# Automatic Assessment of Bradykinesia in Parkinson's Disease Using Tapping Videos

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## ABSTRACT

Parkinson's disease is a chronic neurodegenerative illness that severely affects the everyday life of a patient. The severity of Parkinson's disease is assessed using the MDS-UPDRS scale. In this study, we explore the feasibility of automatically evaluating bradykinesia, a key symptom of Parkinson's disease, from tapping videos recorded on smartphones in everyday settings. We collected a dataset of 183 tapping videos, from 91 individuals. Videos were assessed by neurologist into 5 classes of the MDS-UPDRS scale. For data extraction, we employed MediaPipe Hand, which provides a time series of hand skeleton movements. The data was preprocessed to eliminate noise and subsequently used for either feature construction or directly in neural networks. Utilizing manually created features in a multilayer perceptron classifier resulted in 61 % accuracy and an F1 score of 0.61 on our test set. Employing a fully convolutional network, we improved the accuracy to 78 % and the F1 score to 0.75. Additionally, we developed the tool for visualising tapping and displaying key data, providing detailed insights into tapping patterns.

## KEYWORDS

Bradykinesia evaluation, Finger tapping test, Parkinson's disease, Machine learning, Tapping video analysis

## 1 INTRODUCTION

Parkinson's disease (PD) is a chronic neurodegenerative condition that profoundly impacts daily life. PD affects 1-2 % [23] of the population over the age of 65. Currently, there are more than 1.2 million cases in Europe [4] and this number is forecast to double in the near future due to the demographic problem of an aging population. Its etiology remains incompletely understood, yet researchers suggest that a combination of genetic and environmental factors contributes to its development. Factors such as exposure to polluted air, pesticides, heavy metals, and head injuries have been associated with an increased risk of Parkinson's disease. The most common symptoms include bradykinesia, which is also the main symptom, tremor, rigidity, impaired postural reflexes, and dementia. There are also numerous other symptoms that can accompany the disease, such as sleep disturbances, depression, loss of smell, and fatigue.

The standardized MDS-UPDRS [6] scale is used to assess the stage of Parkinson's disease. It consists of 4 sections that evaluate both motor and non-motor issues experienced by patients. The finger-tapping test is used to evaluate the severity of bradykinesia. This test involves asking the individual to tap their index finger and thumb as quickly as possible with a maximal span, assessing the number of pauses, time taken, decrease in amplitude, and slowing of speed, all contributing to the final score. It was estimated that up to 25 % of clinical diagnoses of PD are incorrect, due to lack of experience or attention during tests [3].

## 2 RELATED WORK

First automated systems for PD detection were based on wearable sensors like gyros and accelerometers [5, 17, 20, 22] or on electromyography sensors [11, 28]. The main issues with sensors are that they are commercially unavailable, require precise placement, and can interfere with tapping test. Therefore, some researchers have utilized keyboard tapping [1, 19] or tapping on a smartphone screen [7, 8] for data acquisition. Sadikov et al. [21] collected data using digital spirometry, where participants traced an Archimedes spiral on a touchscreen device. Advances in hardware and software have made computer vision combined with machine learning a viable alternative for PD recognition, allowing for home testing using a computer or smartphone. Lainscsek et al. [13] used a nonlinear delay differential equation, with the structure selected by a genetic algorithm. While other researchers used machine learning techniques, most focused on manual feature creation and utilized these features in classification models [10, 18, 29, 30] like support vector machines (SVM) and random forests (RF), or regression models [9] like support vector regression (SVR) and XGBoost. Others employed neural networks (NN) to automatically learn patterns from time series data [2, 14]. Researchers used segmentation neural networks or optical flow for hand data extraction, with MediaPipe Hand [16] becoming popular in later works. Due to limited data, most studies combined some classes, and only a few performed full-scale classification [2, 9, 14, 30].

## 3 METHODOLOGY

First, we collected and labeled data and preprocessed it to eliminate noise. We initially applied Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), and Random Forest (RF) with manual feature extraction, then used a Fully Convolutional Network (FCN) directly on the time series.

