Diagnosing Parkinson's Disease Using 1D CNN with DWT Coefficients

Md Somir Khan
Department of Computer Science
University of Louisiana at Lafayette
Lafayette, Louisiana, USA
md-somir.khan1@louisiana.edu

Anthony S. Maida
Department of Computer Science
University of Louisiana at Lafayette
Lafayette, Louisiana, USA
anthony.maida@louisiana.edu

***Abstract*—A progressive neurodegenerative disorder, Parkinson's disease(PD) affects both men and women of all ages. Diagnoses of Parkinson's are mainly clinical exercises because there is no definite medical test for the disease. Despite the fact that guidelines exist, approximately 10-30% of patients are misdiagnosed. It is therefore imperative to have a fast, accurate, and unbiased method for diagnosing diseases. There have been several studies for diagnosing PD. Analysis of gait patterns shown promising results in diagnosing PD. Our aim of this study is to diagnose PD from gait data. we propose a novel method of extracting features from gait data using different levels of Discrete Wavelet Transform(DWT) detailed coefficients. We used the publicly available gait data set of 93 healthy patients and 73 patients diagnosed with PD. We used DWT detailed coefficients as input to 1D Convolutional Neural Network for diagnosing PD. In this study we analyzed DWT detailed coefficients of level 1,3,6 with and without downsampling the gait data and we found that DWT detailed coefficients of level 3 in downsampled gait data as features achieves accuracy of 85.43%.From this study, future works will be better able to evaluate their methods in using DWT detailed coefficients.**

***Index Terms*—Parkinson's Diagnosis, Gait, Signal Processing, Discrete Wavelet Transform, Detailed Coefficients, Convolutional Neural Networks**

I. Introduction

As a neurological disorder, Parkinson's Disease (PD) is caused by a lack of dopamine neurons, nerve cells found in the substantia nigra of the brain [1]. Despite the fact that the disease is not fatal, it can be serious if it persists for a prolonged period of time. Idiopathic Parkinson's disease is primarily caused by aging [2]. The condition is considered a chronic neurodegenerative disease, as neural tissue dies and levels decreases in neurotransmitter [3].After Alzheimer's disease, it is the second most prevalent neurological disorder considered as a chronic illness. Worldwide about 10 million people are affected by PD [4]. The CDC ranks PD's complications as the 14th leading cause of death in the United States of America. As the population ages, PD is likely to affect an increasing number of elderly people. Unfortunately, no cure nor treatment method for this condition exists. It is not possible to diagnose PD with a medical test. Diagnosis remains a medical exercise [5], [6].Currently, Parkinson's disease (PD) patient's clinical assessment methods are patient or caregiver self-descriptions and clinician-moderated questionnaires, including the freezing of gait questionnaire (FOG-Q), Unified Parkinson's Disease Rating Scale (UPDRS), and the Activities of Daily Living (ADL) part 14. [7]. In addition to questionnaires, self-descriptions and neurological examinations, there are other methods of diagnosis. Nonetheless, these methods are subjective and a lengthy process and can give inaccurate diagnoses. 10%- 30% of patients with PD are given a different diagnosis when they are rediagnosed[5], [8]. Overall life experience of PD patients can be enhanced through regular monitoring and medical assessments as the disease develops gradually. There is a possibility of reducing undesired complications by detecting PD and using therapies [6], [9]. Some approaches have been proposed to identify nearly all recognized PD symptoms e.g., dyskinesia [10], bradykinesia [11] and gait [12] by analyzing various types of signals e.g.,plantar pressure [12], acceleration [13], and surface electromyogram [14]. In order to help all those affected by PD, a method that is accurate, quicker, and more efficient needs to be developed. Monitoring PD and developing wearable devices for patients with PD have been greatly improved by applying machine learning techniques to diagnostic methods.

The aim of this study is to develop a deep learning model to diagnose Parkinson's disease from gait while achieving high accuracy and ensuring a low resource design suitable for deployment in embedded systems.

