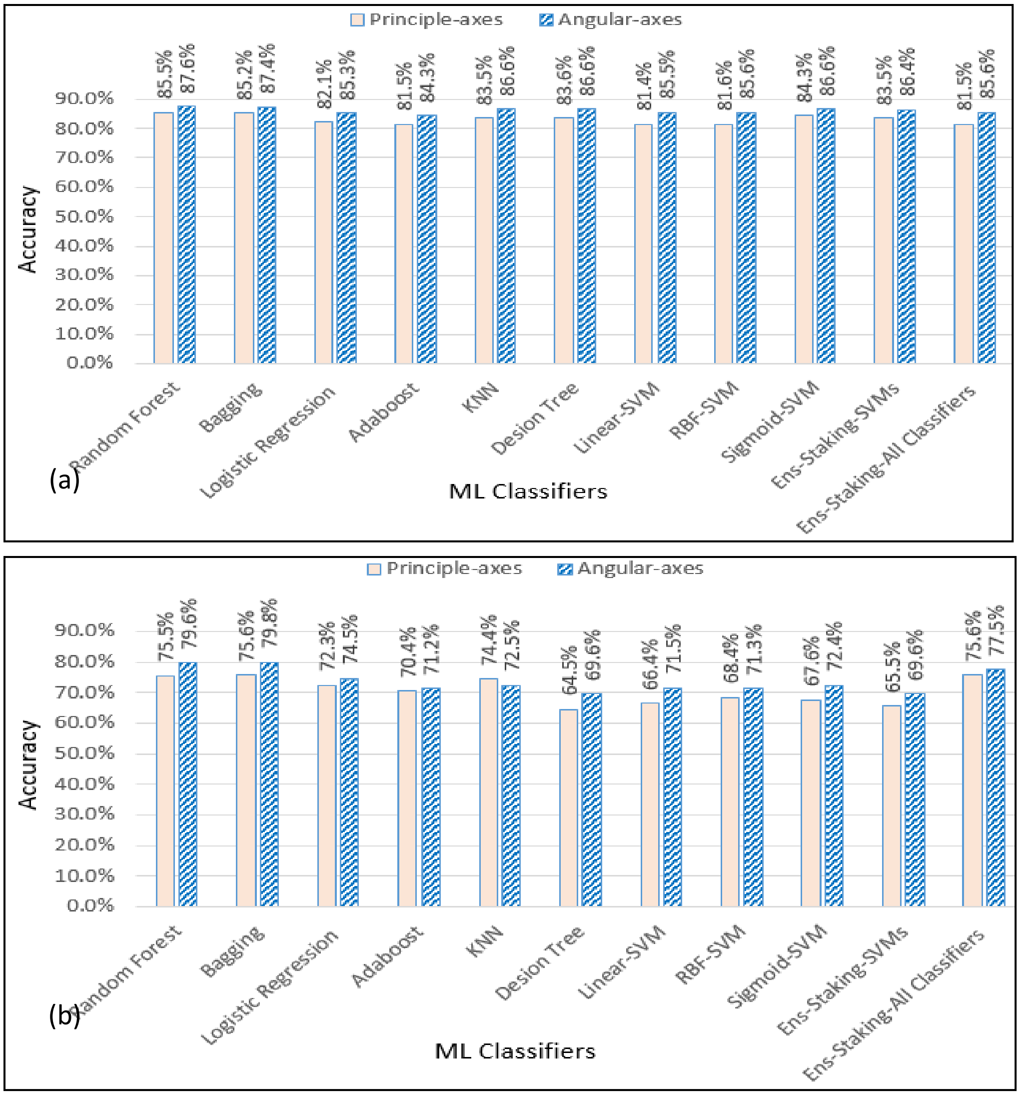

Figure 9. Classification accuracy measurement using spectrogram-based CNN learned features for FoG detection, (a) without using PCA and (b) using PCA

Table 1. Precision, recall, and f-measure performance measurements of ML classifiers using angular-axes and the time-frequency features with and without applying PCA for FoG detection and prediction (Time-frequency features)

