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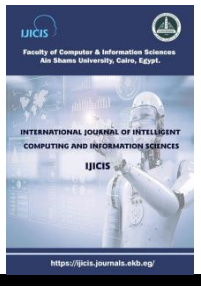

BRADYKINESIA DETECTION IN PARKINSON'S DISEASE USING MACHINE LEARNING TECHNIQUES

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Abstract *– Bradykinesia is the most side effect of Parkinson's Diease (PD), and poses significant challenges in motor function, complicating accurate and timely diagnosis. This survey investigates the implementation of machine learning (ML) techniques in detecting and quantifying bradykinesia among PD patients. This survey evaluated the performance of various machine learning models, including Variational Autoencoders (VAEs), ROCKET, and InceptionTime, using the GENEActiv dataset to detect bradykinesia. The survey delves into key features extracted for ML models—such as movement speed, rhythm, and amplitude—highlighting their relevance in enhancing diagnostic precision. Micheal J. Fox Foundation (MJFF) Levodopa Response dataset is used as an input for the previously mentioned Machine Learning Models. All participants wore a sensor device (GeneActiv) on the wrist of their most affected limb. Our findings also highlight the potential of the InceptionTime and ROCKET models, 0.673 and 0.567 of mean average precision and balanced accuracy respectively for the InceptionTime model. The ROCKET model achieved 0.727 of mean average precision.*

Keywords: *Artificial Intelligence, Machine Learning, Signal Processing, Parkinson's Disease, Bradykinesia.*

1. Introduction

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Deep learning has shown noticeable effectiveness in medical diagnosis despite numerous challenges in medical imaging [1]. It presents a more accurate and faster identification of the symptoms because of its ability to analyze vast amounts of data. Additionally, AI can assist healthcare professionals by providing predictive insights and recommending personalized treatment plans [2,3]. Parkinson's disease [4,5] affects the patient's movement, this effect happens because the disease affects the nerve areas in the brain and is characterized by a variety of symptoms [6]. PD affects the way people move, balance, walk, and posture which may lead to falls. Motor and non-motor symptoms may be experienced by patients with PD.

Motor Symptoms [7] are the hallmark signs of PD and are primarily related to movement. There are several motor symptoms of PD such as bradykinesia, rigidity, tremors, freezing of gait, and postural instability. The most noticeable motor symptom of the PD is the resting tremor [8], it often begins with one hand or finger and may eventually affect other limbs or the jaw. Bradykinesia [9] is characterized by movement slowness and the loss of spontaneous and automatic movement. Tasks such as buttoning a shirt or walking may become difficult and time-consuming. Stiffness or rigidity in the muscles can occur, making it challenging to initiate and maintain movements. This stiffness can contribute to muscle pain and reduced motion with respect to the range. For postural instability [10] patients with PD may face difficulties with balance and posture, leading to a stooped or hunched posture. Freezing of gait [11] is characterized by brief episodes where a person feels feet freezing on the ground, causing difficulty in processing or continuing walking.

One of the things that can also make the quality of life of PD patients more difficult is the non-motor symptoms [12]. These symptoms can affect various bodily systems beyond movement. Bradyphrenia, Mood changes, Sleep disturbances, Orthostatic hypotension, Constipation, and Loss of smell are the non-motor symptoms that may impact PD patients. Bradyphrenia [13] is a decline in thinking skills, memory problems, and difficulty concentrating. PD patients can go through mood changes such as Depression, anxiety, and apathy. These can have a significant impact on a person's overall well-being. Patients with PD may experience problems in sleep, such as rapid eye movement, sleep behavior disorder, Willis-Ekbom disease, and sleeplessness. A reduced ability to smell (hyposmia) or a complete loss of smell (anosmia) is often an early symptom of PD. Constipation [14] is known as a slowed movement in the digestive tract that can lead to constipation and other gastrointestinal issues. Orthostatic hypotension [15] is characterized by decreasing in the patient’s blood pressure which in turn resulting in fainting, and dizziness.

