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Parkinson's Disease Prediction Assistant Using Webcam-Based Eye-Blinking and Finger-Tapping Analysis.

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A B S T R A C T

Parkinson's disease (PD) is a progressive neurological disorder that can affect movement, coordination, and motor control. Early identification of relevant symptoms may support further clinical assessment. This paper proposes a webcam-based research system that combines eye-blinking analysis with finger-tapping analysis to study behavioral patterns associated with Parkinson's disease. The existing approach uses computer vision to analyze finger movements, while the proposed extension incorporates facial landmark tracking to estimate eye-blinking patterns. Quantitative features extracted from both activities are intended to be evaluated using Logistic Regression and Random Forest classifiers. Logistic Regression provides a statistical classification approach, while Random Forest combines multiple decision trees to model potentially complex relationships in the extracted features. Both models will be compared using appropriate performance metrics on labelled data. The system aims to provide a low-cost, non-invasive framework for preliminary research. Its reliability must be established through appropriate data validation and further clinical evaluation. It is not intended to replace professional medical diagnosis.

Keywords: Parkinson's disease, computer vision, eye-blink analysis, finger-tapping analysis, machine learning, Logistic Regression, Random Forest.

1. INTRODUCTION

Parkinson's disease is a neurodegenerative disorder characterized by the loss of control of movement, which can affect body movements or muscles. Motor symptoms include, but are not limited to, slowing down of movement (bradykinesia), muscular stiffness, trembling (tremor) when not actively using muscles, and unsteady gait and balance. The specific symptoms experienced and their severity can differ from person to person and may evolve over time.

A typical assessment includes history, a neuro exam, movement analysis, and standardized motor testing, one example being a finger tapping test. When finger tapping is used as a motor test a patient is asked to tap the thumb and index finger repetitively and the rater then observes the movement rate, amplitude, rhythm, and regularity of the finger tapping. These parameters are useful but depend on the assessment method and clinician.

The field of computer vision continues to develop to allow the extraction of numerical features from video. This means that, rather than only looking at a video and deciding what we see, computer vision algorithms can be used to, for example, track body landmarks in a video and extract features of the movement. These features can then be used in statistics or machine-learning models. Finger-tapping analysis is relevant to this project because finger-tapping tests require repetitive coordinated finger movements. It has been studied by others to use videos of these tests to quantify motor performance and progress of Parkinson's disease. Some of this research could inform computer vision-based systems to quantify finger movement.

Eye-blink rate, a third easily observed behavior that can be examined via video, is the rate of blinking, and the duration of that blink, that can be inferred from facial landmarks as long as the face is visible to a sufficient degree, and landmark tracking is robust. However, blinking varies on a per-person basis, as a result of fatigue, medication, lighting, and attention, among other factors, so that eye-blink measures can serve as research features rather than as stand-alone evidence.

The finger-tapping and eye-blinking modules are integrated into a single webcam-based project. The finger-tapping component is dedicated to quantifying repetitive movements of the hand, while the eye-blinking module estimates eye-blinking features from facial landmarks. The output features are designed to form a structured dataset for machine-learning classification.

Logistic Regression and Random Forest algorithms are chosen for comparison. Logistic Regression is a fairly simple classification model that attempts to calculate the probability of a class, while Random Forest is an ensemble of decision trees that can model arbitrarily complex relationships. By comparing two models, it is hoped to assess which models performs better on the labelled data set. The main motivation is to study the usefulness of supplementing finger-tapping with eye-blinking features in addition to finger-tapping alone. A webcam based method could also potentially require less equipment and

could be more accessible in terms of data collection. However this does not make the system medically safe. It will need to be evaluated on suitable labelled data, participant-independent testing and then eventually clinical validation. experts.