Metrics / Classifiers	Precision		Recall		F-measure	
	using PCA	without PCA	using PCA	without PCA	using PCA	without PCA
Random Forest (Detection)	78.3%	**88.5%**	79.6%	89.3%	78.9%	**88.8%**
Random Forest (Prediction)	75.8%	81.7%	78.5%	82.8%	77.1%	82.2%
Bagging (Detection)	79.1%	86.6%	80.4%	86.1%	79.7%	86.3%
Bagging (Prediction)	75.6%	81.1%	77.4%	81.5%	76.4%	81.2%
Logistic Regression (Detection)	74.1%	85.1%	74.2%	84.8%	74.1%	84.9%
Logistic Regression (Prediction)	75.2%	80.1%	76.2%	79.4%	75.6%	79.7%
Adaboost (Detection)	71.2%	84.1%	70.8%	82.8%	70.1%	83.4%
Adaboost (Prediction)	74.8%	78.5%	75.4%	78.5%	75.1%	78.5%
KNN (Detection)	72.3%	85.5%	72.5%	86.2%	72.4%	85.8%
KNN (Prediction)	76.2%	78.2%	75.5%	77.8%	75.8%	77.9%
Decision Tree (Detection)	68.9%	85.8%	69.8%	86.2%	69.3%	86.1%
Decision Tree (Prediction)	68.9%	67.8%	69.8%	67.9%	69.3%	67.8%
Linear-SVM (Detection)	71.5%	85.2%	71.6%	85.5%	71.5%	85.3%
Linear-SVM (Prediction)	76.2%	80.1%	75.5%	80.6%	75.8%	80.3%
RBF-SVM (Detection)	71.5%	85.5%	71.2%	85.2%	71.3%	85.3%
RBF-SVM (Prediction)	74.6%	77.5%	75.6%	77.6%	75.1%	77.5%
Sigmoid-SVM (Detection)	72.5%	86.5%	72.6%	85.7%	72.5%	86.1%
Sigmoid-SVM (Prediction)	77.5%	80.5%	77.4%	80.4%	77.4%	80.4%
Ens-Staking-SVMs (Detection)	70.1%	86.5%	70.1%	85.8%	70.1%	86.1%
Ens-Staking-SVMs (Prediction)	75.5%	75.6%	76.4%	75.2%	75.9%	75.3%
Ens-Staking-All Classifiers (Detection)	77.2%	85.5%	77.1%	85.5%	77.1%	85.5%
Ens-Staking-All Classifiers (Prediction)	76.5%	79.5%	76.6%	78.8%	76.5%	79.1%

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Table 2. Precision, recall, and f-measure performance measurements of ML classifiers using angular-axes and the time-domain features with and without applying PCA for FoG detection and prediction (Time-domain features)

Metrics / Classifiers	Precision		Recall		F-measure	
	using PCA	**without PCA**	**using PCA**	**without PCA**	**using PCA**	**without PCA**
Random Forest (Detection)	75.2%	80.5%	71.2%	79.8%	73.1%	80.1%
Random Forest (Prediction)	72.9%	**81.2%**	73.7%	80.6%	73.2%	**80.8%**
Bagging (Detection)	77.1%	82.1%	76.5%	82.5%	76.7%	82.2%
Bagging (Prediction)	74.5%	77.9%	75.5%	78.6%	74.9%	78.2%
Logistic Regression (Detection)	60.1%	75.9%	61.4%	77.9%	60.7%	76.8%
Logistic Regression (Prediction)	70.2%	74.1%	70.4%	71.6%	70.2%	72.8%
Adaboost (Detection)	60.8%	79.6%	61.8%	80.1%	61.2%	79.8%
Adaboost (Prediction)	65.9%	71.4%	67.2%	71.8%	66.5%	71.5%
KNN (Detection)	70.5%	79.7%	70.4%	79.5%	70.5%	79.5%
KNN (Prediction)	71.4%	74.2%	71.5%	74.7%	71.4%	74.4%
Decision Tree (Detection)	59.5%	78.4%	60.1%	78.6%	59.7%	78.4%
Decision Tree (Prediction)	56.4%	65.5%	56.2%	65.7%	56.2%	65.5%
Linear-SVM (Detection)	61.2%	74.6%	61.5%	75.5%	61.3%	75%
Linear-SVM (Prediction)	71.2%	71.2%	71.5%	71.4%	71.3%	71.2%
RBF-SVM (Detection)	64.5%	74.6%	65.7%	75.8%	65%	75.1%
RBF-SVM (Prediction)	70.1%	74.5%	69.5%	75.8%	69.7%	75.1%
Sigmoid-SVM (Detection)	60.4%	76.1%	60.5%	76.4%	60.4%	76.2%
Sigmoid-SVM (Prediction)	72.6%	76.8%	73.1%	77.6%	72.8%	77.1%
Ens-Staking-SVMs (Detection)	61.7%	82.1%	62.5%	82.6%	62%	82.3%
Ens-Staking-SVMs (Prediction)	70.8%	74.9%	70.9%	74.5%	70.8%	74.6%
Ens-Staking-All Classifiers (Detection)	66.2%	85.5%	67.1%	85.8%	66.6%	85.6%
Ens-Staking-All Classifiers (Prediction)	73.5%	75.6%	73.6%	75.8%	73.5%	75.6%