II. Related Works

The application of Machine Learning and Deep Neural Networks in various clinical conditions has gained great traction in recent years. PD diagnosis was not overlooked. There has been great success in diagnosing PD with a variety of machine learning models. Researchers have succeeded in achieving their goals in a variety of ways. [15]–[18] analyzed speech signals,[19], [20] analyzed hand drawing data, [21] analyzed telemonitoring data in PD diagnosis. There have been several studies in analyzing Gait Data. [22] examined swing time, stride time variablity and center of pressure to find useful features for diagnosing PD. They acheived an accuracy of 93.6% but their gait dataset was small(29 PD patient and 18 healthy paitents). [23] used wavelet-based feature extraction in a neural network based on weighted fuzzy membership acheived 77.3% accuracy. [24] propsed a dual-

modal deep-learning-based model. They used convolutional neural network followed by an attention-enhanced long short-term memory (LSTM) network to model left and right gait seperately. [25] They considered speech, handwriting and gait to extract transitional information and trained a convolutional neural network by extracted informations to diagnose PD. [26] used different feature extraction techniques like Local Binary Pattern (LBP), Local Neighbour Descriptive Pattern (LNDP), Local Neighbour Gradient Pattern (LNGP), and Local Gradient Pattern (LGP) with feature selection to create a optimal set of features then trained in Artificial Neural Network. They acheived 96.28% accuracy. Deep learning techniques utilized in recent studies shows promising outcomes in the diagnosis of PD Disease.The hybrid CNN-LSTM model of Zhao et al.[27]achieves 98.6% accuracy, the 1D CNN model of Maachi et al.[28] achieves 98.7% accuracy,a deep attention based neural network was used by Xia et al.[24] to achieve 99.07% accuracy. [29] proposed a light weight Gait classification Network (LPGNet) which can be used in embedded systems. They used a deep learning model which uses Linear Prediction Residual as features from gait data and acheived 90.3% accuracy.

We found various feature extraction techniques and deep learning models for diagnosing PD from previous studies conducted by researchers.We were inspired by [29]. Our goal is a light weight model which can be used in embedded system.

III. Materials And Methods

A. Dataset

The dataset we used to perform our experiments are collected from PhysioBank [12]. The dataset have 306 gait recordings of 166 patients where 92 gait recording is collected from 73 healthy patients and 214 gait recording is collected from 93 patients who have Parkinson's disease. All the recordings are measurement of Vertical Ground Reaction Forces (VGRF) of sampled in 100 Hz and the duration of each recording is 2 minutes. Each sample consists of 18 time series signals where (1-8) signals are from 8 sensors placed under left foot, (9-16) signals are from 8 sensors placed under right foot, 17th and 18th signals are Total force under left and right foot respectively.

B. Discrete Wavelet Transform

Wavelet Transform is a very common method for analyzing time series signals. Wavelet transform has the ability of analyzing localized features of a signal. This ability is the advantage of wavelet transform over Fourier transform. DWT transforms time series data into two wavelet coefficients approximation coefficient and detailed coefficient.

$$W_{\phi(j_0,k)} = \frac{1}{\sqrt{M}} \sum_{x=0}^{M-1} f(x)\phi_{j_0,k}(x) \quad (1)$$

$$W_{\psi(j,k)} = \frac{1}{\sqrt{M}} \sum_{x=0}^{M-1} f(x)\psi_{j,k}(x) \quad (2)$$

where $f(x)$, $\phi_{j_0,k}(x)$, and $\psi_{j,k}(x)$ are functions of the discrete variable $x = 0, 1, 2, \ldots, M-1$. The coefficients from Equations (1) is approximation coefficient and coefficient from equation (2) is detailed coefficients [30].