2.LITRATURE SURVEY

Author and year	Method / Architecture	Dataset / Data used	Accuracy results	Main contribution
D. L. Guarín et al. (2024) [1]	Video-based finger-tapping analysis using computer vision and movement feature extraction.	Videos of the finger-tapping test from individuals with Parkinson's disease.	A directly comparable numerical accuracy value is not reported here.	Studies disease progression through video-based finger-tapping measurements and demonstrates the potential of computer vision for movement assessment.
Javier Amo-Salas et al. (2024) [2]	Survey of computer vision techniques for Parkinson's disease evaluation, focusing on finger-tapping analysis.	Previously published research studies and finger-tapping datasets.	Not applicable; this is a survey paper.	Reviews computer vision approaches for evaluating finger-tapping movements and discusses their potential and limitations.
S. Williams et al. (2020) [3]	Computer vision-based measurement of finger-tapping bradykinesia.	Finger-tapping recordings from individuals performing the clinical test	A directly comparable classification accuracy value is not stated here.	Investigates whether computer vision can measure finger-tapping bradykinesia and support objective assessment.
C. Lugaresi et al. (2019) [4]	MediaPipe framework for real-time perception and landmark detection.	General visual and perception tasks; not specifically a Parkinson's disease dataset.	Not applicable; the paper introduces a framework rather than a Parkinson's classifier.	Introduces MediaPipe, which provides a framework useful for extracting facial and hand landmarks from webcam video.
G. Pal and C. G. Goetz (2013) [5]	Clinical assessment and evaluation of bradykinesia in parkinsonian disorders.	Clinical observations and assessment methods discussed in the research paper	Not applicable; this is a clinical assessment review.	Explains the importance of bradykinesia assessment and the evaluation of movement abnormalities in Parkinsonian disorders.
AI Video Analysis in Parkinson's Disease (2025) [6]	Systematic review of AI and computer vision methods for disease diagnosis, symptom monitoring, and therapy management	Previously published studies involving video-based Parkinson's disease assessment.	Not applicable; this is a systematic review of multiple studies	Highlights the growing use of video-based AI methods and the need for standardized recording procedures and external validation.

