Parkinson’s Disease Severity Estimation using Deep Learning and Cloud Technology

Parkinson's Disease Severity Estimation using Deep Learning and Cloud Technology

Asma Channa
Computer Science
University of POLITEHNICA Bucharest
Bucharest, Romania
DIIES Department
University Mediterranea of Reggio Calabria, Italy
asma.channa@stud.acs.upb.ro

Giuseppe Ruggeri
DIIES Department
University Mediterranea of Reggio Calabria, Italy
giuseppe.ruggeri@unirc.it

Nadia Mammone
DICEAM Department
University Mediterranea of Reggio Calabria, Italy
nadia.mammone@unirc.it

Rares-Cristian Ifrim
Computer Science Department
University of POLITEHNICA Bucharest
Bucharest, Romania
rares.ifrim@stud.acs.upb.ro

Antonio Iera
DIMES Department
University of Calabria, Italy
Arcavacata di Rende (CS), Italy
antonio.iera@dimes.unical.it

Nirvana Popescu
Computer Science Department
University of POLITEHNICA Buchares
Bucharest, Romania
nirvana.popescu@upb.ro

2022 IEEE International Conference on Omni-layer Intelligent Systems (COINS) | 978-1-6654-8356-8/22/$31.00 ©2022 IEEE | DOI: 10.1109/COINS54846.2022.9854945

***Abstract*—The management of motor complications in Parkinson's disease (PD) is an unmet need. This paper proposes an eHealth platform for Parkinson's disease (PD) severity estimation using a cloud-based and deep learning (DL) approach. The system quantifies the hallmark symptoms of PD using motor signals of patients with PD (PwPD). In this study, the dataset named "The Michael J. Fox Foundation-funded Levodopa Response Study" is used for the development and evaluation of computational methods focusing on severity estimation of motor function in response to the levodopa treatment. The data is derived from a wearable inertial device, named Shimmer 3, to collect motion data from a patient's upper limb which is more affected by the disease during the performance of some standard activities selected by MDS-UPDRS III and at home while performing daily life activities (DLAs). Seventeen PwPD were enrolled from two clinical sites, who have varying degrees of motor impairment. An incorporated cloud-based framework is proposed where patients' motion data is saved in MS Azure cloud where an automatic evaluation of patients' motor activities in response to the levodopa dose is performed using continuous wavelet transform and CNN-based transfer learning approach. Experimental results show that the efficiency and the robustness of the proposed procedure are proven by 90.0% accuracy for tremor estimation and 86.4% for bradykinesia, with good performance in terms of sensitivity and specificity in each class.**

***Index Terms*—Parkinson's disease, cloud computing, deep learning, severity estimation.**

I. Introduction

Parkinson's disease is a neurocognitive disorder (NCD) with the unascertained aetiology identified by the progressive loss of dopaminergic neurons in substancia nigra pars compacta [1]. PD assessment is currently based on rating scales [2]. Two standard and common scales are used often; Movement Disorder Society-Unified Parkinson's Disease Rating Scale (MDS-UPDRS) and Hoehn and Yahr (H & Y) [3], but both are non-objective, insufficient, and prone to inter and intra-rater reliability problems. Apart from this, to guarantee proper clinical treatment and the right portion of the medication for an individual, PwPD is periodically assessed through subjective clinical assessments by an observer dependent on these rating scales. Because of the unpredictability and heterogeneity of PD signs in understanding [4], the clinical assessment dependent on rating scales and single observer is challenging, time consuming and fluctuate colossally. In parallel, a patient's motor state during clinical examination may differ from a usual condition, it might be altered due to fatigue, anxiety, or dehydration from travelling. Hence a clinical expression is only a photo in time, lacking complete information of before and after examination. Consequently, the only solution that correctly defines and outlines the patients' motor locomotion is to continuously assess their body movements for a prolonged period instead of for few minutes while performing tailored exercises.

While treating PwPD neurologists recommend Levodopa (L-dopa) [5], [6], a naturally occurring amino acid that is metabolized to dopamine in the brain and contemplated as most adequate symptomatic therapy available for PD [7] but a prolonged administration of L-dopa can have several side effects [8] like hallucinations, delusions, psychosis, agitation, hip fractures, mild increase in homocysteine levels, low serum vitamin B12 production, cardiac arrhythmias, motor complications, somnolence, elevated methylmalonic acid levels and increased chances of sensorimotor peripheral neuropathy. Since the side effects associated with the administration of L-dopa outgrow its positive effects, therefore, it becomes of utmost

importance to have an idea about how a patient suffering from PD will respond to the drug so, as to safeguard the patient from the ill effects of the drug. In [9] authors evaluates a machine learning (ML) method that analyses the signals provided by a accelerometer placed on the waist of PwPD in order to automatically assess bradykinetic gait unobtrusively. However, the method is validated only in 12 patients and does not include DLAs. Similarly in [10] developed and tested a new keyboard-tapping test for objective and remote distal motor function in PD patients. But this system lacks validation of being used as a supplementary clinical tool for diagnosis and remote monitoring of PD motor complications.

