

NeuroInsight-PD: Early Detection and Classification of Parkinson's Disease

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Abstract

Most people with Parkinson's Disease are diagnosed too late. By the time a neurologist discovers the condition through standard clinical tests, the brain has already lost 60% or more of its dopamine-producing cells. At this stage, the disease has progressed to a level where slowing its progression becomes challenging. The earliest signs are overlooked and only become apparent during clinical evaluation. There is a gradual decrease in handwriting, along with traces of tremor. Finger dexterity becomes rhythmically inaccurate. Changes in gait patterns are practically unnoticed by the naked eye but can be measured using sensors. The first stage of the NeuroInsight-PD project is devoted to the initial state of the motor dysfunction. The platform records locomotor pattern on a set of wearable sensors, fine motor skill with a series of tremor and finger-tapping tests, and spatial anomalies known of micrographia with a set of handwritten samples. Instead of implementing one of the three modalities, the system combines all three streams of data into the different streams of processing them: a Random Forest classifier is used on the structured sensor data, and an

EfficientNetB0 convolutional neural network processes the handwriting images. The scores are then combined as the final results. through the weighted decision-fusion layer, which generates a single likelihood estimate of the Parkinson disease. Experimental analysis shows that the combined system has a 94.6% accuracy and 94.9% precision, which is always higher than the model that is solely dependent on one of the modalities. Ablation analysis indicates that elements such as hard negative mining, threshold calibration, and other elements significantly contribute to the sensitivity of early detection. The solution is deployed to FastAPI back-end and ReactJS front-end offering the ability to screen in real time and be scaled.

Keywords: Parkinson's disease, Early detection, Multimodal data fusion, Gait analysis, Motor assessment, Handwriting analysis, Micrographia, Random Forest, EfficientNet-B0, Convolutional neural networks, Transfer learning, Decision fusion, Digital biomarkers, Wearable sensors, Precision neurology.

1. INTRODUCTION

Parkinson neurodegenerative disorder, which is an unremitting disease of the brain, impairs the clinical integrity of the motor system by causing hallmark symptoms of tremors, rigidity, and a deepening of slowing of physical movements called bradykinesia [1]. Although the final etiology condition has hit a critical international level now having over 10 million cases and this figure has increased more than 100 percent in the past 25 years [2]. This deterioration has a pathological basis in the systematic deterioration of dopaminergic neurons in the substantia nigra pars compacta. This loss triggers a severe deficiency of dopamine, the neurotransmitter that cannot be done without in the regulation of fluid motor activity [3]. Although the final etiology is still a complicated interaction of factors, there is a growing scientific agreement that a complex of genetic predisposition, mitochondrial pathology, and environmental toxicity are the main disease causes [4].

Early diagnosis of Parkinson's disease still hasn't been achieved and is an unsolved problem. Clinicians usually rely on subjective parameters that is UPDRS and the Hoehn-Yahr staging system which helps in tracking disease progression [5]. By the time the diagnosis is confirmed 60–70% of dopaminergic neurons are already damaged [6]. The chances for neuroprotective cure become negligible. Motor signs that include micrographia (small handwriting), hypomimia (poor facial expression), slowness of fine motor skills, and minor gait abnormalities, are often used as early warning sign of PD, which are not significant in traditional assessment practices [7, 8].

The current-day fast rates of changes in the spheres of artificial intelligence and machine learning demonstrate fresh possibilities of objective and data-driven disease diagnosis. Deep learning algorithms can be able to identify complex patterns in non-invasive data sources, which would aid in early accurate diagnosis of diseases [9]. Recent studies have also used deep learning to analyse brain images in cognitive impairment, including Parkinson's disease [10].

High-resolution data regarding motor activity is recorded by wearable technology like accelerometers, gyroscopes, IMUs, and digital tablets [11, 12]. Tan et al. (2024) [13], used video-based gait measurements to detect Parkinson's disease without attaching sensors to participants. Their work focused on gait and did not combine several different motor tests. However, there are many challenges involved in applying such models in clinical settings, including data imbalance, sensor

noise, individual variability, and lack of large-scale clinical validation [14]. Therefore, there is an urgent need for an interpretable and applicable model that can combine multiple physiological signals to facilitate an in-depth detection of Parkinson's disease.

NeuroInsight-PD is built to ensure these gaps are filled. It helps in detecting it early and also identify the category of Parkinson's Disease.. I built the model considering three main factor.. First is the gait analysis that uses sensors, which track step timing and balance shifts. Second is motor test which is conducted through tremor analysis and finger tapping tests. Third is one of the advanced technique, it is analysing of handwriting captured on digital devices, since micrographia and stroke irregularities often surface years long ago. I chose these three methods because each one identifies different area which help in diagnosing Parkinson's disease.