The detailed wavelet coefficients are very useful in analyzing Abrupt changes and spikes in time series data as it record detailed features. The approximation wavelet records feature which can produce rough estimate of actual data.[31] we have used DWT detailed coefficients of VGRF signals to detect the differences in signals of a healthy patient and a patient with Parkinson's Disease.

C. 1D Convolutional Neural Network (1D-CNN)

For image processing, recognition and pattern matching CNN is widely used as it performs very well in these tasks.A 1D convolutional neural network (1D CNN) is a form of neural network architecture designed to analyze one-dimensional sequential data. It is made up of convolutional layers that learn features from input data by sliding a window (kernel) over it, conducting element-wise multiplication and summing, and producing a feature map. During the training process, the kernel weights are learned, allowing the network to extract the most significant features from the input data. The output of the last convolutional layer is flattened and fed into a fully connected layer or a series of fully connected layers, On the basis of the extracted features, classification or regression is performed.

1D CNNs have been widely used in a variety of applications, including speech recognition, natural language processing, and time series analysis. They are particularly effective when the input data has a sequential structure and local patterns in the data are important for the task at hand.

IV. Methodology

The experiments are done in 3 steps which are: preprocessing, feature extraction, using 1D CNN for diagnosis of Parkinson's disease.

A. Data Preprocessing

We have experimented with downsampling Each sample to 50Hz and without downsampling (100Hz). We normalized the data. We used order 2 moving average filter while downsampling so that artifacts can be avoided.

B. Feature Extraction

We performed Discrete Wavelet Transform (DWT) in the preprocessed data to obtain approximate and detailed coefficient. In several experiments we used different level to get different level detailed and approximate coefficients.

C. 1D CNN Architecture

We used 1D convolutional neural network consisting of 3 blocks which is depth-wise separable convolutions [32]. The depth-wise separable convolution replaces the normal convolution with Convolutions at both points and channels in succession reduce computation time and the network's parametric complexity power but maintaining predictive power. In

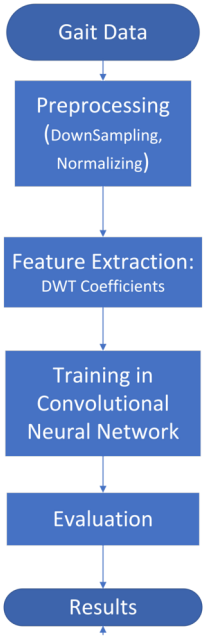
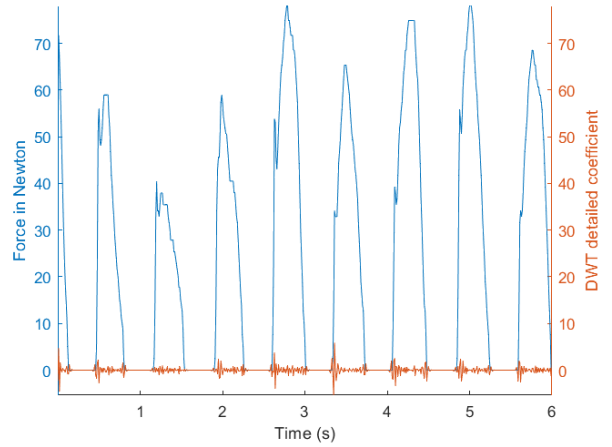