The following survey focuses on the motor symptom bradykinesia [16] which is a core motor symptom of PD. Bradykinesia is the hallmark feature that often lead to significant functional impairment in patients. Bradykinesia is characterized by slowness and decreasing amplitude of voluntary movements, affecting both the initiation and execution of movement. Patients with bradykinesia experience difficulty starting, continuing, and completing movements, leading to reduced fluency and efficiency of their motor functions [17]. Assessments of bradykinesia can be classified into clinical assessments and non-clinical assessments.

Clinical assessments [18] of bradykinesia are typically conducted by healthcare professionals, such as neurologists or movement disorder specialists. These assessments involve direct observation and evaluation of the patient's motor function. Some common clinical assessments for bradykinesia include Unified

Parkinson's Disease Rating Scale (UPDRS), Movement Disorder Society-Unified Parkinson's Disease Rating Scale (MDS-UPDRS), Finger Tapping Test, and Purdue Pegboard Test. UPDRS [19] was the most widely used assessment as a scaling measurement for detecting the symptom severity and keeping track of the motor progression in PD patients. MDS-UPDRS [19], the aim of developing the MDS-UPDRS was to address the limitations of the original scoring scale UPDRS. The scaling in the original UPDRS was as follows 1,2,3,4 for mild, moderate, severe, and marked, respectively. A new scaling was needed to distinguish between the no motor and the mild motor. Therefore, the newly developed MDS-UPDRS has the following scaling, 1, 2, 3, 4 for slight, mild, moderate, and severe respectively. It assesses various aspects of Parkinson's disease, including bradykinesia. It involves the evaluation of tasks such as finger tapping, hand movements, and walking speed [20]. Finger Tapping test [20] measures the speed and rhythm of finger-tapping movements. PD patients were asked to tap quickly with their fingers for a specified duration, and the number of taps was recorded. The Purdue Pegboard test [21] assesses manual dexterity and finger-hand coordination. The patient is asked to place and remove pegs on a pegboard within a given time limit.

Non-clinical assessments (digital assessments) [22] of bradykinesia are typically self-administered or performed outside of a clinical setting. These assessments can be useful for monitoring symptoms over time or for research purposes. Some examples of non-clinical assessments for bradykinesia include Smartphone Applications, Wearable Devices, Motion Capture Systems, Motor skills assessment tools, Virtual Reality (VR) systems, and home monitoring systems. Smartphone Applications [23], there are smartphone apps available that utilize the device's sensors to detect and measure bradykinesia. These apps often involve performing various tapping or movement tasks and provide objective measurements of movement speed and amplitude. Wearable Devices [24] such as smartwatches can be used to monitor movement and detect bradykinesia. These devices can provide continuous data on movement patterns and allow for long-term monitoring of symptoms. Motion Capture Systems [25], sophisticated motion capture systems (gait analysis systems), including optical cameras or inertial sensors, can be used to track and analyze movement. These systems are often used in research settings to assess bradykinesia objectively and in a controlled environment. Motor skills assessment tools [26], patients with PD suffer from the inability to make movements using small muscles in the hands or the wrists called (fine motor skills), considered the hallmark of PD. A lot of tools were implemented to measure the changes in fine motor skills. The tools are focused on features like movement slowness associated with PD Bradykinesia, or motion analysis. Fine motor skills tools such as action research arm test, finger tapping, spiral drawing, and coin rotations were used through tablets, touch screen devices, and handwriting [27].

Virtual Reality (VR) systems [28] are increasingly recognized as a valuable tool for investigating and addressing gait and balance challenges in individuals with PD. This innovative approach enables users to immerse themselves in a personalized and stimulating environment, offering a unique and tailored experience for assessment and rehabilitation purposes. VR applications for PD patients have primarily focused on exploring and addressing issues related to gait and balance difficulties. Home monitoring systems [29] utilize various technologies to monitor movement, activities of daily living medication adherence, and other relevant parameters specific to Parkinson's disease remotely. It can include the previously illustrated clinical or non-clinical assessments.

2. Literature Review

The aim in [30] was to extract features from accelerometer and gyroscope sensors in a try to predict the severity and the existence of PD. Two main datasets were used in the challenge: mPower and MJFF. The mPower dataset included accelerometer and gyroscope data from a gait and balance test performed by 4,799 subjects, which was used to have the ability to predict if a subject had PD. The Levodopa Response Study (MJFF) included accelerometer recordings from two watches namely: GENEActiv and Pebble of 25 PD patients, used to predict symptom severity during specific motor tasks related to tremor, dyskinesia, and bradykinesia. Random forest, logistic regression with L2 regularization, and Support Vector Machine (SVM) with RBF kernel were implemented for severity prediction.