3.SYSTEM ARCHITECTURE

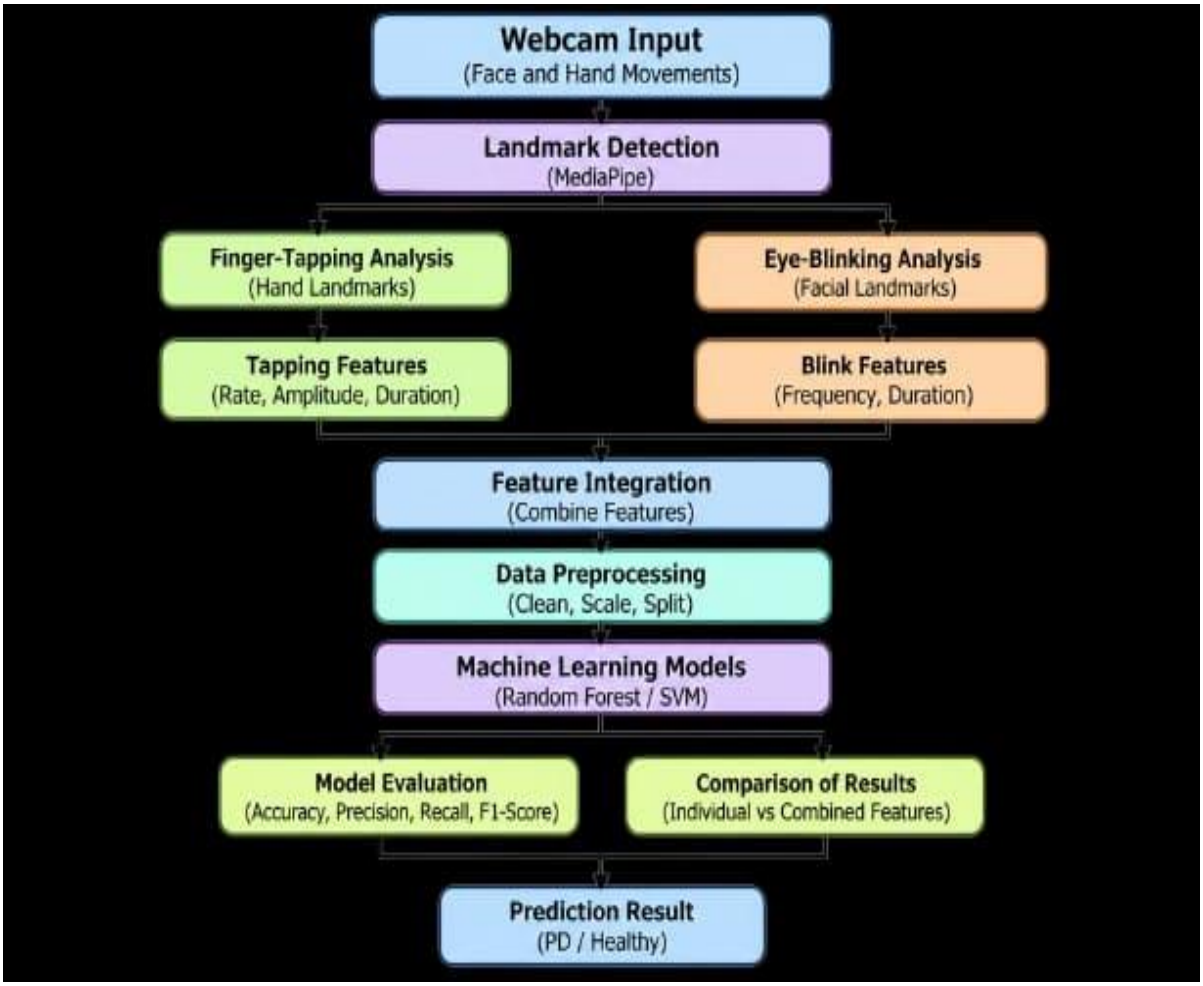


Fig. 1. Proposed system architecture for webcam-based Parkinson's disease prediction.

4. METHODOLOGY

The proposed system processes webcam recordings, detects facial and hand landmarks, extracts behavioral features, and prepares the resulting data for machine-learning analysis. Its main stages are video acquisition, landmark detection, finger-tapping analysis, eye-blinking analysis, feature integration, model training, and performance evaluation. vision .

1. Video Acquisition

A webcam films the participant doing the task. Hand – The hand has to be in sight during the finger tapping task. Face / Eye – Face and eyes need to be in sight during the eye-blinking task. Ensure recording conditions, such as lighting, camera position, length of recording, and task instructions are similar across all trials. -Glare, motion blur, camera position changes, and partial occlusion can impact landmark-detection accuracy. Recordings with low tracking quality should be identified or eliminated according to set criteria.

2. Finger-Tapping Analysis

The algorithm tracks the position of the Media Pipe hand landmarks of the thumb tip and index finger tip in subsequent frames of a video. The Euclidean distance is computed between these hand landmarks which serve as the finger distance change signal. This finger distance change signal can be filtered and the peaks of movement can be detected to infer the repeated tapping rate.

- Tapping rate: How times the tapping happens in a certain time.
- Movement amplitude: The difference between the farthest and closest distance of the fingertips in one cycle.
- Cycle duration: How long it takes between one movement and the next.
- Rhythm variability: How much the time between taps changes.

- Amplitude decrement: How much the movement size changes from the start to the end of the task.

3. Eye-Blinking Analysis

The eye-blinking module utilizes facial landmarks to derive the eye dimensions in the vertical and horizontal directions. The values can then be combined into an EAR value indicating eye openness which can then be used to derive an appropriate threshold or rule for eye closure detection and a closure that opens again is then checked against the defined rules and counted as a blink.

The following things can be found:

- Blink frequency: How many blinks are found during the time observed.
- Blink duration: How long it takes from when the eye closes to when it opens.

Blink detection might be affected by glasses, lighting, moving the head, camera quality and mistakes in finding the points. So the system should check how good the tracking is before using the found details. Eye-blink details are things that are being looked into. They are not on their own a sign of Parkinson's disease.

4. Feature Integration and Preprocessing

Combine the features from finger-tapping and eye-blinking modules into a feature set. An example record has to be for each participant/recording, with a true target label for supervised classifications. The data set needs to be examined for missing data, duplicate records, implausible measurements and inconsistent feature definitions. Measures that are missing or unreliable should be addressed according to a set of defined procedures. Standardising the features is recommended in the case of Logistic Regression, as differences in feature scales can influence the regularisation. Random Forest does not need to standardise features.

