Ince-PD Model for Parkinson's Disease Prediction Using MDS-UPDRS I & II and PDQ-8 Score

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Abstract. Parkinson's disease (PD) is one of the most prevalent and complex neurodegenerative disorders. Timely and accurate diagnosis is essential for the effectiveness of the initial treatment and improvement of the patients' quality of life. Since PD is an incurable disease, the early intervention is important to delay the progression of symptoms and severity of the disease. This paper aims to present Ince-PD, a new, highly accurate model for PD prediction based on Inception architectures for time-series classification, using wearable data derived from IoT sensor-based recordings and surveys from the mPower dataset. The feature selection process was based on the clinical knowledge shared by the medical experts through the course of the EU funded project ALAMEDA. The algorithm predicted total MDS-UPDRS I & II scores with a mean absolute error of 1.97 for time window and 2.27 for patient, as well as PDQ-8 scores with a mean absolute error of 2.17 for time window and 2.96 for patient. Our model demonstrates a more effective and accurate method to predict Parkinson Disease, when compared to some of the most significant deep learning algorithms in the literature.

Keywords: Deep Learning models · Parkinson's Disease · MDS-UPDRS · PDQ-8 · Wearable Sensors · Convolution Networks

1 Introduction

Parkinson's disease (PD) is a progressive, chronic and common neurodegenerative disease that affects more than 10 million people worldwide [1]. The prevalence of PD has been increased in recent decades, and it's estimated that almost 1% of people above 60 years old in industrialized societies are affected by the condition. However, the symptoms of PD can often go unnoticed in the early stages, which might delay early diagnosis and accurate treatment [2, 3]. Usually, the symptoms are both motor and non-motor, but in the early stages, they are mostly linked with dyskinesia, tremor and muscle stiffness. Severity of PD is commonly assessed using the Movement Disorder Society-Unified

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Parkinson's Disease Rating Scale (MDS-UPDRS) and Parkinson's disease Questionnaire (PDQ-8). The MDS-UPDRS is a revision of Unified Parkinson's Disease Rating Scale (UPDRS) and developed to resolve some flaws of the original scale [4]. The MDS-UPDRS consists of 4 different parts, MDS-UPDRS I, II, III and IV, which are used to monitor and evaluate motor and non-motor aspects of experiences and activities of daily living (ADL), mood and mental state, complication in treatment and more. Moreover, PDQ-8 is an 8-item questionnaire and a shortened version of PDQ-39. It requires the patient to answer eight questions relevant to their mood, physical condition, Activities of Daily Living (ADL) and mental state where a high accumulated score signifies poor quality of life. Overall, both of these assessment tools are considered as reliable and valid measures and are widely used in clinical practice and research settings [5, 6].

In recent years, the extensive use of Artificial Intelligence (AI) and Internet of Things (IoT) technologies to monitor patients with Parkinson's disease has been gaining traction in the healthcare industry [7]. Especially during the COVID-19 pandemic era, the advanced need for PD patients to continue their treatment in a riskless way highlighted the necessity for personalized and remote monitoring [8, 9]. To achieve that, sensors such as magnetometers, accelerometers, gyroscopes, are increasingly being used in wearable devices like smartwatches and smart insoles to collect real-time data on patients with the aim of providing better health services and improving their living conditions [10–12]. This data can be used in combination with Machine Learning (ML) and Deep Learning (DL) techniques to predict disease stage, severity, symptoms or medical test scores, providing more flexible ways of handling large medical datasets, minimizing the costs of medical care and assisting healthcare professionals to make timely decisions [13].

The ALAMEDA project[1], funded by the EU, aims to provide personalized rehabilitation treatment assessments for patients with neurological disorders such as Parkinson's, Multiple Sclerosis and Stroke, using AI. One of the key goals of the project is to assist healthcare professionals in making timely and accurate decisions (e.g. diagnosis) without requiring patients to make physical visits to a clinic or hospital. To achieve this goal, the project is using various wearable sensors, such as accelerometers, to collect real-time data on patients' movements and other physical indicators. This paper presents a deep learning-based algorithm for estimating total MDS-UPDRS (parts I and II) and PDQ-8 score from data collected from wearable sensors. More specifically, we present Ince-PD, a highly accurate model for PD prediction based on the InceptionTime architecture for time-series classification [14]. For comparison purposes, we implemented a number of deep learning models based on LSTM and CNN architectures.