In [31] the aim was to accurately identify OFF symptoms, as reported by the subject, using real-world data that was collected from a mobile application and a Garmin Vivosmart-4 device. The study employed Variational Autoencoders (VAEs) to process and identify movement states from accelerometer data. Two datasets were used: the Self-Collected Dataset, which included accelerometer data and symptom reports from a cohort of 42 PD patients over approximately four weeks, with patients self-reporting a total of 7,590 symptoms during this period; and the MJFFd Dataset, which re-analyzed data from the levodopa MJFF dataset recording data from 30 patients using accelerometer. This dataset was utilized for training the VAEs and comparing movement state predictions.

Using wearable accelerometer data, [32] the study investigated methods for continuous monitoring of PD symptoms, aiming to improve detecting the Bradykinesia, Dyskinesia, Tremor. which are crucial for optimizing treatment and enhancing patient quality of life. The study employed two advanced time series classification techniques: InceptionTime, which was designed to model complex movement patterns due to its high learning capacity, and RandOm Convolutional KErnel Transform (ROCKET), which was tailored for small datasets, making it suitable for the limited data available in PD research. The performance of these methods was compared against a baseline multi-layer perception classifier. The dataset used in the study was a subset of the publicly available MJFF Levodopa Response Study, which included acceleration data from twenty-seven PD subjects who wore GENEActiv smartwatches on their most affected limb, with additional data collected from Shimmer sensors on both wrists. The dataset comprised multivariate time series recorded during predefined motor tasks, with symptom severity annotations provided by a clinician. The data was characterized by a substantial imbalance in class labels, with more instances of mild symptoms than severe ones.

In [33], the authors explored the impact of using a single model that was trained on a short-timescale classification of naturalistic bradykinesia fluctuations in patients with PD. Data was collected from 20 patients using a two-sided wrist accelerometer during two sessions each a one-hour duration: the first session is OFF medication and the second session is ON medication, both conducted during daily activities in the participants' homes. The recording was divided into two phases: a pre-medication phase, captured in the morning following an overnight withdrawal of dopaminergic medication, and a post medication phase, recorded after participants experienced the full clinical effects of their regular dopaminergic medication. Various time-series data were extracted such as x, y, z, and vector magnitude including temporal and spectral domain features. These features were then used as input for classification models, specifically a support vector machine and a random forest classifier.

In this study [34], the author's aim was to provide an objective assessment to PD patients that suffers from tremor and bradykinesia using a wearable device. To achieve this, the researchers developed the A-WEAR bracelet, which incorporated inertial sensors (a 3D accelerometer and gyroscope) to record the physical movements of participants. The collected data was presented from a bracelet and was analyzed using both supervised (K-Nearest Neighbors (KNN) and unsupervised (neural net clustering) machine learning classifiers to differentiate between patients with Parkinson's disease and healthy subjects. The dataset consisted of 40 participants aged over 60 years, including 20 Parkinson's Disease patients (10 having tremor and 10 having bradykinesia) and 20 healthy older adults. Participants performed upper extremity motor activities as per the Unified Parkinson's Disease Rating Scale (UPDRS) during the data collection process.

The primary aim of the study [35] was to develop a robust, cloud-connected wearable device that allowed for continuous monitoring of PD symptoms, providing healthcare professionals with real-time insights into patient conditions. The research introduced a wrist-based wearable device that utilized inertial sensors to collect motion data from PD patients. This data was processed using Continuous Wavelet Transform (CWT) to create time-frequency (TF) representations, using a deep learning model for analyzation, specifically the CNN (AlexNet). The system was cloud-connected, allowing for the storage and analysis of data on the MS Azure platform, facilitating easy access for both patients and healthcare providers. The study utilized datasets collected from the MJFF levodopa dataset, which included motion data from PD patients used to train and validate the proposed deep-learning model. The bracelet was equipped with a 3D accelerometer to monitor patient movements. CWT was employed to convert inertial sensor data into scalograms.