Train only on the training data for the preprocessing parameters – these should be learned using just the training data. Consider partitioning the dataset on the participant level, wherever feasible (i.e. The same participant does not have recordings in the training and test dataset) – preventing data leakage and giving a more realistic estimate of generalization to unseen participants.

5. Machine-Learning Models.

Logistic Regression

It's a supervised machine-learning classification algorithm. It computes the probability of each input sample as Parkinson's disease group and healthy-control group and making the most probable prediction in a binary classification process.

This weighted sum of the inputs is then transformed by the logistic (sigmoid) function and converted into a probability, which is then compared against the classification threshold for a class prediction.

Logistic Regression as a baseline model is used since it is easy to train and easy to interpret as the sign of the coefficient of a feature may be indicative of the feature having a positive or negative association with the predicted class (not causal). Standardization of the features and suitable regularization parameter helps.

It may also perform poorly if the features to class relationship is strongly non-linear unless feature transformations and interactions are added to the model. Its performance can then be judged using experiment on the labelled dataset.

For binary classification, the probability can be represented as:

[

P(y=1\mid \mathbf{x})=

\frac{1}{1+e^{-(\beta0+\sum{i=1}^{n}\betai xi)}}

]

Where (P(y=1\mid\mathbf{x})) is the predicted probability of positive class, (xi) is an input feature, (\betai) is the learnt coefficient for that feature, and (\beta_0) is the bias or intercept.data.

Random Forest

Random forest is an ensemble-learning algorithm for classification and regression. The classification process is done by constructing individual decision trees on the subset of the training set and using a subset of features to determine the candidate splits. The aggregation of the predictions will result in the final class. Random Forest can model nonlinearities and interactions of finger-tapping and eye-blinking features. It can also give feature-importance estimates, which can then be used to analyze what features feed the model. It is worth noting that feature importance should be taken with a grain of salt, especially when features are correlated.

Other key hyperparameters are the number of trees, maximum depth of the trees, minimum sample size at a node to split, and number of features to be used at a node. These parameters should be chosen with cross-validation on the training data .Random Forest usually needs relatively less feature scaling

compared to Logistic Regression. But it can still be affected by bad data, data imbalance, the quantity of data and how well the participants resemble the population. labels.

Logistic Regression Vs Random Forest

The two algorithms use different classification algorithms. Logistic Regression allows for estimating the class probability by computing a weighted linear combination of features, whereas the Random Forest can identify more complex nonlinear models through an ensemble of decision trees.Linear Regression provides a relatively interpretable baseline and may perform well if your class boundary is close to linear. Random Forest is able to model more complex interactions between features, but the model parameters will need to be tuned to prevent overfitting.

No model can be assumed to outperform the other prior to testing. Honest comparison needs identical validated target labels, training and test partition, and evaluation metric. Hyper-parameter optimization must be done on the training data only, with the final test data being held out for an independent evaluation

6. System Workflow

1. Video Acquisition
2. Landmark Detection
3. Finger Tapping Analysis
4. Eye-Blinking Analysis
5. Feature Integration & Processing
6. Machine Learning Models
7. Performance Evaluation
8. Experimental Output

5. MODELING AND ANALYSIS

1. Feature Extraction

The proposed system extracts quantitative features from webcam recordings of finger-tapping and eye-blinking activities. MediaPipe hand landmarks are used to track the thumb and index fingertip. The distance between the fingertips is calculated across video frames to create a movement signal Movement features such as tapping rate, amplitude, cycle duration, rhythm variability, and amplitude decrement can be derived from this signal. Facial landmarks are used to estimate eye openness and identify blink events, from which blink frequency, duration, and inter-blink intervals can be calculated. These features describe observable behavior. Their predictive value must be tested using a suitable labelled dataset.

2. ***Data Preprocessing***

The extracted features are organized into a structured dataset. Preprocessing includes identifying missing or invalid values, checking for duplicates, applying predefined data-quality rules, and preparing target labels. Feature standardization should be included in the Logistic Regression pipeline when appropriate. Random Forest can generally operate directly on numerical features without standardization. Any imputation, scaling, feature selection, or other learned preprocessing must be fitted only on the training data.The target labels must be supported by reliable ground truth. If the available data contains only webcam measurements without verified disease-status labels, it is not sufficient to train or evaluate a supervised Parkinson's disease classifier.