### 3.1 Dataset

Since datasets of tapping videos were not publicly accessible, we assembled our own database. From each participant, we collected two videos: one of the left-hand tapping and another of the right-hand, as they are independent from each other and have their own score. Videos were recorded at a resolution of 3840 x 2160 or 1920 x 1080 at 60 or 30 fps. All PD patients were recorded in a clinical setting, while some participants of the healthy group were recorded in various other environments.

| MDS-UPDRS score | 0 | 1 | 2 | 3 | 4 | Sum |
|---|---|---|---|---|---|---|
| Number of videos | 49 | 51 | 53 | 23 | 7 | 183 |
| Percentage % | 26 | 28 | 29 | 13 | 4 | 100 |

**Table 1: Number of videos in each class.**

We excluded videos with significant tilts, incomplete hand visibility, and participants scoring above 0 on MDS-UPDRS without confirmed PD. In total, we compiled 183 videos from 91 different individuals. The distribution of data between classes can be observed in Table 1. As this study involves clinical data, ethical approval was obtained as part of a larger research project approved by the Neurological Clinic.

## 3.2 Preprocessing

Since datasets were collected without any professional equipment we were dealing with different illuminations, angles, camera tilts, distances between camera and hand, noise, and motion blur. Videos were cut, so only hand is visible, due to privacy and faster processing. We used Mediapipe Hand [16] to extract the thumb and index finger positions and computed the Euclidean distances between their endpoints to generate time series data. Occasionally, there were single-frame misses where Mediapipe detected previous and next frames but missed the current one. We used linear interpolation to fill these gaps, but avoided interpolating longer gaps to preserve tapping integrity. To reduce noise caused by inaccurate detections from MediaPipe, we implemented a combination of low-pass and moving average filter. Filtering also helped to eliminate tremor which is not part of MDS-UPDRS, but masked tapping. We balanced filtering and signal preservation using weaker filters. The Low-pass filter addressed high-frequency noise from tremors and MediaPipe Hand's misalignment, which caused slight shifts between frames even when the hand was still. We implemented the Butterworth low-pass filter due to its flat response. The cutoff frequency set uniquely for each input based on a specified influence percentage k, as defined by the equation: $f_{cutoff} = f_{max} + \frac{\text{bandwidth}*k}{2}$. Additionally, a moving average with a window size of 5 was used to further smooth the data and reduce erroneous detections, such as spikes. We restricted tapping sequences to a maximum of 15 taps, as the MDS-UPDRS scale does not require longer sequences and participants may tire during extended sessions. We also applied min-max normalization to account for varying distances between the camera and the hand. The finalised graphs of the processed data are depicted in Figure 1.

## 3.3 Feature Engineering

In the **1st method** we created a larger number of features following the MDS-UPDRS scale to comprehensively describe finger tapping. In addition to Euclidean distances between the endpoints of the thumb and index finger, we included distances between the last joints and absolute wrist movement as additional time series data. We hypothesized that these metrics could provide supplementary but limited insights into finger tapping, although movements in these areas are typically less pronounced. The time series of distances represents the amplitude spectrum, from which we derived 4 additional spectra: velocity, acceleration, frequency, and spectrum of amplitude peaks. Additionally, we included the spectrum of absolute wrist movement. From these 6 spectra, we extracted 193 statistical features. Our goal was to capture dependencies at global and local levels, describing hesitations, slowdowns, amplitude decreases, data distributions, tapping energy, and other characteristics.

In **2nd method** we designed features closely aligned with the MDS-UPDRS scale, categorizing them into 3 parts reflecting its criteria. The first part assesses hesitations and freezes, the second part measures reduced speed and the third part evaluates decreased amplitudes. In our final analysis, we utilized 145 features, with 90 being coefficients from linear regressions to assess reductions in amplitudes and velocities of finger tapping. These coefficients were derived from local maxima of amplitudes and velocities. The remaining 55 features were derived from amplitudes, velocities, their extremes, and autocorrelated velocities and amplitudes.