The rest of this paper is organized as follows. In Sect. 2, a literature review on previous related works on Parkinson's disease prediction using wearable sensors and deep learning techniques is presented. In Sect. 3, the Ince-PD architecture and the implementation of the model for PD prediction is introduced. In Sect. 4, the experimental setup, the comparative and evaluation methods are described. Finally, in Sect. 5 the results obtained of the proposed framework are discussed and in Sect. 6, the conclusions and future research directions are presented.

[1] https://alamedaproject.eu/.

2 Related Work

In the existing literature, there are numerous studies on the PD detection, the stage and severity of the disease and the prediction of variables pertinent to the use case. Some of the most common machine learning and deep learning models for Parkinson's disease are logistic regression, k-nearest neighbors, Support Vector Machine, classification trees and neural networks [15–19]. Nilashi et al. [20] used supervised and unsupervised learning methods to perform PD diagnosis through UPDRS prediction. Their study's results demonstrated that Expectation-Maximization (EM) with Support Vector Regression (SVR) ensembles provide better performance than decision trees and SVR combined with other clustering approaches. An ensemble deep model for continuously estimating UPDRS III based on free-body motion data was presented by Hssayeni et al. [21]. The evaluation with Leave-One-Out Cross-Validation (LOOCV) indicated high correlation and a low Mean Absolute Error (MAE) of 5.95. Rehman et al. [22] applied Deep Learning techniques to wearable-based gait data to predict MDS-UPDRS III scores. Their proposed DL Convolutional Neural Network (CNN) achieved a MAE of 6.29. A gait analysis-based PD auxiliary diagnosis system proposed by Chen et al. [23]. The system collected data from embedded devices, which was then analyzed by a 1D CNN model. The system achieved a high recognition accuracy of 91.4% for abnormal gait. Setiawan et al. [24] also implemented a DL algorithm based on Vertical Ground Reaction Force (VGRF) time frequency features for PD detection and severity classification. The best average accuracy of this algorithm was 96.52% using ResNet-50. Papadopoulos et al. [25] focused on the unobtrusive detection of PD from multi-modal and in-the-wild sensor data using a deep learning model that consists of three parts: the feature extraction module, the attention module and the final classifier module. Asuroglu et al. [26] presented a deep learning model, which combines CNNs and Locally Weighted Random Forest (LWRF) for PD severity assessment using wearable sensor data and achieved 3.009 MAE. Zhao et al. [27] presented a deep learning architecture that combines CNN and Long shot-term memory (LSTM) that outperforms other previous studies in terms of accuracy in Parkinson's Disease prediction. In a recent study, Yang et al. [28] developed an objective method to automatically classify patients with Parkinson's Disease and Health Controls (HC) using PD-ResNet from gait data. Interestingly, they achieved better results than previous methods in terms of accuracy, precision, F1-Score and recall. Balaji et al. [29] presented an automatic and non-invasive method for PD diagnosis, using LSTM network for severity rating of PD. Finally, Bobic et al. [30] introduced a predictive model for bradykinesia in PD, using CNN architectures.

Even though Time Series Classification (TSC) is considered as a complex problem, the arise of deep learning showed promising results for its solution. The InceptionTime, as presented by [14], is an ensemble of deep CNN models, which provide great results for TSC. The core parts of an inception network are the two residual blocks, each of one consists of three Inception modules, which replace the traditional fully convolutional layers. Each inception module is composed of multiple layers like the Bottleneck layer, the convolution layer, the max pooling layer and the depth concatenation layer. A linear shortcut connection is used to transfer the input of every residual block to the next block's input. After deploying the residual blocks, a Global Average Pooling (GAP) is utilized which computes the average of the output multivariate time series of the whole

dimension. Lastly, a traditional fully connected Softmax layer is used. Figure 1 presents the basic structure of the InceptionTime network.