Fig. 1. Pipeline of Experiment

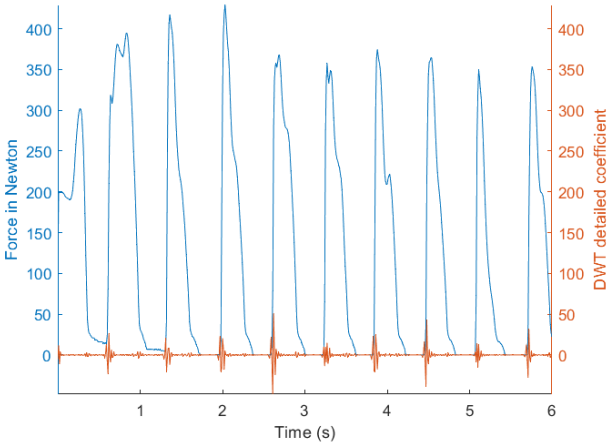
addition, because they have fewer learnable parameters than a normal CNN, they are less prone to overfitting. Each convolution block consists of a separable convolution layer, batch normalization layer, ELU activation and a matrix pooling operation that is preceded by the application of ELU activation. In order to compute the average over taken the time dimension, we perform a global average pooling operation after the three blocks. As a result, for the final fully connected layer, we have a fixed-dimensional vector with sigmoid activation. By using global average pooling at this level, model can accept time series data of different lengths and we can perform one-step inference without requiring padding or windowing.

D. Training in 1D CNN

While training the CNN the generated DWT coefficients are divided into windows of 2 seconds. There is a overlap of 50% between the current window and it's successive window. We labeled each window with the label of source sample. For classifying these windows we trained a CNN. When the network converges the trained weights were freezed and used in the fully connected layer for classifying 2 minutes samples. The average pooling operation of first step reduces the dimensionality of the input to the fully connected layer. The second training step helps to calibrate the last fully connected layer to changes from average pooling over the entire sample. we used ADAM optimizer with its default parameters, Binary cross-entropy with label smoothing as the objective function. At the input to CNN and at the input to final logistic layer we used spatial dropout. To maintain stability of training we used L2 regularization along with gradient clipping on all learnable parameters.



(a) Healthy Patient



(b) PD patient

Fig. 2. Detailed Coefficent of level 1 in downsampled recordings

E. Evaluation

For evaluation 10-fold cross-validation is used. F1 scores, accuracy and AUC are measured over 10 folds.

V. Experiments

A. Experiment 1

1) Method: We downsampled the VGRF recordings to 50Hz. DWT level 1 detailed coefficients were extracted from the recordings. There are noticeable differences on extracted coefficients between a healthy patient and a patient diagnosed with PD which is shown in Fig 2. The extracted coefficients were trained on the convolutional neural network for diagnosing Parkinson's Disease. The description of CNN models are show in Table I and II respectively.

2) Result: We used 10 fold cross validation for evaluating results. Table III shows the result obtained from this experiment.

TABLE I
FIRST CNN MODEL LAYERS AND PARAMETERS

Layer (type)	Output Shape	Param #
InputLayer	(None, None, 18)	0
SpatialDropout1D	(None, None, 18)	0
GaussianNoise	(None, None, 18)	0
SeparableConv1D	(None, None, 32)	734
BatchNormalization	(None, None, 32)	128
Activation	(None, None, 32)	0
MaxPooling1D	(None, None, 32)	0
SeparableConv1D	(None, None, 32)	1216
BatchNormalization	(None, None, 32)	128
Activation	(None, None, 32)	0
MaxPooling1D	(None, None, 32)	0
SeparableConv1D	(None, None, 64)	2208
BatchNormalization	(None, None, 64)	256
Activation	(None, None, 64)	0
GlobalAveragePooling1D	(None, 64)	0
Dropout	(None, 64)	0
Dense	(None, 1)	65
Total params: 4,735		
Trainable params: 4,479		
Non-trainable params: 256		

TABLE II
FINAL CNN MODEL LAYERS AND PARAMETERS

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	(None, None, 18)	0
model_1 (Model)	(None, None, 64)	4670
global_average_pooling1d_1 (GlobalAveragePooling1D)	(None, 64)	0
dropout_1 (Dropout)	(None, 64)	0
dense (Dense)	(None, 1)	65
Total params: 4,735		
Trainable params: 65		
Non-trainable params: 4,670		

B. Experiment 2

1) Method: We downsampled the VGRF recordings to 50Hz. DWT level 3 detailed coefficients were extracted from the recordings. There are noticeable differences on extracted coefficients between a healthy patient and a patient diagnosed with PD which is shown in Fig 3. The extracted coefficients were trained on the convolutional neural network for diagnosing Parkinson's Disease. We used the same configuration CNN models which was used in Experiment 1.