In recent time there is surge of many wearable sensors and devices for monitoring and assessment of PD patients symptoms severity and response to therapy [11]–[13]. However, these devices have issues with respect to long battery lifetime and lack of cloud based assessment. Lately, researchers have concentrated on the prediction of cardinal motor symptoms, evaluating the progression of the disease by using DL that outperform a classical ML model applied on hand-crafted features in the time series classification task [14], [15]. As in [16]–[18] the authors main objective is to use deep brain simulation and inertial sensors data from single PD subject to quantify PD hand tremors. Since the model is trained and validated on single subject motor signals the DL model obtained considerable accuracy but for proper adoption and acceptance in clinical site the data density matters. However, a limited number of studies have explored or compared medication state (ON or OFF) effect on objective measurement of tremor and bradykinesia severity. Contrary to the existing solutions, our study proposes an eHealth monitoring system for PD patients based on DL and cloud technology. This study is aimed at creating a DL model that can predict the response of patients suffering from PD to L-dopa drug. The insights obtained from this analysis will provide means to improve patients' quality of life by providing useful information to their clinicians in terms of dose optimization (thus reducing medication risk effects).

The remaining paper is structured as follows. Section II elaborates the whole architecture of the system. This section provides a description of data description, experimental protocols, signal analysis using CWT and mapping scalograms to the participant's UPDRS III score to estimate the degree of PD severity using the CNN-based transfer learning–AlexNet network. Experimental outcomes are explained in section III, and finally, in section IV some conclusions are provided.

II. Proposed Framework

In comparison to other controlled studies, we are proposing an integrated system which addresses most of the problems in remote and continuous monitoring of PwPD and assimilate diverse aspects such as patient's physical health in ON and OFF state while performing different tasks; walking, swing, and set of DLA tasks. Likewise, it generates precise, viable and opportune capacity and handling of gathered inertial sensors data, effective data analysis, processing and producing accurate and authentic information to the respective end users.

Fig. 1. presents the architecture of the proposed cloud-based PD monitoring system. The person is wearing a Shimmer device and is performing some movements by his most affected limb. The device is wirelessly connected with MS azure cloud which provides ServiceNow platform in the form of a web application where a database is created of motion data transferred from Shimmer. That data goes to the module developed for monitoring and assessment of PD patients' symptoms in cloud. First, the module converts the inertial sensor data to scalograms using CWT and then passes it to CNN based transfer learning module to find the severity level. Finally, the results are updated in the ServiceNow stage which can be checked by the patient as well as by the clinical expert who received access to cloud administration.

A. Data Description

The dataset used in this study is MJFF Levodopa Wearable Sensors Dataset supported by the Michael J. Fox Foundation at: https://www.michaeljfox.org/news/levodopa-response-study, [19]. Subjects who participated in this study were recruited from two clinical sites, and were monitored both in-clinic, while performing a set of standard activities, and at home while performing their DLAs. All study participants wore a Shimmer 3 on the wrist of the most affected limb. In total 17 individuals participated in this study i.e., 6 women, 11 men with mean age $\pm$ standard deviation (SD) of 69.52 ± 8.76 years old. The demographic details of these patients are given in Table I. The accelerometer data is collected from PwPD in ON and OFF state and labelled according to neurologists based on UPDRS scoring.

TABLE I
Demographic details of PD Patients

Patient	Gender	Age	Dominant hand	More affected upper limb
3BOS	Female	86	Right	Right
4BOS	Female	52	Right	Right
5BOS	Male	74	Right	Right
6BOS	Male	62	Right	Left
7BOS	Male	74	Right	Right
8BOS	Male	64	Right	Right
9BOS	Female	69	Right	Left
10BOS	Male	83	Right	Right
11BOS	Male	61	Right	Right
12BOS	Female	82	Right	Right
13BOS	Male	68	Right	Right
14BOS	Male	65	Right	Right
15BOS	Female	70	Right	Right
16BOS	Male	70	Right	Bilateral
17BOS	Female	60	Left	Bilateral
18BOS	Male	65	Right	Right
19BOS	Male	77	Right	Right

B. Study Protocol

To appraise clinically pertinent measures of the severity of PD signs, including motor symptom fluctuation in response to levodopa drug, the experimental study is based on four continuous days of monitoring.