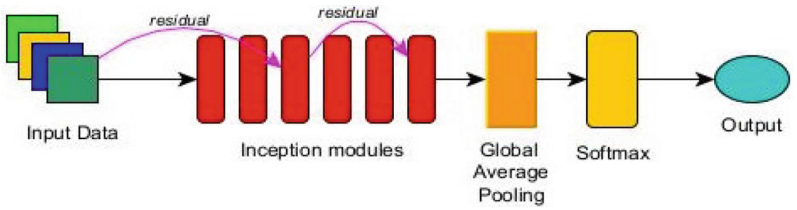

Fig. 1. The Inception network of InceptionTime model.

The present study uses several residual connections and modified inception modules as key components of its architecture to predict PD stage using total MDS-UPDRS I & II and PDQ-8 scores. To the best of our knowledge, this is the first regression model for PD prediction that is based on the InceptionTime network and the efficiency of the model provides great potential for future work. As in most cases the DL algorithms perform better in PD prediction, we utilized some of the most efficient architectures as the comparison base for our approach.

3 Methodology

Machine Learning and Deep Learning techniques have shown great potential in predicting and diagnosing diseases, including Parkinson's disease. This study utilizes the InceptionTime architecture, a novel architecture for Time Series Classification (TSC), to build Deep Learning models able to diagnose Parkinson's Disease through predicting total MDS-UPDRS I & II and total PDQ-8 scores. InceptionTime architecture is presented in Sect. 2 and our proposed Ince-PD is presented in detail in Sect. 3.3. The proposed framework for deep learning modeling for Parkinson's disease diagnosis, as shown in Fig. 2 can be highlighted in 3 specific stages:

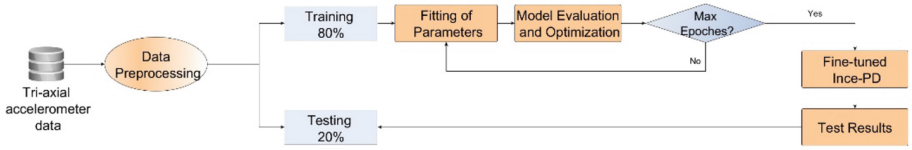

Fig. 2. Flow of the proposed Ince-PD framework for PD prediction.

- *Data acquisition*, where the data is acquired and evaluated based on the clinical requirements and the needs of the project.
- *Data preprocessing,* where the data is converted into defined sets.
- *Model implementation and total MDS-UPDRS I & II and total PDQ-8 prediction,* where the model architecture is built and the target labels are predicted.

3.1 Data Acquisition

This study used data acquired from the mPower Public Research Portal [31]. The mPower is a clinical observation study on PD that collected data from sensor-based recordings and surveys over a large number of participants. The whole study carried out through a mobile application interface and its 7 tasks are divided in activities (walking, memory, tapping and voice) and survey questionnaires (demographic survey, MDS-UPDRS survey and PDQ-8 survey).

Based on the suggestions from the medical experts, we utilized four out of seven tasks (the walking task, the demographics survey, the PDQ-8 and MDS-UPDRS survey). The walking test consists of three different segments: outbound, rest and return. The accelerometer and gyroscope of the smartphone capture the three-dimensional linear and angular acceleration of each participant during this test. The purpose of utilizing these data is the evaluation of any movement limitation that is relevant to PD and discriminating PD patients from healthy control subjects, while predicting disease stage using the scores of the questionnaires. Table 1 summarizes the number of participants and the unique tasks per activity in the mPower dataset.

Table 1. Data availability in mPower dataset.