In [36], the aim was to predict bradykinesia symptoms by focusing on implementing an automated method to detect the presence of bradykinesia using wearable inertial sensors. The study aimed to collect motion data from various tasks performed by individuals with PD and introduce a novel approach for quantifying upper limb bradykinesia, thereby improving the differentiation between healthy individuals and patients. Motion signals were recorded using two types of inertial sensors: the MPU6050 for capturing finger movements and the lpms-b2 sensor for wrist movements. The number of features extracted from the motion data was thirty-five, including metrics such as RMS along with several entropy measures. An MLP neural network was implemented for classification, using the activation function (tanh) and for the output layer, a softmax activation function was applied.

Study [37] examined the influence of using different data measurements on the accuracy of detecting PD symptoms, specifically tremor and bradykinesia, using wearable sensor technology. The primary objective was to demonstrate the relationship between aspects such as sensor type, sampling rate, and feature complexity, and the performance of machine learning models for classifying PD symptoms. The study aimed to streamline data collection methods without compromising model accuracy, thereby improving the practicality of long-term symptom monitoring. Random forest (RF) classifiers were employed to analyze data from wearable sensors, with model performance compared across different sensor types (accelerometer and gyroscope), up to 62.5 Hz sampling rate, and up to 148 engineered features. Statistical methods, including repeated measures ANOVA and paired test data that were used to evaluate the differences in model performance across these variables. The dataset included recordings from 13 individuals with Parkinson's

disease. Participants wore a tri-axial accelerometer and gyroscope sensors on the most affected hand (skin-mounted BioStampRC), as well as an Apple Watch, which collected tri-axial accelerometer data.

Authors in [38] proposed machine and deep learning algorithms to help in diagnosing and assessing the severity of bradykinesia symptom, using the A-wear bracelet. Spectral and temporal features were extracted from accelerometer data to distinguish patients from healthy individuals. Participants included 40 individuals, 20 PD patients with different levels of bradykinesia and tremor, while the remaining 20 served as healthy controls. Patients performed specific tasks such as opening and closing a fist, tapping with a finger, and pronation-supination tests to facilitate bradykinesia detection. The raw accelerometer data underwent preprocessing using extracted time-domain and frequency-domain features and the IIR filter (Butterworth bandpass). The time-domain extracted features were RMS, skewness, kurtosis, mean, peak, and non-linear metrics like entropy and correlation dimension. The frequency-domain extracted features were the band power, and peak frequency-amplitude. Two classification approaches were explored: a neural network clustering method based on the Self-Organizing Map (SOM) batch unsupervised algorithm and a K-Nearest Neighbor (KNN) classifier (supervised). Additionally, a CatBoost classifier was used for signal analysis.

The study of [39] represents the use of a deep learning model for the bradykinesia classification and evaluation in patients with PD using kinematic parameters obtained from a wearable sensor system. The aim was to determine whether these kinematic features could differentiate between PD patients with varying severities of bradykinesia and healthy controls. To achieve this, the researchers developed a wearable system called the A-WEAR bracelet, which contained a triaxial accelerometer, gyroscope, and magnetometer, and recorded kinematic data during specific tasks such as tapping with fingers, hand clenching, and pronation-supination. Both time-domain and frequency-domain features were used including parameters like mean, std, Entropy, Mean, Peak, and Band Power. The A-WEAR bracelet system was validated against the MDS-UPDRS clinical assessments. The dataset included data from twenty-five PD patients and twenty healthy controls. The deep learning approach utilized a neural network model based on the LSTM architecture, as it have the ability to capture temporal dependencies and complex patterns in the sensor data.

The following study [40] investigated a machine learning-based classification approach to identifying PD symptoms using data collected from wearable sensors. The cohort included 50 participants, comprising 30 PD patients and 20 healthy subjects. Participants were asked to perform different motor tasks such as walking and finger-tapping while wearing sensors on their wrists and ankles. These sensors, equipped with tri-axial accelerometers and gyroscopes, recorded motion data used to extract features, including mean, variance, skewness, kurtosis, peak amplitude, and power spectral density. Both time and frequency domain features were analyzed to assess symptom severity and classify participants. To enhance model performance, the researchers utilized cross-validation techniques and feature selection methods such as Recursive Feature Elimination (RFE). Different classification models were implemented such as random forest and XGBoost. Those models were trained using different performance measurements such as sensitivity, ROC curve, specificity, and accuracy.