2) Result: We used 10 fold cross validation for evaluating results. Table IV shows the result obtained from this experiment.

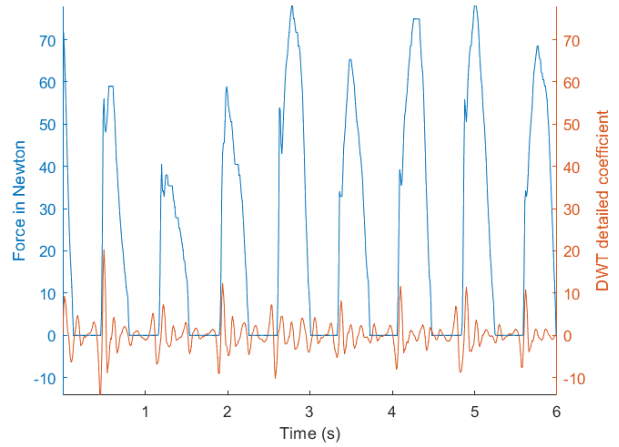
C. Experiment 3

1) Method: We downsampled the VGRF recordings to 50Hz. DWT level 6 detailed coefficients were extracted from the recordings. There are less noticeable differences on extracted coefficients between a healthy patient and a patient diagnosed with PD which is shown in Fig 4. The extracted coefficients were trained on the convolutional neural network for diagnosing Parkinson's Disease. We used the same configuration CNN models which was used in Experiment 1.

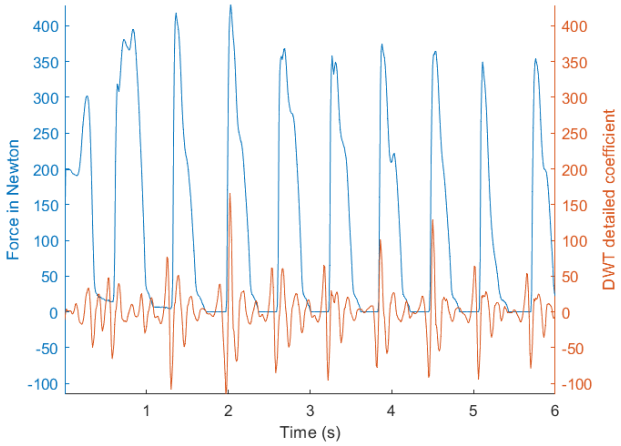
2) Result: We used 10 fold cross validation for evaluating results. Table V shows the result obtained from this experiment. In this experiment we noticed accuracy drop comparing with previous experiments except experiment 3.

TABLE III
MEAN AND STANDARD DEVIATION OF AUC, ACCURACY, AND F1SCORE OF EXPERIMENT 1.

Metric	Mean	Standard Deviation
AUC	0.8749	0.1020
Accuracy	0.8518	0.0619
F1Score	0.8954	0.0443