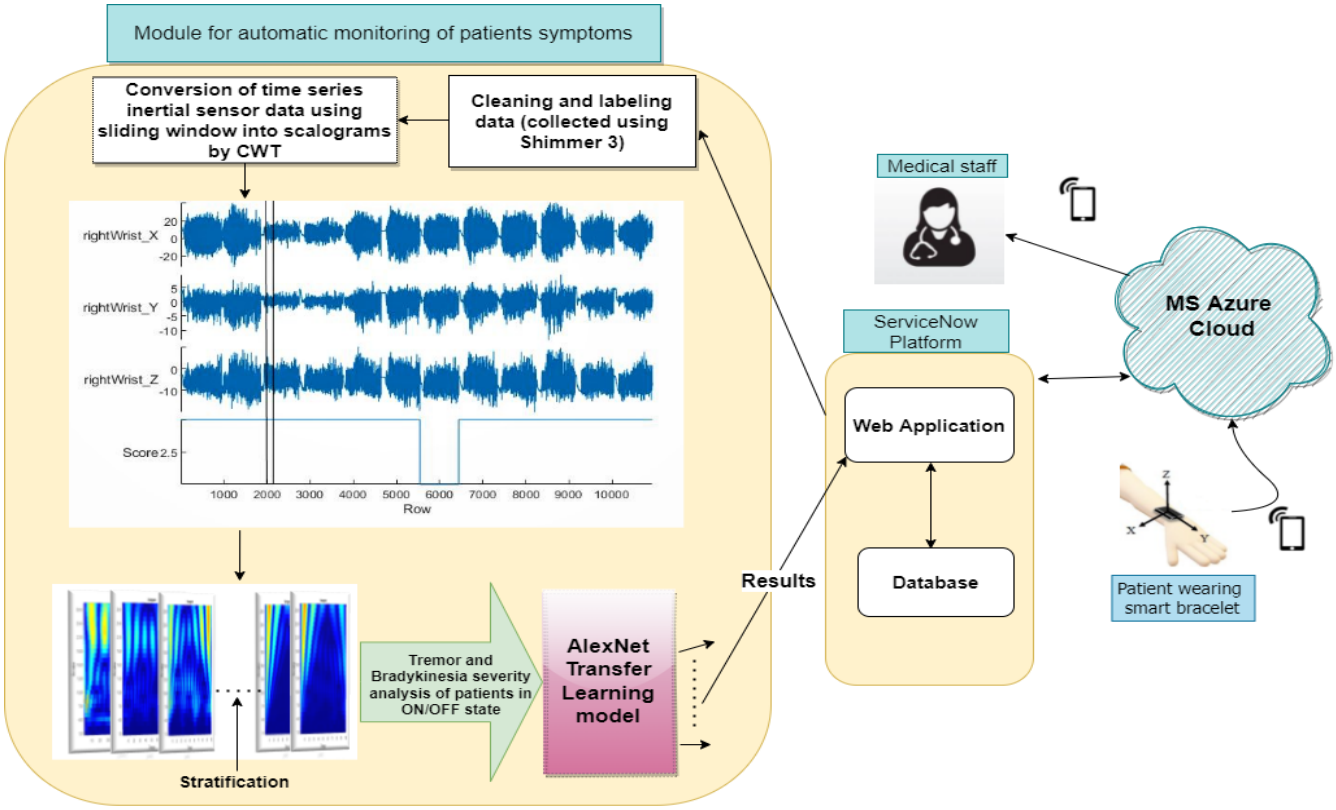


Fig. 1. Block diagram of the proposed PD monitoring system.

On the first day of trial, study participants came to the laboratory after taking their medication(s), answered demographic as well as medical history questions. Then, they performed section III of the MDS-UPDRS and daily routine tasks. The rundown of activities performed incorporate standing, strolling in an orderly fashion for 30s, strolling in straight line for 30s while counting in reverse, strolling higher up, strolling down steps, strolling through a limited passageway, executing finger-to-nose practice for 15s (twice with each arm), rotating hand movements for 15s (twice with each arm), drawing, opening a jug and pouring water (multiple times), organizing pieces of paper in folder (twice), gathering stray pieces for 30s, folding a towel multiple times, and sitting. This arrangement of errands endured around 20 minutes and, barring strolling here and there steps, was rehashed 6-8 times at 30-minute spans. For each case of each undertaking performed, clinical marks of manifestation seriousness and additionally indication presence were given by a clinician.

During Day 2 and Day 3, study participants were instructed to conduct their usual activities. The subjects were likewise approached to perform a short arrangement of set of tasks corresponding to specific items of section III of the MDS-UPDRS (i.e., rotating hand developments for 30s (once with each arm), finger-to-nose for 30s (once with each arm), and sitting discreetly for 30s) every 30 minutes, for a total of 7 times on each of the two days at home.

On Day 4, subjects were asked to come to the laboratory in state when medication(s) were withheld overnight for approximately 12 hours. The same procedures that were performed on Day 1 were performed once again on Day 4.