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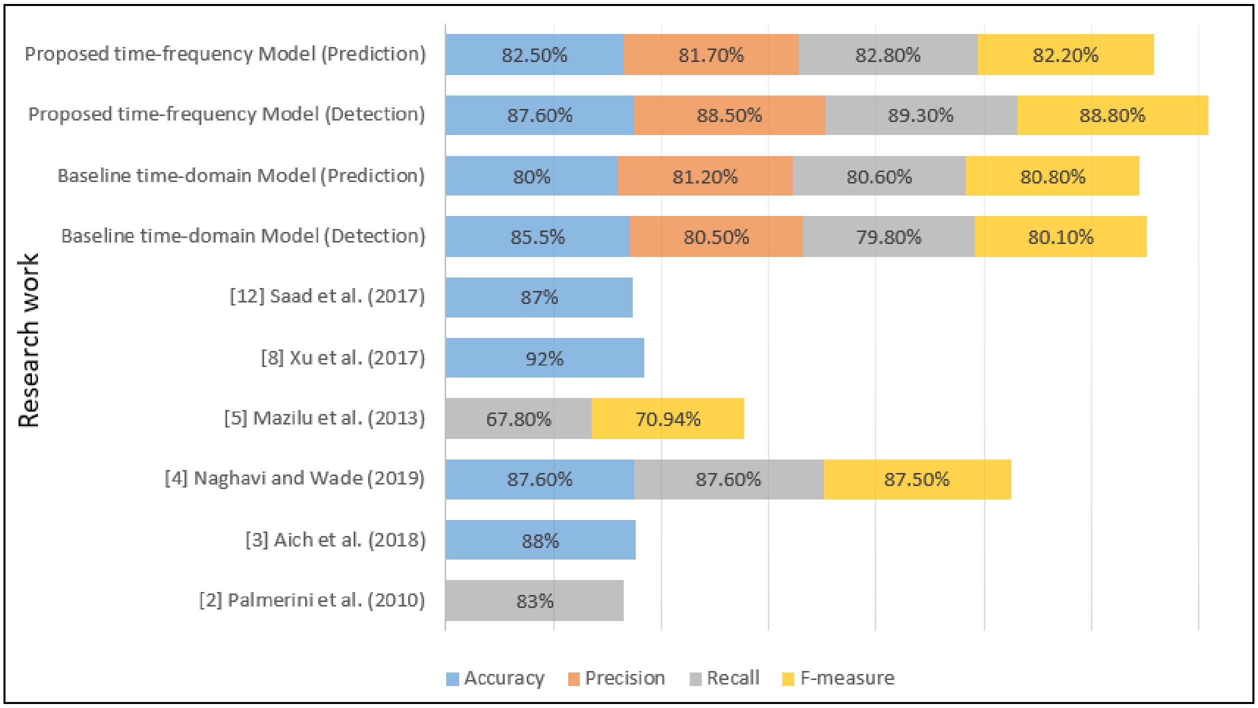

Figure 10. Related work and proposed models comparison between different performance measurements of all implemented models

4. Conclusions and Future Work

The extracted spectrogram CNN learned time-frequency features outperforms using time-domain features. There were also seven classifiers were used in this study, Random Forest achieves the best results. The extracted features were implemented with and without using PCA that has led to observe the effectiveness of using those feature vectors in detecting and predicting Freezing of Gait episodes. Wherefore, it has been concluded that using the proposed spectrogram CNN time-frequency approach without applying PCA dimensionality reduction achieves the best enhancement in Freezing of Gait episodes prediction along with the use of angular-axes instead of principle-axes.

A lot of different approaches and features could be adopted and discussed in the field of predicting and detecting the Freezing of Gait episodes in future work. The severity of PD patients with FoG and other clinical assessments could be considered in increasing the performance of the detection and prediction.

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