NeuroInsight is a technology that is focused on developing an AI system that is trusted, understood, and safely used by individuals. It is also a tool for the advancing concept of precision neurology, which utilizes machine learning with various digital biomarkers to provide better diagnosis, reduce the time to diagnosis, and improve patient outcomes [15].

2. RELATED WORK

Early computer-assisted studies of Parkinson's disease (PD) often used one type of movement or physiological measurement. Peng et al. (2025) [16], examined short motor tasks performed by 100 patients with PD, using features at both segment and sample levels to assess motor symptoms and disease severity. The results of this study indicate that even short movements can help in obtaining valuable measurements, but it should be noted that the conditions for testing are also relevant. Shyamala and Navamani (2024) [17], proposed a method to solve the problem of speech data detection using machine learning, which included the process of selecting features and finding solutions to the imbalanced classification problem. Thus, the two studies highlight the importance of selecting relevant features, but one of the tasks does not address the issue of detecting changes in walking or delicate hand movements.

Gait analysis proves to be an effective tool since PD often alters an individual's manner of walking. Li and Li (2022) [12], explored the use of machine learning algorithms in order to classify PD based on gait characteristics. In turn, Priya et al. (2025) [18], addressed a closely related topic in a slightly more complex manner, comparing various signal-processing techniques and learning algorithms in order to classify different gait patterns. Their study saw the application of the variational mode decomposition method and a one-dimensional convolutional neural network proving to be the most effective at the given task in terms of their experiment. Furthermore, there is potential for sensor-free movement capture and analysis: according to Tan et al. (2024) [13], smartphone-mounted pose detection is capable of extracting features from a Timed Up and Go test with an accuracy of 89.39%. This approach differs from the previously mentioned ones in that it does not require any special equipment to be worn by the subject. Finally, a study performed by Polvorinos-Fernández et al. (2024) [11], serves as a brief overview of the ways in which wearable technology can be utilized in the assessment of motor functions in PD patients. It is worth noting that the conditions under which the aforementioned experiments were conducted differ, and thus their results cannot be directly compared.

Handwriting provides a different view of motor control. Drotár et al. (2015) [7], studied writing movements using kinematic, spatial and signal-based features, and developed a classifier to distinguish people with PD from healthy controls. More recently, Asci et al. (2025) [8], used AI-based analysis of pen-and-paper samples to measure micrographia. Their study found that reduced stroke size could be identified in early PD, although their model could not distinguish patients in the medication OFF and ON states. Wang et al. [19] examined handwriting images using a coordinate-attention-enhanced Swin Transformer, which was designed to capture both positional information and subtle visual features. Together, these studies make a case for examining handwriting alongside other motor tasks. They also show that what is measured, and how samples are collected, affects the information available to a classifier.

Other signals have also been investigated. Hasib et al. [20] used time-frequency representations of electroencephalogram signals and a deep learning model to distinguish PD cases from controls. Xu et al. [10] conducted a review of the literature on deep learning methods applicable to brain imaging in cognitive impairment, including research involving patients with PD's disease. Such studies indeed expand the range of potential biomarkers, but EEG and brain imaging require different acquisition conditions than those used in everyday motor and handwriting tests. For this reason, the choice of the modality in the context of a practical screening system involves not only considerations of classification power but also of the practicality of acquisition and availability of appropriate data.

There is growing interest in drawing on several measurements rather than relying on a single source. Jiang et al. [21] reviewed studies of PD progression prediction that combined clinical, genetic, biomarker and neuroimaging variables. They reported advantages from using complementary information, although predicting progression is not the same task as identifying PD from motor measurements. Meghashree et al. [22] proposed a system that brings voice, gait and handwriting features together using multimodal learning. More recently, Lee et al. [23] evaluated smartphone-based motor, drawing, speech and questionnaire tasks. Their reduced model, combining touch, spiral drawing and questionnaire features, achieved an AUROC of 0.9053 in the reported evaluation and performed better than the individual tasks. These findings support further study of multimodal assessment, while the choice of inputs and validation procedure remains important.

There are still obstacles to using such systems outside controlled studies. Leming et al. [14] discussed the effects of heterogeneous clinical data, including bias and differences between datasets, on AI-based neurological disease detection. Ahmad Razimi et al. [24] explored wearable sensors and digital biomarkers for chronic disease monitoring, although their work was not specific to PD. Against this background, NeuroInsight-PD examines gait, short motor tasks and handwriting through separate models and combines their outputs at the decision level. This allows each form of data to be processed in a way that suits its characteristics. However, because the present experiments draw on separate public datasets, the combined results should be treated as preliminary. Validation using all three measurements from the same participants will be needed before claims about patient-level screening or clinical use can be made.