C. Signal Processing using Continuous Wavelet Transform (CWT)

In the past, numerous research studies used Fourier transform or Short Time Fourier transform to extract features for PD motor symptoms either from lower body motion signals or upper limb motion signals [20]. However, these methods, erroneously miss many of the important features or it can not be exactly identified where an event occurs [21]; to deal with this, a vast number of features are extracted and as the number of features increases, the energy consumption and the latency affect the data storage, processing and analyzing of the events. Since CWT provides both time and frequency domain features, in this research study we employed CWT method on recorded accelerometer signals from standard hand movements exercises as well as from DLAs of PwPD with varying severity scores. The CWT of a signal is represented by Eq. 1.

$$CWT(a,b) = \langle f, \Psi_{a,b} \rangle = 1/\sqrt{a} \int_{-\infty}^{\infty} f(t).\Psi * (t - b/a)dt \quad (1)$$

Here ψ represents the wavelet mother function, which is a template basis function of finite duration, zero mean and variable frequency content; a and b signify the dilatation and shifting variables respectively; CWT (a, b) addresses the

wavelet coefficients and $*$ is the complex conjugate operator. There is a coordinated correspondence between the scale and the frequency, given the sampling rate and the picked wavelet family. In our case, the 'Morlet' wavelet has been used. The range of scales for CWT analysis [1,s_{max}] is chosen using the frequency scale relationship of the chosen [22], which is presented using Eq. 2.

$$s_{max} = \frac{Fc \times Fs}{f} \tag{2}$$

Here Fc is the central frequency of the mother wavelet, Fs is the sampling period and f is the tremor or bradykinesia frequency. With the experiment conducted in [23], the bradykinesia dominant frequency of patients appeared as 0.32-1.40 Hz while the tremor frequency of upper extremities lies between 3-12 Hz. Considering the chosen wavelet, the central frequency is 0.8125, the sampling frequency of data is 100 Hz and, following the frequency range at which tremor and bradykinesia occurs, the CWT is computed. First, the accelerometer data of participants at which tremor and bradykinesia occurred is filtered out and labelled. Then, the data is sorted out in the form of a matrix based on severity score from which the CWT is computed. This range covers the five main severity levels of general interest. So, for each input signal projected to TF domain by the CWT. After, the raw accelerometer signal prepocessed to eliminate sensor orientation dependency, nontremor data and artefacts, first the raw signal was trimmed to individual procession events through a MATLAB script with the 3-s temporal window preceding motion onset. A total of 7263 scalograms (6763 tremor scalograms and 637 bradykinesia scalograms) are produced from the accelerometer data. The number of samples per class is provided in Table II. These scalograms give intuitive illustration in 3-D, explaining color coded wavelet coefficients of a particular event at a particular time and frequency. We adapted jet colormap for scalograms representation. Motor related disorder specially with such low frequency i.e. tremor and bradykinesia is usually not marked with correct severity score and mostly the features are missed out in hand-crafted feature extraction method, but this CWT method produce the whole spectra of movement and one can visualize the difference in each level. Further,these scalograms are stratified with respect to severity scores in separate folders using MATLAB script and then classified by using a DL classifier.

TABLE II
NUMBER OF SAMPLES PER CLASS

Class	***Number of samples***
Tremor Score 0	2094
Tremor Score 1	2091
Tremor Score 2	1360
Tremor Score 3	1095
Tremor Score 4	123
Bradykinesia Score 0	148
Bradykinesia Score 1	186
Bradykinesia Score 2	113
Bradykinesia Score 3	110
Bradykinesia Score 4	80

D. AlexNet Transfer Learning Model for Classification

The objective of this research is to classify the scalograms built using CWT with high success into various stages of the PD disease patients in their ON and OFF state. With passing time there is a massive growth observed in patients impaired by PD. That is why it is needful to rank the patients into distinct stages of disease from mild to severe in a swift manner. In the present research, the AlexNet TL architecture is the kind of experiment to alter it in different weights to get best results as successfully, also applied to waste sorting tasks to achieve state-of-art performance [24] The architecture has been modified as shown in Fig. 2. and we have striven to increase the classification accuracy in the study of finding the severity level for the better assessment by doctors. The details of hyperparameters is provided in Table III.

The operations associated with the execution of the proposed AlexNet design are depicted in Fig. 2. The initial step is to resize the input scalograms to the size of 227×227×3, which are transferred to the convolutional layer, the max pooling layer, again convolution then max pooling and then 3 convolution layers following max pooling and finally, the fully connected layers. In each layer there is performed a mathematical operation defined using the expression (3), where n is the image height and weight (pixels), s is stride, f is filter used and p is for padding. So, in the particular Fig. 2. the input images go to convolution operation the mathematical operation is performed where n=227, the filter size is 11×11 stride is 2 which produces the images of size 55×55 with kernels=96 then it is passed to max-pooling layer with same mathematical operation remember that in max-pooling layer the kernels are not used so, it will remain same in number now again the images are passed to a convolution layer and here we used padding=2 and stride=1 whenever the s=1 and p=2 the size of image remains same by the end of mathematical operation i.e. 27× 27 here and in last 3 convolution layer it is clearly seen the padding=1 which keeps the size of image same i.e., 13×13 only the kernels are changing and in final max-pooling layer the stride is 2 which makes the size of an image to half i.e., 6x6. The output of neurons is computed as a scalar product of a small portion of the image with their corresponding weights. This cycle continues along the length and breadth. This activity is performed in the convolutional layer. Figue 2 elaborates all the types of layers and learnable parameters. In the Rectified Linear Unit (RELU) layer, an element-wise activation function is employed. In the pooling layer, the samples are decreased along with the spatial coordinates. This interaction is called decimation. The fully Connected (FC) layer registers the class scores for each sample and gives the prediction. The likelihood score for each of the prediction classes is operated and the class that is scoring with a maximum probability score is elected as the predicted class as shown in Fig. 2. The last FCL is revised to five outputs since the original FCLs were