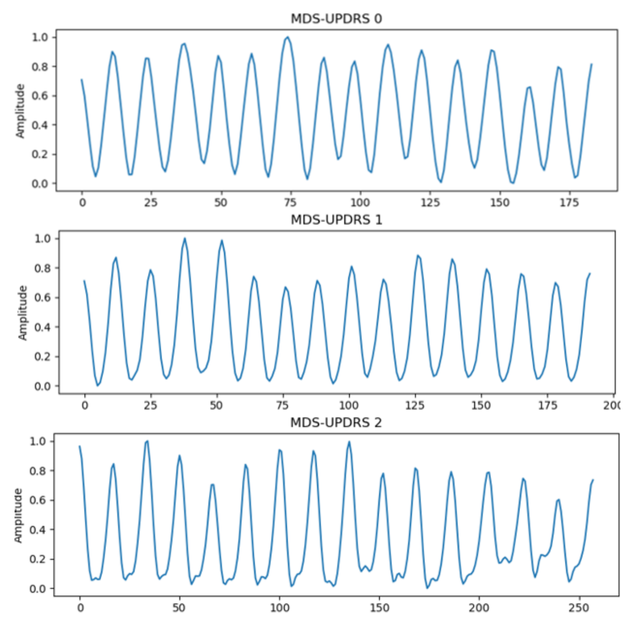


**Figure 1: Amplitude graphs of finger tapping.**

## 3.4 Neural network

We opted for FCN due to its simplicity and efficiency, leaving the exploration of more complex models for future work. We tested the FCN presented by Li et al. [14], using preprocessed time series data directly as input. Since the selected FCN is limited to processing equally long inputs, we padded our time series data with 0 at the end. We later modified the FCN by adding convolutional layers, dropout layers, early stopping, and adjusted input layers to handle

2D inputs consisting of amplitudes and velocities. The architecture of our extended FCN is shown in Figure 2.

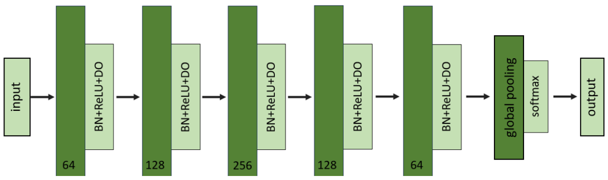


**Figure 2: FCN for classification of bradykinesia.**

## 4 EVALUATION

We created a visualization tool for analyzing finger-tapping dynamics, featuring a built-in video player with a MediaPipe Hand skeleton overlay. Velocity and amplitude graphs on the right side indicate the current frame with a vertical red line (Figure 3). Taps are denoted by red dots and the tool includes a freeze labelling option. This interactive analysis of tapping dynamics could be useful for neurologists in diagnosing and monitoring motor disorders.

All tests were conducted using 10-fold cross-validation due to the relatively small dataset. The F1 score was calculated as the Macro F1= $\frac{1}{C}\sum_{i=1}^{C} \text{F1}_i$, where $C$ is the number of classes and $\text{F1}_i$ is the F1 score for class $i$. In Methods 1 and 2, we used SelectKBest [26] for feature selection. As score functions we tried ANOVA F-test [24] and mutual information for a discrete target [25], with the latter performing better overall. By experimenting with various feature counts, we identified the optimal number that maximized the model's F1 score. Results are detailed in Table 2. Overall, SVM performed the worst in Methods 1 and 2, while RF and MLP achieved the best results, likely due to their superior ability to model complex patterns. Method 1 outperformed Method 2 across all metrics. Approximately 83 % and 73 % of misclassifications from Methods 1 and 2, respectively, differed from the reference tapping scores by exactly 1 class. The FCN from Figure 2 significantly outperformed Methods 1 and 2, achieving a 77 % accuracy. FCN excels at capturing both local and global dependencies in signals by using filters of varying sizes.

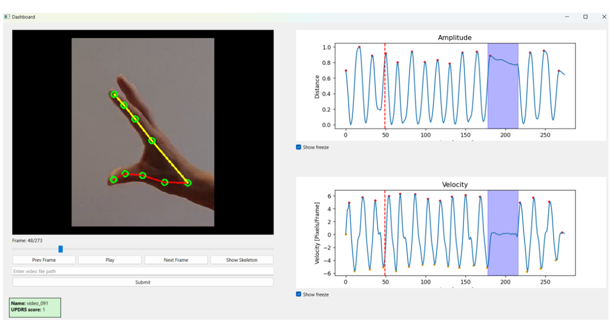


**Figure 3: Tool for detailed visualization of finger tapping.**

## 5 DISCUSSION

Our data set was diverse, assembled by tapping videos of different people among all MDS-UPDRS classes. Since the dataset was collected without any professional equipment we were dealing with different illuminations, angles, camera tilts, distances between hand and camera, noise, and motion blur. That required a robust approach, with filtering being an important part. To balance noise reduction and signal preservation, we opted for milder filtering.