(a) Healthy Patient

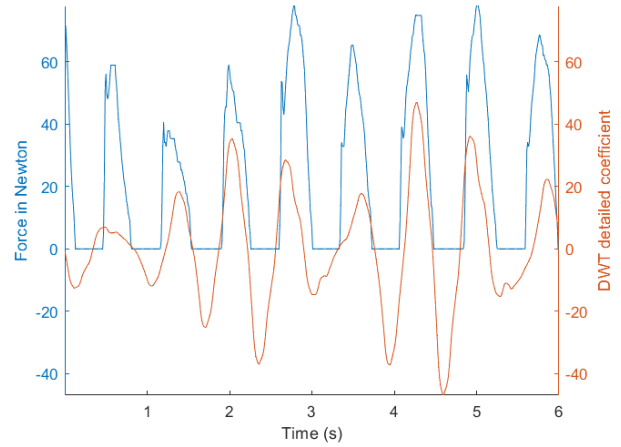


(b) PD patient

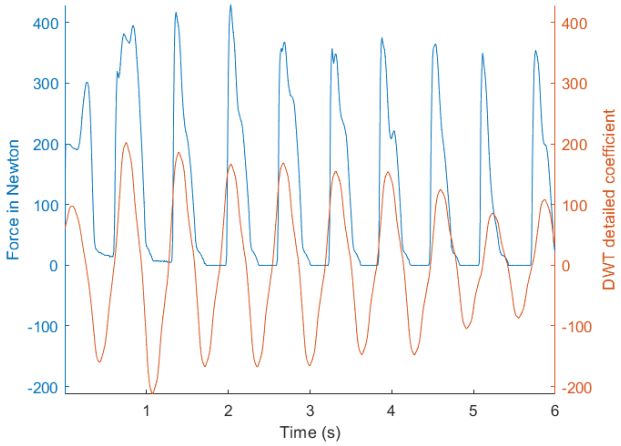
Fig. 3. Detailed Coefficent of level 3 in downsampled recordings

TABLE IV
MEAN AND STANDARD DEVIATION OF AUC, ACCURACY, AND F1 SCORE OF EXPERIMENT 2.

Metric	Mean	Standard Deviation
AUC	0.9082	0.0723
Accuracy	0.8543	0.0752
F1Score	0.8994	0.0515

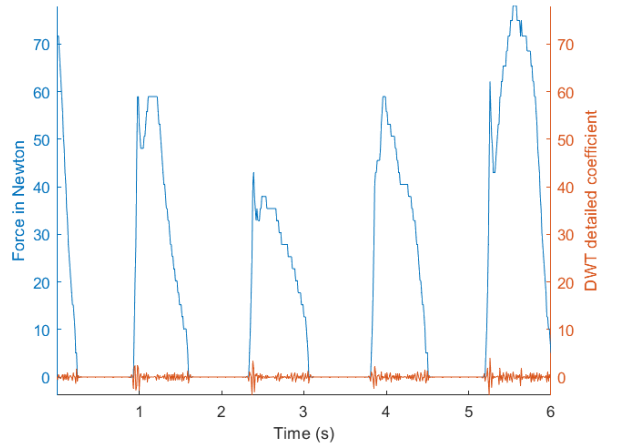


(a) Healthy Patient

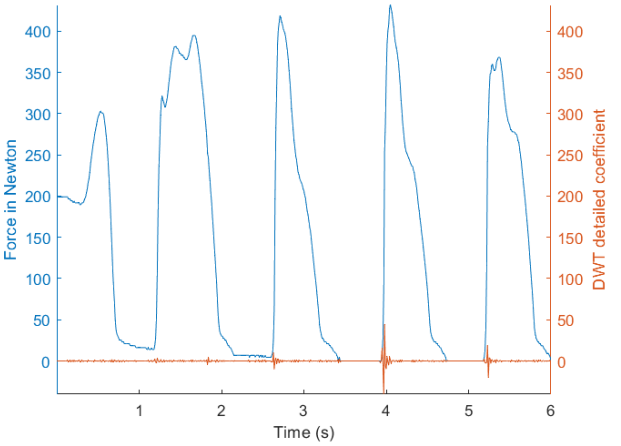


(b) PD patient

Fig. 4. Detailed Coefficent of level 6 in downsampled VGRF recordings



(a) Healthy Patient



(b) PD patient

Fig. 5. Detailed Coefficent of level 1 in VGRF recordings without downsampling

TABLE V
MEAN AND STANDARD DEVIATION OF AUC, ACCURACY, AND F1 SCORE OF EXPERIMENT 3.