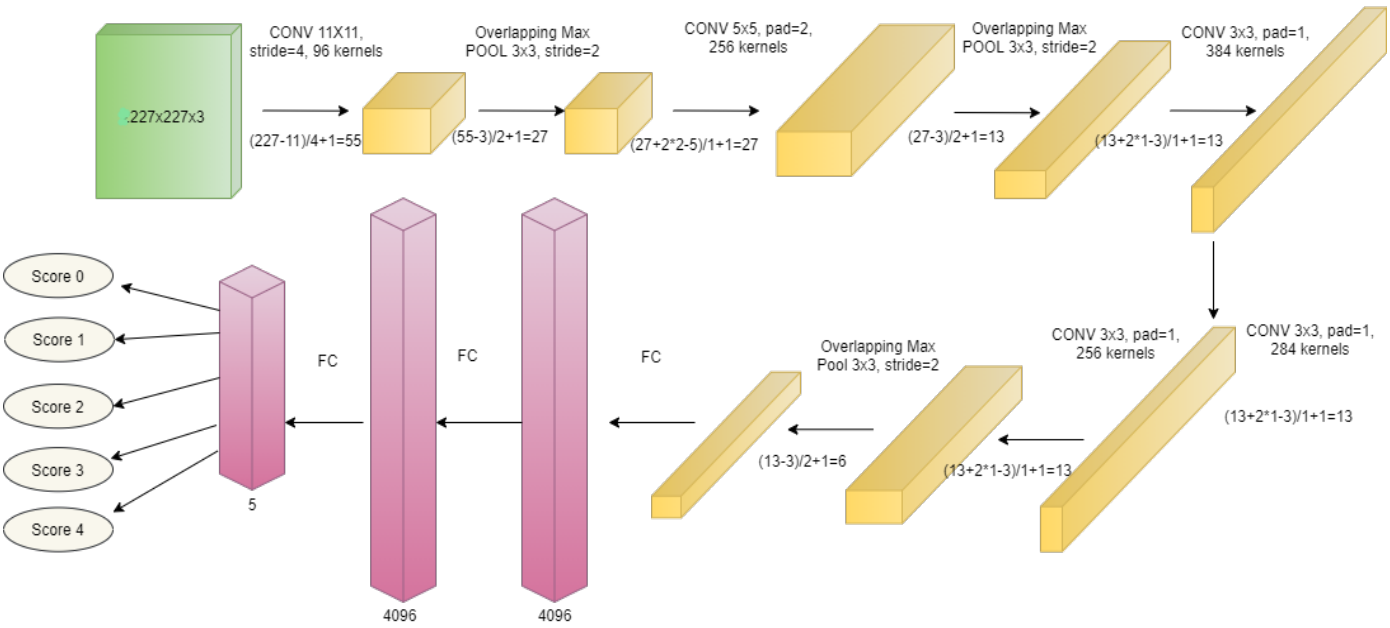


Fig. 2. AlexNet Transfer Learning model architecture

TABLE III
HYPERPARAMETERS ADOPTED

Momentum	Initial Rate Decay Factor	Learning Rate Decay Factor	Moving Average Decay	Number of Epochs Per Decay	Weight Decay	Batch Size
0.9	0.01	0.01	0.999	150	0.0005	128

developed to classify 1,000 categories.

$$\frac{n+2p-f}{s}+1 \tag{3}$$

However, the model is trained on 70% data and tested on 30% data images. Score-wise strategy is adopted in this study. Since data is based on subjects facing different severity levels and all are labelled in form of severity-scores. The hyperparameters adopted in model training are given in Table III. For bradykinesia the model gives 86.4% accuracy and for the tremor severity score analysis it gives 90.9%.

E. Cloud-based data processing and analysis

The role of cloud technology in current system is multifold. For instance, it stores the hefty amount of motion data from the inertial sensors, pre-processes the samples of motor signals and converts to scalograms by utilizing CWT and examines the severity level using CNN model; this process runs when the data is acquired from wearable device and then it classify it into certain stages. The person associates with the authority over the cloud through the web utilizing their smart telephones can monitor the results updated in cloud platform. In cloud, the ServiceNow platform [25], [26] is implemented. This platform can be used as a "tunnel" or "gateway" between the wearable device and the DL computation method, as with ServiceNow we can implement a POST method on top of it (or use the out-of-the-box ones offered) to upload the acquired data to a database table, offering the possibility to a script to fetch these data through a GET method and feed them to the DL algorithm. The whole computing and processing services are provided in a distributed manner. The cloud stage helps in maintaining clients' privacy as well as data security. It is done in various stages in the framework, data assortment, information transmission and cloud data stockpiling scenario. While gathering information, all information is passed to the cell phone in an encrypted format. Additionally, in case of data transmission, encoded data is transmitted to the cloud and only the approved clients can get to it. Since the data measurement is in real time. As each value is stored locally on the device and once all values are read it is uploaded to cloud so there is no such long delay that effects the communication. Also, the data upload speed is dependent on the size of the file created with all values that is read and upload speed. But ServiceNow has an (Avg 53.2 Mbps/25.8 Mbps) user upload speed as shown in Fig. 3. The only bottleneck left is the bandwidth of the users internet. But the inertial data in form of CSV files are in range of a couple MBs at worst so it is really not even that observable delay to upload the data from wearable device to cloud.