| Model | Accuracy % | F1 % | Precision % | Recall % |
|---|---|---|---|---|
| FCN | 72 | 62 | 84 | 63 |
| **FCN+** | **77** | **75** | **88** | **75** |
| Method 1 | 61 | 62 | 67 | 58 |
| Method 2 | 60 | 55 | 67 | 58 |

**Table 2: Results were obtained via 10-fold cross-validation. FCN refers to Li et al.'s neural network [14], while FCN+ denotes our modified version (Figure 2). MLP was used for Method 1, while RF was used for Method 2.**

Due to the low capture speed and fast movement of fingers, motion blur was present in the videos. To address this, we tested two NNs for motion blur removal: Ghost-DeblurGAN [15] and PDV_net [27]. However, both methods introduced artefacts in the frames, prompting us to discontinue their use. We also experimented with upscaling the resolution to 200 % of the original size using Video2x [12]. This aimed to enhance image clarity, potentially improving MediaPipe Hand's skeleton detection precision and reducing noise. Testing on a smaller upscaled subset showed minimal differences in classification performance but significantly increased processing time, prompting us to abandon this approach due to time constraints. Similarities were observed across different classes of tapping, as shown in Figure 1, where the graphs appear similar. Various factors contribute to the overlapping of classes. Small differences in tapping styles between adjacent classes mean even minor decreases in velocity or amplitude can significantly impact the final classification. Normalization contributes to reduced differentiation between classes by masking tapping instances with low amplitudes. However, it is necessary to account for variations in recording distances and resolutions. Additionally, recording angles can distort actual finger distances, leading to misleading data representation. Another factor for class overlap is the possibility of human errors in video assessments. However, within the same class, tapping behaviours can vary significantly. For example, in class 4, participants often showed varying abilities: some managed to perform a few taps despite severe difficulties, while others were unable to tap at all.

Direct comparisons with related research may be challenging due to the use of different datasets. When comparing our Methods 1 and 2 with the method by Yu et al. [30], who derived features based on MDS-UPDRS, we achieved lower scores. They reported 80 % accuracy and 79 % recall on a test set of only 15 videos recorded as close to a 90-degree angle as possible. Frame interpolation they used might distort tapping details with artificial data, risking the reliability of their classification outcomes. Islam et al. [9] investigated SVR, LightGBM, and XGBoost regressor, achieving up to 55 % accuracy. This is lower than the 61 % accuracy we achieved with Method 1, possibly due to their larger database of 489 videos, less effective preprocessing and a feature set of 65 features that may not fully capture tapping dynamics. The FCN presented by Li and colleagues

[14] achieved 72 % accuracy on our dataset, compared to the 80 % reported by the authors. We attribute the slightly lower classification performance on our data to its complexity and heterogeneity, over 37 % smaller size, and the use of 10-fold cross-validation compared to their 5-fold approach. However, by enhancing the FCN (Figure 2) we improved prediction accuracy to 77 %. Alam et al. [2] reported 81 % accuracy and F1 score of 0.81 on their test set using a graph neural networks (GNN).

## 6 CONCLUSION

In conclusion, Method 1 with MLP provided the best performance between the manual methods, with better overall metrics and 10 % fewer misclassifications differing by one class from the reference value. The modified FCN+ (Figure 2 ) further improved accuracy to 77 %. Results are expected, since with manual time-invariant feature extraction it is challenging to capture all unique patterns at various scales in a tapping sequence of around 400 frames. In the future, we plan to expand the dataset, as our class with an MDS-UPDRS score of 4 had a limited population. Increasing the dataset will help achieve more precise results and provide more data to create an unseen test set. Due to only one labeler, we plan to involve another neurologist to cross-validate our dataset and eliminate potential human errors. We also plan to explore regression models on extracted features to predict continuous severity scores, offering a more detailed evaluation of bradykinesia.Given neural networks' superior performance, we aim to explore graph neural networks (GNN) for handling all data points extracted by MediaPipe.

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