In [41], the aim was to enhance the detection of bradykinesia using a deep learning sensor-based model. A convolutional neural network model was implemented to extract features from accelerometer and gyroscope data collected from a wrist sensor device. Twenty-five PD patients and twenty healthy subjects were enrolled

in the study. Participants performed various tasks such as tapping fingers, hand clenching, and pronation supination. The wearable device recorded triaxial accelerometer and gyroscope data, which were then processed using CWT (continuous wavelet transform) to have time-frequency representations of the movement patterns. The resulting scalograms were fed into CNN, which was trained to classify and quantify the severity of bradykinesia. The dataset included kinematic data from 45 participants during multiple motor tasks, with symptom severity labels assigned by a clinical expert.

The study of [42] proposed a deep learning approach to detect bradykinesia for PD patients using wearable sensors and time-frequency representations of motion data. The aim was to develop a reliable and objective method for monitoring bradykinesia symptoms, which could be used in clinical and home settings. The research utilized a wrist-worn wearable device equipped with triaxial accelerometers and gyroscopes to collect motion data from participants. The dataset comprised data from 50 participants (30 PD patients, 20 healthy subjects) who were asked to perform tasks such as finger tapping, hand clenching, and pronation supination. The collected data was processed using continuous wavelet transform (CWT) to create time-frequency representations, which were then input into the AlexNet CNN architecture. The model was trained to detect the presence of bradykinesia with performance measurements such as sensitivity, accuracy, and specificity. The study aimed to validate the wearable system as a practical tool for monitoring PD symptoms in real-world environments.

Authors in [43] presented a deep learning model for the detection of PD symptoms using wearable devices and an extensive range of features derived from accelerometer and gyroscope data. The objective was to evaluate the model's performance in identifying and classifying PD symptoms in real-world scenarios. The wearable system consisted of wrist-worn devices equipped with accelerometers and gyroscopes, which recorded motion data from 60 participants, including 35 PD patients and 25 healthy subjects. Participants performed various motor tasks, such as finger tapping, hand-clenching, and pronation-supination. Time-domain features were extracted such as mean, variance, skewness, and frequency-domain features such as peak amplitude, and power spectral density. These features were then fed into a hybrid architecture of deep learning architecture with a convolutional neural network and a long-term memory model to capture both spatial and temporal dependencies. A cross-validation technique was applied and assessed with performance measurements including f1-score, precision, accuracy, and recall.

3. Methodology

In this section, three methodologies were re-implemented from two selected studies in the related work which were the study of [31] and [32]. The aim of [31] was to employ Variational Autoencoders (VAEs) to process and identify movement states from accelerometer data. An autoencoder [44] (a type of neural network) consists of three layers the encoder layer, latent variable layer, and the decoder layer, respectively that transforms inputs into outputs. The input is compressed by the encoder into a latent variable, in contrast, decoders reconstruct the encoded data back to the original input dimensions. The goal of an autoencoder is to reconstruct values from the latent variables that closely match the original input data. However, a limitation of traditional autoencoders is that the latent space may not be continuous, which can lead to significant computational challenges. Variational Autoencoders (VAEs) [45] are a specific type of autoencoder designed to address this issue. Variational Autoencoders (VAEs) is an unsupervised model and a type of autoencoder

designed to address the previous issue, also used for dimensionality reduction, allowing them to learn representations of complex data without supervision by employing deep neural networks. VAEs differ from traditional autoencoders by utilizing probabilistic distributions in the latent space and imposing specific assumptions about the distribution of latent variables. The encoder in a VAE produces for each latent variable a probability distribution instead of generating a single value for each latent variable.