3. ***Model Training and Testing***

The labelled dataset is divided into training and testing subsets, preferably by participant. Logistic Regression and Random Forest are trained on the same training records and evaluated on the same held-out test records. Cross-validation on the training data can be used to select model hyperparameters. Class imbalance should be examined, and appropriate measures such as class weighting may be considered where justified..

Three feature configurations are proposed:

- Finger-tapping features only.
- Eye-blinking features only.
- Combined finger-tapping and eye-blinking features.

This comparison will help determine whether combining both behavioral measurements improves classification performance.

4. ***Performance Evaluation***

The models are evaluated using the following metrics:

- **Accuracy**: proportion of all predictions that are correct.
- **Precision**: Proportion of predicted positive cases that are truly positive.
- **Recall**: proportion of actual positive cases correctly identified.
- **F1-score**: harmonic mean of precision and recall.
- **Confusion matrix**: summarizes correct and incorrect predictions for each class.

The positive class must be explicitly defined, for example, as the Parkinson's disease-labelled group. Results should be reported only after evaluation on the held-out test data. Where possible, uncertainty estimates and class-wise metrics should accompany the reported performance.

5. Analysis of Results

The proposed system investigates whether behavioral features extracted from webcam recordings of finger-tapping and eye-blinking activities can support the classification of Parkinson's disease and healthy-control groups. The extracted features are processed and evaluated using two supervised machine-learning algorithms: Logistic Regression and Random Forest. Both models will be trained and tested using the same labelled dataset and evaluation procedure to ensure a fair comparisonThe analysis focuses on three aspects: the characteristics of the extracted behavioral features, the comparative performance of the two classification models, and the potential contribution of combining finger-tapping and eye-blinking features. The actual effectiveness of the system must be established experimentally using reliable labelled data.procedure.

A. Finger-Tapping Analysis

Finger-tapping analysis is used to quantify repetitive finger movements by measuring changes in the distance between the thumb tip and index fingertip over time. Hand landmarks are detected using MediaPipe, and the distance between the two fingertips is calculated for successive video frames. This produces a time-series signal representing the opening and closing movements of the fingers. The recorded signal can be processed using smoothing techniques to reduce minor fluctuations caused by landmark-detection errors. Peak-detection methods can then identify repeated movements and estimate the timing and magnitude of tapping cycles.

features provide numerical descriptions of movement speed, range, consistency, and change over time. They can be used as inputs to Logistic Regression and Random Forest for classification experiments. However, differences in these features are not specific to Parkinson's disease and must be interpreted alongside reliable participant labels and other relevant factors.

B. Eye-Blinking Analysis

The extracted measurements are intended to characterize blinking patterns rather than independently determine disease status. Blink behavior may vary due to fatigue, attention, environmental conditions, medication, and individual differences. Consequently, consistent recording conditions and reliable landmark tracking are important for meaningful analysis. The resulting eye-blinking features are combined with finger-tapping measurements or evaluated separately to determine their contribution to classification performance.

C. Comparing various Machine Learning Models

The proposed system evaluates Logistic Regression and Random Forest as alternative approaches for classifying the extracted behavioral features.

1. Logistic Regression:

Logistic Regression estimates the probability that a participant belongs to a particular class using a weighted combination of input features. In a binary classification experiment, the model estimates the probability of the Parkinson's disease-labelled class relative to the healthy-control class.The model is useful as a baseline because it is comparatively simple and its coefficients can be examined to understand the direction of associations between features and the predicted probability. Numerical features should generally be standardized as part of the training pipeline. The regularization strength should be selected using cross-validation on the training data. Logistic Regression may perform well when the relationship between the features and the target class can be represented adequately by a linear decision boundary. However, it may not capture complicated nonlinear relationships without additional feature transformations.

2. Random Forest

Random Forest combines the predictions of multiple decision trees. Each tree learns decision rules from the training data, and the individual predictions are aggregated to generate the final classification.The model can represent nonlinear relationships and interactions among tapping rate, movement amplitude, rhythm variability, blink frequency, and other extracted features. It can also provide feature-importance estimates that help investigate which measurements contribute to its predictions.The number of trees, maximum tree depth, and other model parameters should be selected through cross-validation on the training data. Random Forest generally does not require feature standardization, although missing values and invalid measurements must still be handled appropriately.