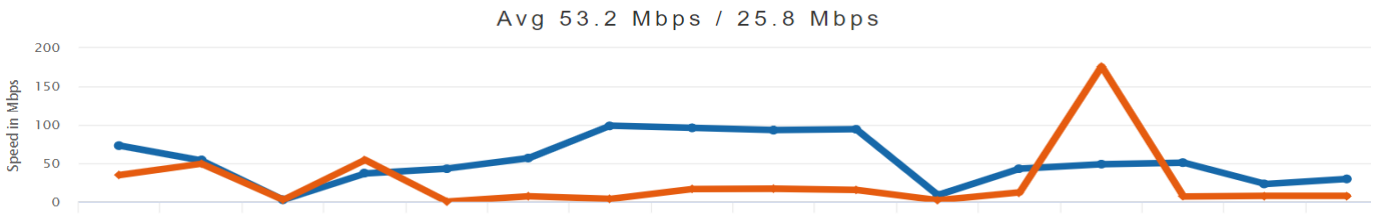


Fig. 3. ServiceNow speed test. The blue line shows the download speed and orange line depicts the upload sped of data

III. Results and Discussion

Since the model is trained and tested separately for tremor and bradykinesia, the confusion matrix generated by each model is shown in Fig. 4(a). and 4(b). The red boxes show the number of wrong predictions while the green box depicts correct predictions. Each score is considered as a separate class. The performance metrics of the algorithm are depicted in the form of sensitivity and specificity for each class. To calculate the sensitivity and specificity we followed the mathematical formula as mentioned in Eqs 4 and 5 The TPR represents the true positive rates, FNR means false negative rates, TNR represents true negative rates and FPR shows false positive rates. The overall produced results are elaborated in Table IV.

$$Sensitivity = \frac{TPR}{TPR + FNR} \tag{4}$$

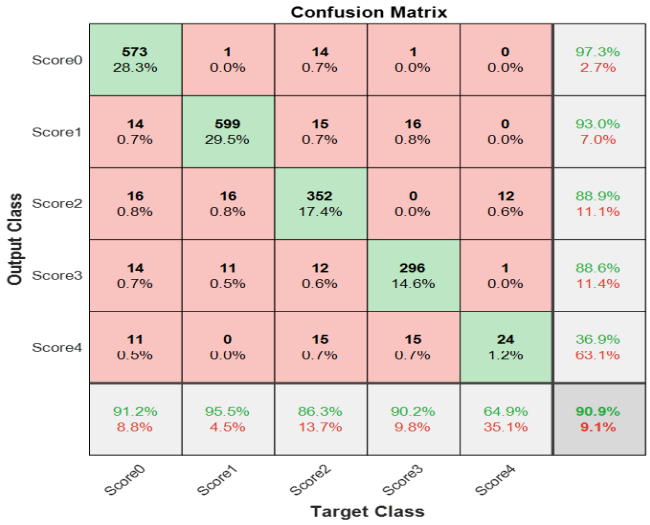
$$Specificity = \frac{TNR}{TNR + FPR} \tag{5}$$

The model is trained and tested separately for tremor and bradykinesia severity score analysis. AlexNet model shows very promising results by giving 86.4% accuracy for bradykinesia estimation and 90.9% for tremor with a good sensitivity and specificity in terms of each scoring class as elaborated in Table IV.

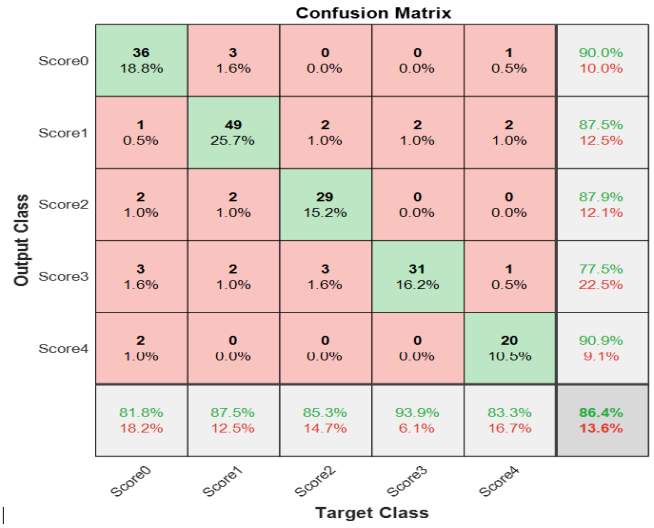
TABLE IV
Sensitivity and Specificity of each class