Activity	Number of Unique Participants	Unique Tasks
Demographics	6805	6805
PDQ-8	1334	1641
MDS-UPDRS	2024	2305
Walking total	3101	35410
Walking outbound acc	3101	35407
Walking return acc	2807	23883
Walking rest acc	3101	35407

3.2 Data Preprocessing

Numerous studies have shown that pre-processing the data is necessary for MDS-UPDRS and PDQ-8 prediction to be more accurate [32, 33]. In the preprocessing stage, missing values, noise and inconsistencies in the dataset are addressed. The first step was to determine which of the available data is useful for the requirements of the project and the management of the missing values, as they can be an essential obstacle for Deep Learning Algorithms. Feature selection aims to reduce model's complexity and provides faster and easier training and interpretation. In this work, participants who performed both surveys and specific walking tasks were selected by utilizing information derived from the clinicians of the project. Converting the raw data to appropriate input format for training models was important part of the preprocessing, while the definition of the common keys addressed the overlapping values of the dataset. The following step was

the segmentation of the time sequences into smaller fragments by using sliding windows of 5 s (500 rows given a sampling rate of 100 Hz), corresponding to 50% overlap. For the dataset partitioning, the 80% of the data was the training sample, while the 20% was utilized for testing purposes.

3.3 Proposed Model Architecture and Implementation

In this study, the InceptionTime, a novel architecture for TSC, is utilized for total MDS-UPDRS I & II and PDQ-8 prediction. The main parts of the Inception network architecture are described in Sect. 2. Several significant modifications have been implemented in the architecture, which are classified into two distinct categories: Firstly, alterations pertaining to the Bottleneck layer inside the inception modules. Secondly, changes have been made to the overall framework, including the addition of dropout and batch normalization layers, as well as the utilization of different activation functions. The residual blocks are essential parts as the connection at every third inception module provides better optimization capabilities and overall performance. Thus, they remained as proposed in the original work. The Bottleneck layer inside the inception module is removed, as experiment results suggested that without it, better efficiency is achieved. After the modified inception modules, a batch normalization layer is deployed, followed by a Rectified Linear activation function (ReLU). The output from the ReLU activation function is passed on to an one-dimensional Global Average Pooling before passing to the output layer where instead of the Softmax layer, a Rectified Linear activation function (ReLU) is deployed to achieve faster learning and better performance. To overcome overfitting problems, tuning of the kernel size of the convolution has been implemented, while adding a Dropout layer with 0.5 rate after Inception modules improve the generalization of the model and prevent it from relying too heavily on any set of features. Other parameters that needed to be modified were the depth and the number of filters. The final stage of the implementation process was the prediction stage. At this point, the models predicted the total MDS-UPDRS I & II and PDQ-8 according to the input data. The proposed Ince-PD model is built by utilizing InceptionTime and differentiating essential components, as detailed above. In Fig. 3, a schematic diagram of the proposed Inception model for PD prediction is depicted.

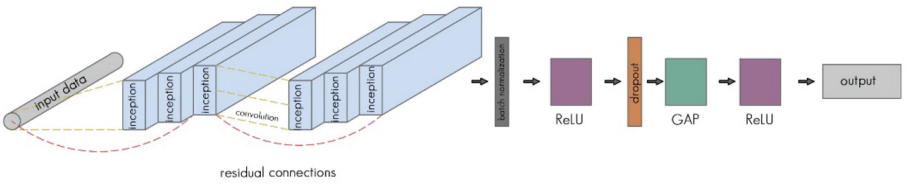

Fig. 3. The architecture of the proposed Ince-PD model for total-MDS-UPDRS I & II and PDQ-8 prediction.

After implementing several experiments, we concluded that the use of convolution layers between the inception modules is a sensible decision with respect to performance and computational complexity.

4 Experiments

4.1 Model Performance Evaluation

The performance evaluation of the Inception model was carried-out by using the Mean Absolute Error (MAE) and Mean Square Error (MSE) per-window and per-patient basis. The mathematical formulas of MAE and MSE are presented in Eq. 1 and Eq. 2, respectively, where $\widehat{y_i}$, y_i are the predicted value and the actual value. The character n represents the entire set of the samples.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{1}$$

$$\text{MSE} = \sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n} \tag{2}$$

To further evaluate our model, a variety of different approaches in literature for estimating the total MDS-UPDRS I & II and PDQ-8 were used for comparison purposes. The proposed method was compared to the same dataset for both target labels with the architectures that will be introduced in the next sections.