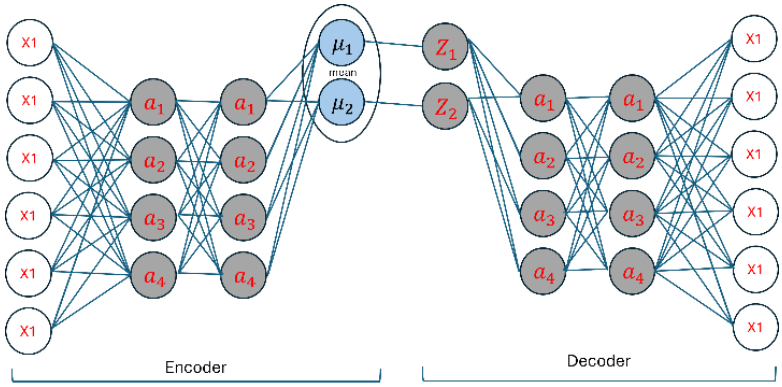

Figure. 1: Variational Autoencoders

Variational Autoencoders (VAEs) [46] comprise three key components: encoder, decoder, and loss function, as shown in Figure 1. In VAEs, a latent variable (z) is used to generate the input data (x) which is a random variable following by a prior distribution p(z). The steps is as follows, first, sample the (z) from the prior, second, sample the (x) from the conditional likelihood p(x|z).

The decoder represented as generator function p(x|z), modeling the distribution of the reconstructed data based on the encoded representation. Conversely, the encoder capturing the distribution of the latent variables and approximates the conditional probability q(z|x). The loss function in the VAEs model contains two components: a reconstruction loss that maximizes the likelihood of accurately reconstructing the regularization term and the input to ensure the learned distribution q(z|x) aligns closely with the p(z) [46].

The objective in [32] was to enhance the detection of motor bradykinesia by employing two cutting-edge time series classification methods: The InceptionTime model and the (ROCKET) RandOm Convolutional KErnel Transform. These methods achieve state-of-the-art classification accuracy in a fraction of the time compared to other modern scalable approaches using the random convolutional kernels to transform the time series data and leveraging the resulting features for training using a linear classifier. This innovative approach, referred to as ROCKET [47], is highly scalable, with training complexity increasing linearly with both the time-series length and number of samples.

In ROCKET a large set of random convolutional kernels are generated each varying in parameters like length, padding, weight, bias, and dilation to be fed and train into a linear classifier [47] as shown in Figure 2. The hybridization between the logistic regression model and the ROCKET randomly initialized a kernel weights from the single-layer convolutional neural network with the transformed features fed as an input to be trained on a linear classifier [47]. While ROCKET is compatible with various classifiers, it is particularly effective

with linear classifiers, as they efficiently utilize a small amount of data from each large number of features [47].

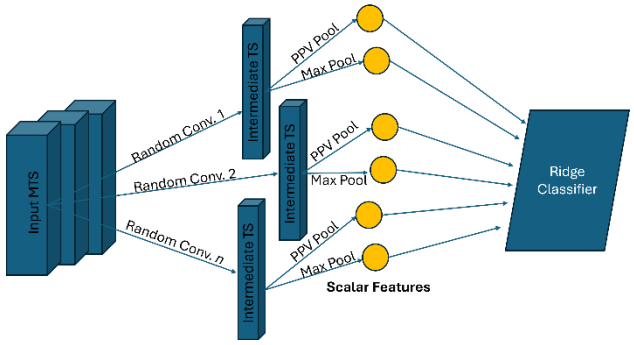

Figure. 2: ROCKET module

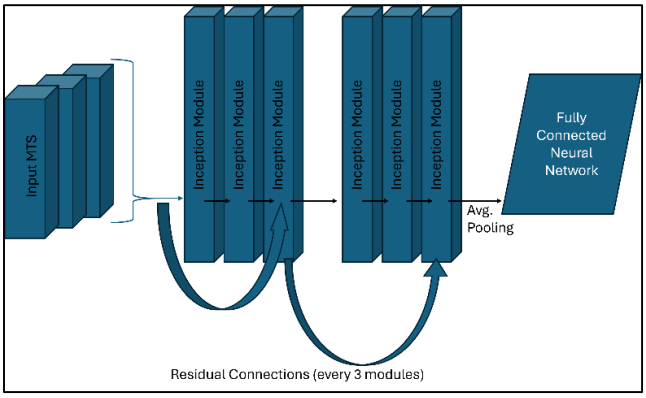

Figure. 3: InceptionTime module

InceptionTime is an ensemble architecture of deep convolutional neural network models inspired by Inceptionv4. It consists of 5 models designed for time-series classification, each implemented by stacking multiple inception modules. While all models in the ensemble share the same architecture, they differ in their weight values [48]. Applying multiple filters of different lengths simultaneously to a time-series input is the main idea of the Inception module. This makes the extraction of short and long time-series features more effective [48]. Key components of the InceptionTime architecture include Inception Modules, Convolutional Layers, Stacked Inception Modules, an Ensemble of Models, global average pooling, and fully connected layer, as shown in Figure 3 [48].