Class	*Sensitivity*	*Specificity*
Tremor Score 0	0.97	0.95
Tremor Score 1	0.93	0.97
Tremor Score 2	0.88	0.96
Tremor Score 3	0.88	0.97
Tremor Score 4	0.36	0.99
Bradykinesia Score 0	0.90	0.94
Bradykinesia Score 1	0.87	0.94
Bradykinesia Score 2	0.87	0.96
Bradykinesia Score 3	0.77	0.98
Bradykinesia Score 4	0.90	0.97

Considering the existing methods which show poor interpretability, our study shows promising results in extracting potentially useful features using CWT for identifying symptoms that are often overlooked by manual features. The system tracks PD symptoms and analyzes medication effect on patients utilizing the MDS-UPDRS data as ground truth.



(a) Confusion matrix for tremor severity



(b) Confusion matrix for bradykinesia severity

Fig. 4. Confusion matrix

IV. Conclusion

Nowadays, PD administration depends on normal clinical visits for evaluation and close checking of PD side effects which eventually creates trouble for patients and their families. To solve this issue, remote monitoring of PwPD brings light to considerable measures such as home-based continuous

monitoring of patients, check seriousness of symptoms, correct diagnosis and treatment of patients which reduces the burden on medical practitioners and create easiness for patients and their care takers. The final severity results obtained assess the L-dopa drug effect on patient's symptoms and help them in deciding the drug dosage variation. The work in this study helps clinicians to identify subtle changes in motor performance that characterize PD onset in response to their recommended treatment. In this work the patients while wearing Shimmer 3 device perform various physical activities in ON and OFF state and the data from Shimmer 3 goes directly MS azure cloud. In lieu of extracting temporal and spectral features, CWT creates scalograms which are further classified using AlexNet. The users can access the updated results in the form of a medical report on the web application. The entire system is very well developed and easy to implement. In future, we are developing a new IoT based bracelet for a comparative analyze with Shimmer results.

ACKNOWLEDGMENT

The authors would like to acknowledge the Levodopa Response Trial Data collected by Michael J.Fox Organization under the umbrella of MJFF funding.

FUNDING

The authors gratefully acknowledge funding from European Union's Horizon 2020 Research and Innovation program under the Marie Skłodowska Curie grant agreement No. 813278 (A-WEAR: A network for dynamic wearable applications with privacy constraints, http://www.a-wear.eu/). This work was also supported in part by a grant from the Romanian National Authority for Scientific Research and Innovation, UEFISCDI project PN-III-P3-3.6-H2020-2020-0124.

REFERENCES

[1] O. Hornykiewicz, "Biochemical aspects of parkinson's disease," *Neurology*, vol. 51, no. 2 Suppl 2, pp. S2–S9, 1998.

[2] R. Bhidayasiri and P. Martinez-Martin, "Clinical assessments in parkinson's disease: scales and monitoring," *International review of neurobiology*, vol. 132, pp. 129–182, 2017.

[3] J. M. Rabey, H. Bass, U. Bonuccelli, D. Brooks, P. Klotz, A. D. Korczyn, P. Kraus, P. Martinez-Martin, P. Morrish, W. Van Sauten, *et al.*, "Evaluation of the short parkinson's evaluation scale: a new friendly scale for the evaluation of parkinson's disease in clinical drug trials.," *Clinical neuropharmacology*, vol. 20, no. 4, pp. 322–337, 1997.

[4] C. Stamate, J. Saez Pons, D. Weston, and G. Roussos, "Pdkit: A data science toolkit for the digital assessment of parkinson's disease," *PLoS computational biology*, vol. 17, no. 3, p. e1008833, 2021.

[5] A. W. Loranger, J. E. Lee, and F. McDowell, "Levodopa treatment of parkinson's syndrome: Improved intellectual functioning," *Archives of General Psychiatry*, vol. 26, no. 2, pp. 163–168, 1972.

[6] P. A. LeWitt, "Levodopa for the treatment of parkinson's disease," *New England Journal of Medicine*, vol. 359, no. 23, pp. 2468–2476, 2008.

[7] R. Katzenschlager and A. J. Lees, "Treatment of parkinson's disease: levodopa as the first choice," *Journal of neurology*, vol. 249, no. 2, pp. ii19–ii24, 2002.

[8] M. Pederzoli, F. Girotti, G. Scigliano, G. Aiello, F. Carella, and T. Caraceni, "L-dopa long-term treatment in parkinson's disease: Age-related side effects," *Neurology*, vol. 33, no. 11, pp. 1518–1518, 1983.

[9] A. Samà, C. Pérez-López, D. Rodríguez-Martín, A. Català, J. M. Moreno-Aróstegui, J. Cabestany, E. de Mingo, and A. Rodríguez-Molinero, "Estimating bradykinesia severity in parkinson's disease by analysing gait through a waist-worn sensor," *Computers in biology and medicine*, vol. 84, pp. 114–123, 2017.