4.2 Experimental Setup

The Inception model that is presented in this study was developed with "Python 3.8" and operated on a PC with an Intel(R) Xeon(R) Silver 4210 CPU @ 2.20 GHz processor. The developed network was implemented in TensorFlow [34] and the models trained on 10 epochs, allowing the model to demonstrate better performance by learning from the training data. During the training process, the fit method was applied to the training data and target labels, and the Adam optimizer, an adaptive learning rate optimizer, was used for efficiency and speed purposes [35]. The model's hyperparameters tuning was implemented heuristically, using TensorFlow's HParams library. The optimization and tuning processes utilized MAE and MSE to define the effectiveness of the model and were important for the optimal configuration of the model. The aim was to minimize the MAE and MSE without sacrificing the speed and complexity of the model, while comparing our results with optimized models that achieved efficient results on the same dataset. In the following Table 2, some essential parameters of our model are presented.

4.3 Comparative Methods

In order to facilitate comparisons, we trained some models based on CNN and LSTM architectures described in the literature. All the models were trained and evaluated on the same train and test set to achieve meaningful comparison. The first model is an 1D Convolutional Neural Network (1D-CNN) that consists of four convolutional layers, two pooling layers and two fully connected layers proposed in [23]. The second model is introduced in [21] and describes a 1-D CNN-LSTM (1D-CNN-LSTM) network, consisted of three convolutional blocks with a max pooling layer deployed between each block. The third model, which is presented in [22], is based on CNN architecture (CNN),

Table 2. Specification of parameters of the model.

Parameters	Specification
Activation function	ReLu
Batch size	256
Epochs	10
Optimizer	Adam
Metric	Mean Absolute Error (MAE)
Loss function	Mean Squared Error (MSE)

where the first block of the convolutional layers (each one consists of four 1-D Convolutional layers) is followed by a fully connected layers block. Between each 1-D convolutional layer a Rectified Linear Activation Function (ReLU) is deployed. The fourth model that was implemented is based on [29] and was a class of recurrent neural network, a Long Short-Term Memory (LSTM), which is followed by a Fully Connected Layer and a Softmax layer. The last model that designed was a Convolutional Neural Network (CONV-1-CONV-2) proposed by [30] which comprised of a convolutional layer (CONV-1) with 16 filters followed by a batch normalization layer, a ReLU activation function layer, and a max-pooling layer and convolutional layer (CONV-2) with 32 filters size, followed by the same architecture.

5 Results

5.1 Total MDS-UPDRS I & II and PDQ-8 Results

The first step of evaluating our model was the verification of its superiority against the previously described models. Due to the combination of inception modules with ReLU function, residual connections and dropout layer the Ince-PD provide better learning capabilities, while being computationally efficient and speeding up the training process. Despite optimizing the parameters of the comparative methods, our proposed model demonstrates the best performance compared to them, achieving a MAE of 1.97 on per-window and 2.27 on per-patient basis for total MDS-UPDRS I & II and a MAE of 2.17 on per-window and 2.96 on per-patient basis for total PDQ-8. Table 3 lists the results for MDS-UPDRS I & II and PDQ-8.

After implementing multiple experiments, it was concluded that the appropriate number of epochs is 10, as the model reached saturation. To verify this, we run our experiments for 13 epochs, but the performance of the models did not show significant improvement, comparing to 10. Figure 4 depicts the comparative results in MAE for the different models for PDQ-8 after running experiments for 10 and 13 epochs.

Table 3. MAE for Total MDS-UPDRS I & II and PDQ-8 on per-window and per-patient basis.