4. Experimental Results

Data collection- In the Micheal J. Fox Levodopa (MJFF) dataset [49], participants in the study were equipped with either 3 or 8 sensors to monitor their movements and symptoms. All participants wore a GeneActive device on the wrist of the most affected limb, as well as on the least affected limb. A Pebble smartwatch was placed on the wrist of the least affected limb, and a Samsung Galaxy Mini smartphone was carried in a fanny

pack at the front of their waist. These sensors were worn continuously throughout the study. Participants were recruited from the Boston study site, known as the 'Shimmer subjects'. Three shimmer sensors were placed one on the lower back and the others on each limb.

The study protocol included various tasks to assess motor function, such as standing, and walking in a straight line for 30sec. once and once while counting, walking upstairs and downstairs, walking in a narrow corridor, twice with each arm for 15 seconds patients were asked to perform the finger-to-nose test, alternating hand movements (twice with each arm for 15 sec.), for 30 seconds patients were asked to draw and type on a keyboard, for three times patients were asked to open a bottle and pouring water, arranging a bunch of papers into a folder twice, classifying and for 30 seconds assembling nuts, folding a towel three times, and sitting.

Clinical labels were provided by clinicians for the presence of symptom severity and each task completed by the participants. For the left-right arm and left-right leg, there are limb-specific tremor severity ratings from 0 to 4, as well as assessments of dyskinesia and bradykinesia presence in the upper and lower limbs. Additionally, bradykinesia and dyskinesia severity (rated 0-4) were recorded for a subset of tasks performed by participants with Shimmer sensors.

After completing the data collection in the lab on Day 1, participants continued to wear all the sensors and went about their usual activities at home on Days 2 and 3. Different tasks were asked to be performed by Shimmer subjects. These tasks were a short set of motor tasks aligned with different specific items from section III of the MDS-UPDRS. MDS-UPDRS tasks included for each arm to alternating hand movements for 30 seconds, performing once to each arm finger-to-nose tasks for 30 seconds, and sitting quietly for 30 seconds. Every 30 minutes these tasks were repeated seven times daily while at home on both Days 2 and 3. On Day 4, participants returned to the lab to repeat the same steps conducted on Day 1.

The architecture for the Variational Autoencoders (VAEs) described in [31] consisted of an encoder that contains a two-layer fully connected neural network. The first layer included 400 nodes, and the second layer had 20 nodes, paired with a symmetric decoder. From the MJFF dataset a subset of right-handed patients, who wore the accelerometer sensor on the right hand, were used as input for the model with the original accelerometer axes. WAE model was trained using ten-second segments of 3-channel accelerometer data. For classification, a model with two fully connected hidden layers was presented each one with 50 nodes. The classification accuracy was achieved using k=5 cross-validation, resulting in a mean classification accuracy of 0.48.

Both ROCKET and InceptionTime [32], the default architecture parameters were employed to detect bradykinesia. The study primarily relied on using the sensor GENEActive to implement and evaluate machine learning models due to its larger dataset compared to Shimmer. The data was split into three portions namely training, testing, and validation. Specifically, a five-fold cross-validation approach was used, maintaining balanced class proportions across each fold and preventing patient overlap. Each fold was split with 80% training and 20% validation. InceptionTime achieved the highest average precision (AP) scores for bradykinesia prediction.