3. ***Experimental Comparison***

For a fair comparison, both models must use the same labelled participants, training and testing partitions, input feature configurations, and evaluation metrics. Hyperparameter selection must be completed without using the final test set..

D. Interpreting the Final Outcome

The final analysis will compare the performance of both models across the three feature configurations. The results should be reported using measured experimental values rather than assumptions about which model will perform better.

The positive class should be defined consistently, for example, as the Parkinson's disease-labelled group. Recall is particularly relevant when assessing how many labelled positive cases the model identifies, while precision indicates how many of its positive predictions are correct. Neither metric alone is sufficient to establish clinical usefulness.

The interpretation will consider several possible outcomes:

- If Logistic Regression performs well, the extracted features may contain useful information that can be separated reasonably well by a relatively simple classification model.
- If Random Forest performs better, nonlinear relationships or interactions among the features may be contributing to classification performance on the evaluated dataset.
- If the combined-feature configuration performs better than the finger-tapping-only configuration, the eye-blinking features may provide additional predictive information under the experimental conditions.
- If the combined configuration does not improve performance, the eye-blinking features may provide limited additional information, or the dataset may be insufficient to establish a benefit.
- If performance differs substantially between training and testing data, the models may be overfitting or the dataset may not represent unseen participants adequately.

These interpretations are conditional and must be supported by the actual results. Recordings from the same participant should not be divided between training and testing sets, because this can produce overly optimistic performance estimates.

Overall, the analysis is designed to determine which model and feature configuration performs better on the available labelled dataset. Even if the combined model achieves better classification results, independent validation and clinical assessment would still be required before considering its use in a medical setting.

6. Discussion

The proposed system integrates computer vision-based finger-tapping and eye-blinking analysis with Logistic Regression and Random Forest classifiers. It provides a framework for extracting behavioral measurements and investigating their usefulness for supervised classification.

Logistic Regression offers a comparatively simple baseline whose coefficients can be examined to understand how features relate to estimated class probabilities. Random Forest provides a more flexible approach that can capture nonlinear patterns and interactions between features. Comparing the two models can help assess whether the added complexity of an ensemble provides a measurable benefit on the available dataset.However, experimental results for the combined system must be obtained before making claims about accuracy or model superiority. No specific accuracy value or improvement should be reported without a completed and documented evaluation. Performance estimates may also be misleading if recordings from the same participant appear in both training and testing data, if the labels are unreliable, or if the dataset is too small or unrepresentative.

Accuracy alone may not adequately describe performance when the dataset contains unequal class sizes. Precision, recall, F1-score, balanced accuracy, and confusion matrices should therefore be considered together. Because the intended application concerns health, false-positive and false-negative predictions must be discussed carefully. Further validation on independent participants and assessment by qualified medical professionals would be necessary before considering any clinical use.

The system should consequently be presented as a research and screening-support framework, not as a standalone diagnostic tool.

6. CONCLUSION

This paper proposes a webcam-based research system for analyzing finger-tapping and eye-blinking behavior in the context of Parkinson's disease studies. Building on video-based finger-tapping analysis, the proposed approach adds facial landmark tracking to estimate eye-blinking characteristic.The methodology includes video acquisition, hand and facial landmark detection, behavioral feature extraction, data preprocessing, model training, and performance evaluation. Logistic Regression and Random Forest are selected as the two classification algorithms. Logistic Regression provides a comparatively interpretable baseline, while Random Forest can model more complex relationships between the extracted features.

The proposed evaluation compares finger-tapping-only, eye-blinking-only, and combined feature configurations using accuracy, precision, recall, F1-score, balanced accuracy, and confusion matrices. The actual performance of the models must be determined through testing on reliable labelled data that is independent at the participant level. The system's effectiveness has not been established by the proposed methodology alone. No claim of diagnostic accuracy or improved clinical outcomes can be made without experimental evidence and appropriate validation. The system should be viewed as a framework for research and preliminary screening support rather than a replacement for professional clinical assessment.

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