Automated Platform for the Kinematic Assessment of Hand Motor Deficit in Patients with Neurological Diseases

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Abstract. This work presents an automated video analysis platform for assessing hand motor function in patients with stroke, multiple sclerosis, and Parkinson's disease. Videos of patients performing hand exercises were processed with MediaPipe Hands to extract 21 keypoints per hand, from which kinematic metrics (distances, angles, velocities) and statistics were computed. These features were used in binary and multiclass classification models to identify pathology. A web application integrates the full workflow—video upload, automated analysis, and PDF report generation.

Keywords: Neurological Disorders · Motor Function Assessment · Machine Learning · Hand Movement Analysis

1 Introduction

Neurological disorders are a leading cause of disability worldwide, affecting over a billion people globally and representing a growing public health challenge due to population ageing [1, 2]. Conditions like stroke, Parkinson's disease (PD), and multiple sclerosis (MS) are characterized by motor alterations, especially affecting the hands, which are highly debilitating as they hinder basic daily activities and reduce functional capacity [3, 4]. Symptoms such as loss of mobility, spasticity, or movement slowness compromise patient autonomy and reduce physical and emotional well-being [5].

In this context, early, precise, and objective detection of neurological deficits is fundamental to improving functional prognosis, optimizing healthcare resources, and allowing for a more tailored personalization of treatment and rehabilitation, according to each patient's individual needs [6]. To achieve this, the implementation of effective clinical protocols and continuous training for healthcare professionals are essential. However, the predominantly clinical nature of diagnosis and the wide heterogeneity in the manifestations of these pathologies make objective assessment by healthcare personnel difficult [7, 8].

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Given this limitation, the development of more precise and objective diagnostic tools presents itself as a priority medical need. Recent works have explored the use of markerless, automated video-based motion analysis (computer vision) to provide quantitative, non-invasive assessments of motor deficits in neurological disorders [9]. A systematic review highlighted that these approaches can achieve high diagnostic accuracy while allowing for valid evaluations in real-life or clinical settings. However, for practical adoption in clinical routines, physicians require a protocol that is easy to apply and seamlessly integrated into a digital platform.

Therefore, the objective of this work is the design and implementation of an interactive platform, capable of automatically analyzing movement captured in videos of patients performing four specific hand exercises. From these videos, the aim is to extract kinematic parameters that can be compared with a dedicated database of patients and controls, allowing for the estimation of the degree of motor deficit. Finally, using classification algorithms, the goal is to detect the presence of functional alterations and, where applicable, identify the associated neurological disease.

2 Methodology

This chapter outlines the methodology used to develop the automated platform, from data capture to its integration into a web application. Participants first perform specific hand exercises, which are recorded using an RGB camera. The videos are processed with MediaPipe Hands to extract hand keypoint coordinates, from which kinematic metrics are computed to quantitatively characterize movement. These features are then used to train classification algorithms for pathology identification, applied in both binary (patients vs. controls) and multiclass (differentiating specific neurological conditions) scenarios. The following sections provide a detailed description of each step.

2.1 Motion Capture and Video Processing

To analyze voluntary hand movement in basic functional tasks, a simple and reproducible battery of exercises was designed in collaboration with the Neurology team at Hospital Universitario La Paz. The selected movements reflect common daily actions and patterns from clinical motor evaluation scales and can be recorded simultaneously for both hands using a single zenithal RGB camera mounted on a metal structure [8]. The exercise are: (1) **finger separation**, consisting of lateral opening and closing of the fingers; (2) **fist opening and closing**, involving repeated alternation between a fist and an open hand; (3) **pinch opening and closing**, a thumb–index pinch with the remaining fingers extended; and (4) **wrist extension-flexion**, consisting of alternating maximum wrist extension and flexion from the neutral position.

Hand motion was then represented through the automatic detection of 21 anatomical keypoints (wrist and finger joints) per hand using MediaPipe Hands [10], an open-source computer vision tool that estimates their 3D positions directly from RGB video. This solution is computationally efficient, robust to variable conditions, and requires no prior training.

2.2 Calculation of Kinematic Statistics and Database Creation

From the three-dimensional (x, y, z) coordinates extracted by MediaPipe for each hand, kinematic parameters were computed to characterize movement, including Euclidean distances, velocities, and angles. Although MediaPipe provides depth (z), only the x and y coordinates were considered to focus on displacements in the image plane. Distances were calculated between anatomically relevant pairs of landmarks—namely, the metacarpophalangeal (MCP), proximal interphalangeal (PIP), and fingertip (TIP) joints of each finger—to capture finger separation, hand opening, and inter-finger coordination. Velocities were derived from frame-to-frame displacements of fingertip coordinates, quantifying both the speed and smoothness of finger trajectories. To reduce tracking noise while preserving motion dynamics, trajectories were smoothed using a Savitzky–Golay filter (window = 3, poly = 1). Angular features included the angles formed by triplets of keypoints (e.g., MCP–PIP–TIP) to describe joint flexion and extension, and a zenith angle estimating wrist extension based on variations in projected hand length within the XY plane.

For each exercise, specific landmarks were used: fingertips and selected MCP, PIP, and distal joints for E1, MCP joints and index fingertip for E2, thumb and index joints with the middle fingertip as reference for E3, and all fingertips plus the middle MCP and tip for E4, capturing hand posture and wrist orientation. The dataset comprised 66, 24, 42, and 36 features for Finger, Fist, Pinch, and Wrist, respectively, prior to feature selection.

2.3 Training of Classification Algorithms

To evaluate the usefulness of kinematic statistics as indicators of neurological status, two classification approaches were implemented: binary classification, grouping all neurological subjects as Patients vs. Controls; and multiclass classification, preserving specific diagnoses (Stroke, MS, PD, Control). Both approaches were applied independently to the kinematic data of each exercise, yielding eight classification processes (four binary, four multiclass).