In the proposed survey VAEs, ROCKET, and InceptionTime were implemented using the same dataset and hyperparameters for each model presented in the related work. In the validation study [31], the accuracy was 0.48 mean classification accuracy in contrast our results achieved 65% for the mean classification accuracy. This variability between the two results was due to the use of a subset of the dataset considering only the right-hand patients without specifying which patients they selected. For InceptionTime and ROCKET models, the study of [32] achieved 0.673 and 0.567 of mean average precision and balanced accuracy respectively for the InceptionTime model. The ROCKET model achieved 0.727 of mean average precision as shown in the following table. In contrast, the re-implemented InceptionTime model achieved 0.71 and 0.66 for the mean average precision and the balanced accuracy respectively. For the re-implemented ROCKET model, it achieved a mean average precision of 0.65% and a balanced accuracy of 0.7%. From Figure. 4, it could be observed that the best result was obtained from the ROCKET model against the InceptionTime and the VAEs, with a mean accuracy of 0.727.

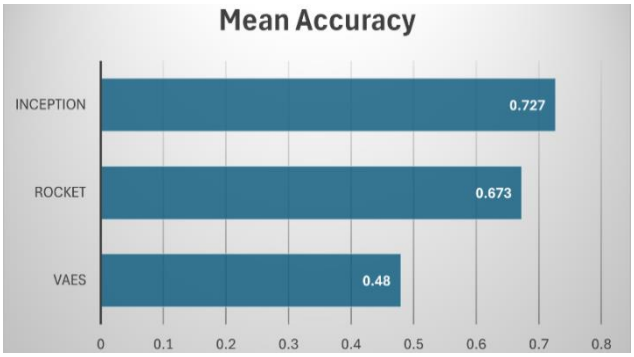

Figure. 4 presents the mean accuracy for the three used models

Table 1 Summary of the studies used the MJFF dataset

Ref	Dataset	Aim	Methodology	Results
[31]	Using a subset from the MJFF dataset from the right-hand patients.	Accurately identify OFF symptoms (Bradykinesia)	VAE	The result obtained was 0.48 for the mean classification accuracy.
[32]	MJFF	Continuous monitoring of PD symptoms, aiming to improve the detection of motor symptoms.	ROCKET and InceptionTime modules	0.673 and 0.567 of mean average precision and balanced accuracy respectively for the InceptionTime model. The ROCKET model achieved 0.727 of mean average precision.

5. Conclusion

Through this survey, several key insights have been identified as crucial for the effective detection of bradykinesia, a primary symptom of PD. One of the most important findings is the significant influence of movement state on the visibility and severity of PD symptoms. Specifically, bradykinesia is characterized by a decreasing in the speed and amplitude values, which can vary considerably depending on the patient's

overall state of motion. Additionally, there was a lack of benchmark datasets that specifically target the detection of Bradykinesia.

The classification performance of the VAE was suboptimal, yielding an accuracy of 0.48 when evaluated with a fully connected neural network classifier with two hidden layers which contain fifty nodes each implemented in the scikit-learn library. This performance was confirmed through fivefold cross-validation. The low accuracy observed could be attributed to the subset of right-handed patients used in the training data, without clear criteria for patient selection. Our re-implementation, using a well-defined patient-disjoint split for training, validation, and testing, and ensuring consistent class proportions across folds, led to a marked improvement in classification accuracy, achieving 65% mean accuracy. This highlights the critical importance of dataset preparation and the impact of patient selection criteria on model performance.

For the ROCKET and InceptionTime models, we adhered to the default architecture parameters described in related works and focused on detecting bradykinesia. The comparative analysis revealed notable differences in model performance metrics between our implementation and the previous studies. Specifically, the InceptionTime model from the related work achieved a mean average precision (AP) of 0.673 and a balanced accuracy of 0.567. In our implementation, the InceptionTime has a higher mean value AP of 0.71 and a balanced accuracy of 0.66. Similarly, the ROCKET model reported in the previous study obtained a mean AP of 0.727. However, our implementation of the ROCKET model resulted in a lower mean AP of 0.65 but demonstrated a balanced accuracy of 0.7. The variations in performance between the two studies emphasize the sensitivity of these models to specific hyperparameter tuning, dataset characteristics, and evaluation methodologies.

Overall, the improved classification accuracy achieved through careful dataset management suggests that such practices are crucial for achieving reliable and reproducible results in medical machine-learning applications. Our findings also highlight the potential of the InceptionTime and ROCKET models in clinical settings, where accurate detection of bradykinesia could enhance patient monitoring and treatment efficacy. Future work could explore the integration of additional features, the refinement of model architectures, and the optimization of hyperparameters to further improve model performance.

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