Metric	Mean	Standard Deviation
AUC	0.6697	0.1339
Accuracy	0.7176	0.0769
F1Score	0.8274	0.04909

TABLE VI
MEAN AND STANDARD DEVIATION OF AUC, ACCURACY, AND F1 SCORE OF EXPERIMENT 4.

Metric	Mean	Standard Deviation
AUC	0.8655	0.0795
Accuracy	0.7892	0.1111
F1Score	0.8574	0.0728

D. Experiment 4

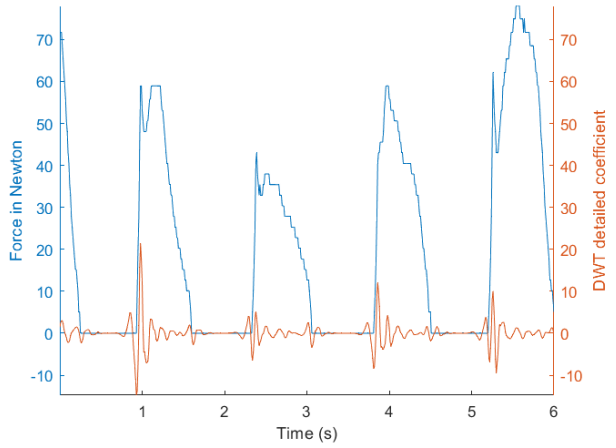
1) Method: In this experiment we used the VGRF recordings without downsampling. DWT level 1 detailed coefficients were extracted from the recordings. The detailed coefficients are shown in Fig 5. The extracted coefficients were trained on the convolutional neural network for diagnosing Parkinson's Disease. We used the same configuration CNN models which was used in Experiment 1.

2) Result: We used 10 fold cross validation for evaluating results. Table VI shows the result obtained from this experiment. In this experiment we noticed accuracy drop compraing with previous two experiments.

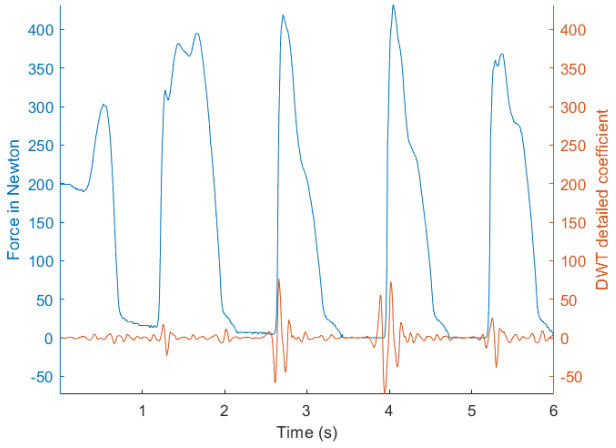
E. Experiment 5

1) Method: In this experiment we used the VGRF recordings without downsampling. DWT level 3 detailed coefficients were extracted from the recordings. The detailed coefficients are shown in Fig 6. The extracted coefficients were trained on the convolutional neural network for diagnosing Parkinson's Disease. We used the same configuration CNN models which was used in Experiment 1.

2) Result: We used 10 fold cross validation for evaluating results. Table VII shows the result obtained from this experiment.