To ensure robust evaluation and avoid overfitting or data leakage, a nested cross-validation strategy was used, with a 5-fold outer loop for unbiased performance estimation and a 2-fold inner loop for model and hyperparameter selection. This separation of training, optimization, and testing data provided a reliable estimate of generalization, even with a limited dataset [11].

Three machine learning pipelines were developed, combining Random Forest (RF), Support Vector Machines (SVM), and Logistic Regression (LR) with feature selection and data balancing. Preprocessing included univariate feature selection (ANOVA F-test), robust scaling to reduce outlier impact, and Borderline-SMOTE oversampling applied strictly within training folds to prevent leakage, addressing class imbalance to prevent bias toward majority classes. Models were implemented with Scikit-learn, and classification performance was assessed under identical preprocessing and resampling conditions.

2.4 Participants

The study included 114 controls, 60 stroke, 45 MS, and 14 PD patients, all volunteers recruited through the Neurology Service of Hospital Universitario La Paz who provided informed consent. The protocol was approved by the hospital's Ethics Committee for Research with Medicines (code PI-4776) and conducted in accordance with good clinical practice and data protection regulations. Demographic details are shown in Table 1.

Table 1. Demographic characteristics of study participants.

	Control	Stroke	MS	PD
Sample Size	114	60	45	14
Mean Age	57.4	69.6	47.9	65.9
Number of Females	61	36	37	6
Number of Males	53	24	18	8

3 Results

3.1 Binary Classification

Among the models tested for each exercise, Random Forest (RF) was the most frequently selected classifier, followed by Logistic Regression (LR) and Support Vector Machines (SVM). The results are summarized in Table 2, which reports the best-performing classifier for each exercise together with its average accuracy and class-wise precision, recall, and F1-score obtained through nested cross-validation. The highest performance was achieved in Exercise 1 with RF (69.11% ± 4.93%), indicating this pipeline as the most suitable for the binary classification scenario. However, accuracy for all exercises remained below 70%, underscoring the difficulty of the task.

Table 2. Best classifiers for binary tasks with accuracy and class-wise precision, recall, and F1-score.

Ex.	Best classifier	Avg. accuracy	Control (P/R/F1)	Patient (P/R/F1)
1	RF	69.11% ± 4.93%	0.72/0.69/0.71	0.71/0.74/0.73
2	LR	63.90% ± 2.60%	0.64/0.66/0.65	0.65/0.63/0.64
3	SVM	60.78% ± 6.94%	0.59/0.65/0.62	0.63/0.57/0.61
4	RF	63.23% ± 5.41%	0.58/0.65/0.62	0.63/0.56/0.59

3.2 Multiclass Classification

In the multiclass setting, SVM was applied using the one-vs-one strategy to handle multiple classes. SVM was the best-performing model of the three of the four exercises, while LR was selected for the remaining one. Table 3 summarizes the results, showing average accuracy and class-wise precision, recall, and F1-score. As in the binary case, Exercise 1 achieved the highest accuracy. Due to class imbalance and the limited representation of PD, this class was excluded from the analysis. Overall, accuracy remained below 70%, highlighting the inherent difficulty of distinguishing multiple neurological conditions.

Table 3. Best classifiers for multiclass tasks with accuracy and class-wise precision, recall, and F1-score.

Ex.	Best classifier	Avg. accuracy	Control (P/R/F1)	MS (P/R/F1)	Stroke (P/R/F1)
1	SVM	52.85% ± 3.67%	0.66/0.72/0.69	0.40/0.36/0.38	0.44/0.41/0.42
2	SVM	43.51% ± 5.39%	0.67/0.55/0.61	0.30/0.5/0.37	0.40/0.33/0.36
3	SVM	50.39% ± 10.36%	0.69/0.61/0.64	0.30/0.47/0.37	0.57/0.47/0.51
4	LR	46.04% ± 4.25%	0.61/0.50/0.55	0.32/0.36/0.34	0.42/0.53/0.47

4 Discussion

The main objective of this work was to design and implement an interactive platform for automatically analyzing hand movement from videos of patients performing four specific exercises. The platform extracts kinematic parameters, which are compared with a database of controls and patients to estimate motor deficits and, through classification algorithms, detect functional alterations and potentially identify underlying neurological pathologies. All project objectives were successfully achieved. Nevertheless, the system has limitations.

The relatively small sample size may restrict model generalization, particularly in multiclass classification. In binary tasks, Random Forest and Logistic Regression reached accuracies near 70%, supporting discrimination between patients and controls. However, multiclass performance dropped below 60%, reflecting the difficulty of differentiating specific diagnoses, especially when motor deficits are subtle. Additional factors, such as video quality or partial hand visibility, may also affect performance.

Furthermore, the current set of kinematic features may not capture sufficient discriminative information for reliable differentiation among neurological conditions. The relatively low accuracy values, comparable to near-random performance in some multiclass cases, suggest that both the dataset and feature design require further refinement. In this regard, the proposed platform should be viewed as an innovative methodological framework rather than a validated diagnostic system. Future developments should focus on expanding the dataset, refining feature extraction, and incorporating more advanced or multimodal models to improve robustness and clinical relevance. Despite these challenges, the platform provides an automated, accessible, and interpretable tool for clinical contexts, delivering detailed results in approximately two minutes.

5 Conclusions and Future Work

The proposed platform introduces an innovative framework for automatic analysis of hand movement from video. While current results are insufficient for clinical interpretation, the work establishes a reproducible foundation for future research. Expanding the dataset, optimizing kinematic features, and exploring advanced machine learning and multimodal strategies will be essential to enhance performance and clinical applicability.

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