Model	Total MDS-UPDRS I & II		Total PDQ8	
	MAE (window)	MAE (patient)	MAE (window)	MAE (patient)
1-D CNN	5.02	6.19	3.11	3.6
1-D CNN-LSTM	5.73	6.93	2.94	3.29
CNN	5.22	6.38	3.04	3.44
LSTM	5.08	5.80	3.62	3.57
CONV-1-CONV-2	5.46	5.12	3.21	3.36
Ince-PD	1.97	2.27	2.17	2.96

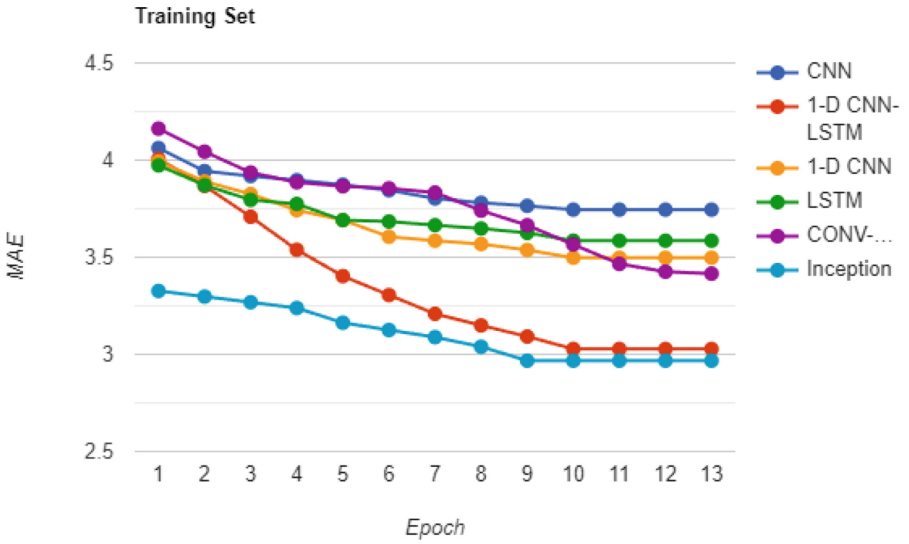

Fig. 4. MAE for PDQ-8 for 10 and 13 epochs.

To observe the model's loss during the training process, we examine the value of the Mean Squared Error during 10 epochs. As seen in Table 4, Ince-PD achieves significant improvement in its performance for both target labels. The MSE of the model steadily decreases from 9.32 to 6.91 for total MDS-UPDRS I & II and from 9.49 to 8.23 for total PDQ-8. This reduction indicates the ability of the proposed method to effectively predict the score of the surveys.

Table 4. The MSE of Ince-PD for total MDS-UPDRS I & II and PDQ-8 for 10 epochs.

Epochs	MDS – UPDRS I & II	PDQ-8
	MSE	MSE
2	9,3224	9,4992
4	9,1288	9,0174
6	8,6521	8,7637
8	7,874	8.4439
10	6,9102	8,2354

6 Conclusion

Nowadays, the use of AI is an important part of the healthcare domain. ML and DL methods are increasingly used to predict Parkinson's disease. In this paper, tri-axial accelerometer data from wearable sensors are given to an Inception based model that estimates the mean absolute error for total MDS-UPDRS I & II and PDQ-8 scores. The combination of the different units of our model provides better learning abilities and generalization. The results obtained far exceed some basic architectures used in the field of neurodegenerative disease prediction. After optimization, the MAE was 1.97 and 2.27 for window and for patient basis for total MDS-UPDRS I & II, while the MAE for PDQ-8 was 2.17 for window and 2.96 for patient. Despite its great performance though, there are limitations that should be addressed in the future. The adaptability of the model to different datasets is a concern, as a small amount of data may affect its efficiency. Furthermore, the framework approaches PD prediction through regression and no classification experiments executed for its evaluation. Future work should expand the model for more target labels (e.g. Hoehn & Yahr) and more neurodisorders like Multiple Sclerosis and Stroke. With its great performance, the Ince-PD model enables an increasingly better assessment of the stage of a patient's Parkinson's disease through the prediction of the score of important questionnaires for medical experts. Experiments show that with proper optimization the MAE is minimized and thus this work provides great potential in the field of PD prediction, helping to minimize costs and to make diagnosis by physicians more efficient.

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