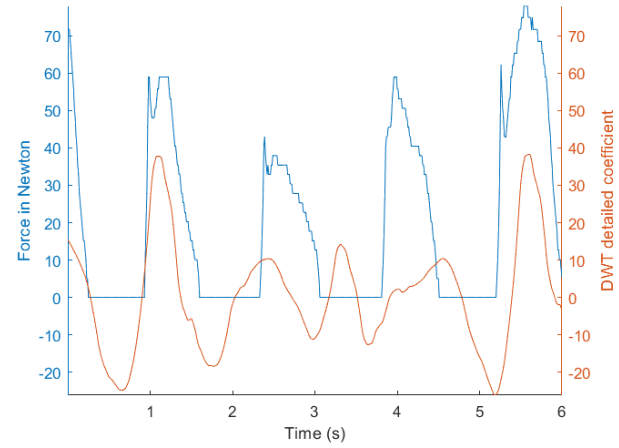


(a) Healthy Patient

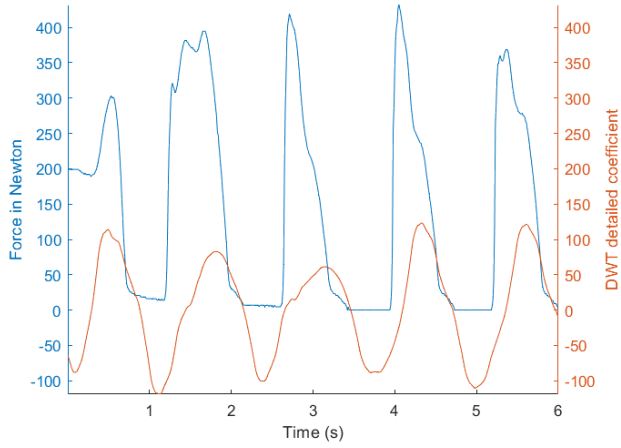


(b) PD patient

Fig. 6. Detailed Coefficent of level 3 in VGRF recordings without downsampling



(a) Healthy Patient



(b) PD patient

Fig. 7. Detailed Coefficent of level 6 in VGRF recordings without downsampling

TABLE VII
MEAN AND STANDARD DEVIATION OF AUC, ACCURACY, AND F1 SCORE OF EXPERIMENT 5.

Metric	Mean	Standard Deviation
AUC	0.8718	0.0823
Accuracy	0.8368	0.0702
F1Score	0.8840	0.0580

TABLE VIII
MEAN AND STANDARD DEVIATION OF AUC, ACCURACY, AND F1 SCORE OF EXPERIMENT 6.

Metric	Mean	Standard Deviation
AUC	0.7188	0.0977
Accuracy	0.7338	0.0596
F1Score	0.8257	0.0501

F. Experiment 6

1) Method: In this experiment we used the VGRF recordings without downsampling. DWT level 6 detailed coefficients were extracted from the recordings. The detailed coefficients are shown in Fig 7. The extracted coefficients were trained on the convolutional neural network for diagnosing Parkinson's Disease. We used the same configuration CNN models which was used in Experiment 1.

2) Result: We used 10 fold cross validation for evaluating results. Table VIII shows the result obtained from this experiment.

VI. DISCUSSION

As we found from experiment 2 that Discrete Wavelet Transform detailed coefficient of level 3 performs better. We also experimented with gait data without downsampling in experiment 4 , experiment 5 and experiment 6 with Discrete Wavelet Transform detailed coefficient of level 1,level 3 and level 6 respectively. From the experiments performed above we see that experiment 2 performs better than other experiments with an accuracy of 85.43% and an F1 score of 89.94%. Discrete Wavelet Transform detailed coefficient of level 3 in downsampled gait data has better features than level 1 or

level 6 in downsampled or without downsampled gait data for diagnosing PD.

VII. Conclusion

Discrete Wavelet Transforms detailed coefficients in various level was experimented with to diagnose Parkinson's Disease using 1D CNN model from Gait Data in this study. The experiments results are not very far from to the state of the art methods for classifying Parkinson's disease used in embedded systems[29].

1) Limitations: The gait dataset for Parkinson's disease is small. Analyzing a large dataset have the potential of introducing more effective feature extraction technique.

2) Future Works: In this study we have only analyzed the DWT detailed coefficients of healty patient and patient with Parkinson's disease. The difference in DWT detailed coefficient of a patient and Average detailed coefficients of PD patients can be experimented. Feature Selection can be applied to these coefficients for better results. Wavelet Scattering is also popular for feature extraction. Wavelet Scattering can be used to extract features. More improved CNN model considering the usability in embedded systems can be developed.

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