[10] N. Akram, H. Li, A. Ben-Joseph, C. Budu, D. A. Gallagher, J. P. Bestwick, A. Schrag, A. J. Noyce, and C. Simonet, "Developing and assessing a new web-based tapping test for measuring distal movement in parkinson's disease: a distal finger tapping test," *Scientific reports*, vol. 12, no. 1, pp. 1–11, 2022.

[11] S. K. Sieberts, J. Schaff, M. Duda, B. Á. Pataki, M. Sun, P. Snyder, J.-F. Daneault, F. Parisi, G. Costante, U. Rubin, *et al.*, "Crowdsourcing digital health measures to predict parkinson's disease severity: the parkinson's disease digital biomarker dream challenge," *NPJ digital medicine*, vol. 4, no. 1, pp. 1–12, 2021.

[12] L. Omberg, E. Chaibub Neto, T. M. Perumal, A. Pratap, A. Tediarjo, J. Adams, B. R. Bloem, B. M. Bot, M. Elson, S. M. Goldman, *et al.*, "Remote smartphone monitoring of parkinson's disease and individual response to therapy," *Nature Biotechnology*, pp. 1–8, 2021.

[13] G. Vergara-Diaz, J.-F. Daneault, F. Parisi, C. Admati, C. Alfonso, M. Bertoli, E. Bonizzoni, G. F. Carvalho, G. Costante, E. E. Fabara, *et al.*, "Limb and trunk accelerometer data collected with wearable sensors from subjects with parkinson's disease," *Scientific Data*, vol. 8, no. 1, pp. 1–12, 2021.

[14] J. Goschenhofer, F. M. Pfister, K. A. Yuksel, B. Bischl, U. Fietzek, and J. Thomas, "Wearable-based parkinson's disease severity monitoring using deep learning," *arXiv preprint arXiv:1904.10829*, 2019.

[15] S. Grover, S. Bhartia, A. Yadav, K. Seeja, *et al.*, "Predicting severity of parkinson's disease using deep learning," *Procedia computer science*, vol. 132, pp. 1788–1794, 2018.

[16] R. LeMoyne, T. Mastroianni, D. Whiting, and N. Tomycz, "Application of deep learning to distinguish multiple deep brain stimulation parameter configurations for the treatment of parkinson's disease," in *2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA)*, pp. 1106–1111, IEEE, 2020.

[17] R. LeMoyne, T. Mastroianni, D. Whiting, and N. Tomycz, "Distinction of an assortment of deep brain stimulation parameter configurations for treating parkinson's disease using machine learning with quantification of tremor response through a conformal wearable and wireless inertial sensor," *Advances in Parkinson's Disease*, vol. 9, no. 3, pp. 21–39, 2020.

[18] R. LeMoyne, T. Mastroianni, D. Whiting, and N. Tomycz, "Parametric evaluation of deep brain stimulation parameter configurations for parkinson's disease using a conformal wearable and wireless inertial sensor system and machine learning," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 3606–3611, IEEE, 2020.

[19] MJFF Levodopa Response Study, "MJFF Levodopa Wearable Sensors Dataset." https://www.synapse.org/#!Synapse:syn20681023/wiki/594678 [Accessed June 15, 2022].

[20] E. Abdulhay, N. Arunkumar, K. Narasimhan, E. Vellaiappan, and V. Venkatraman, "Gait and tremor investigation using machine learning techniques for the diagnosis of parkinson disease," *Future Generation Computer Systems*, vol. 83, pp. 366–373, 2018.

[21] M. D. Djurić-Jovičić, N. S. Jovičić, S. M. Radovanović, I. D. Stanković, M. B. Popović, and V. S. Kostić, "Automatic identification and classification of freezing of gait episodes in parkinson's disease patients," *IEEE transactions on neural systems and rehabilitation engineering*, vol. 22, no. 3, pp. 685–694, 2013.

[22] N. Ji, H. Zhou, K. Guo, O. W. Samuel, Z. Huang, L. Xu, and G. Li, "Appropriate mother wavelets for continuous gait event detection based on time-frequency analysis for hemiplegic and healthy individuals," *Sensors*, vol. 19, no. 16, p. 3462, 2019.

[23] H. Dai, H. Lin, and T. C. Lueth, "Quantitative assessment of parkinsonian bradykinesia based on an inertial measurement unit," *Biomedical engineering online*, vol. 14, no. 1, pp. 1–13, 2015.

[24] S. Niu, J. Wang, Y. Liu, and H. Song, "Transfer learning based data-efficient machine learning enabled classification," in *2020 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech)*, pp. 620–626, IEEE, 2020.

[25] T. Nechyporenko, "Servicenow as a platform–practical research," 2015.

[26] S. Bisser, "Introduction to the microsoft conversational ai platform," in *Microsoft Conversational AI Platform for Developers*, pp. 1–24, Springer, 2021.