3. METHODOLOGY

NeuroInsight-PD is the proposed multimedia framework aimed at diagnosing Parkinson Disease (PD) based on the complementary physiological signals to be used by the system in the very be-

gining of the disease generation. Three of the independent modality pipelines are instantiated in the architecture gait analysis, motor task assessment and handwriting analysis. Each modalities preprocessing, feature extraction, and classification take place separately, followed by a single decision layer, where all these classifications are combined. The system has started with domain-specific data engineering as shown in FIGURE 1, as both raw data of wearable sensors and samples of digital handwriting are standardized. Inertial sensors are used to capture gait and motor signal, and digitized image inputs provide handwriting samples. These nonhomogeneous inputs are run in parallel pipelines that strip out discriminant patterns that are linked to motor impairment that is caused by Parkinsonism.

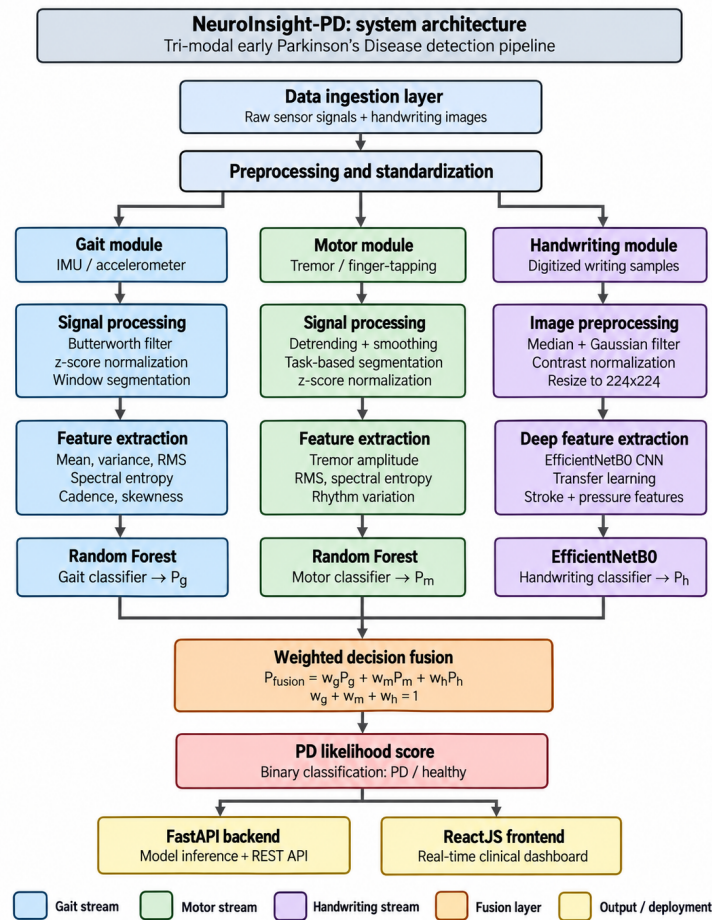


Figure 1: System architecture of the proposed NeuroInsight-PD framework. The pipeline processes three parallel physiological signal streams: gait dynamics, fine motor signals, and handwriting imagery through dedicated preprocessing, feature extraction, and classification modules. Per-modality probability scores are consolidated by a weighted decision fusion layer to produce a final Parkinson's Disease likelihood estimate.

The outputs of the modality-specific classifiers are in terms of probabilistic confidence scores. These predictions are fused on several multimodal fusion module based on weighted decision fusion process to come up with the final Parkinson disease likelihood score.

3.1 Datasets and Experimental Setup

The data for NeuroInsight framework have been extracted from three publicly available datasets. They are used to train and validate. TABLE 1 brief about the three individual streams.

Table 1: Overview for the individual Stream

Modal Stream	Dataset Source	Total Subjects (PD / Healthy)	Age Range (Mean $\pm$ SD)	Sampling Rate / Input Format	Task Protocol	Imbalance & Augmentation Strategy
Gait Analysis	PhysioNet Gait in PD Database	93 PD / 73 HC	39–82 (66.3 $\pm$ 9.4)	100 Hz (Tri-axial Force/IMU Sensors)	2-minute continuous level ground walking	Sliding window overlap sampling + Z-score normalization
Motor Analysis	mPower Parkinson Assessment Dataset	85 PD / 70 HC	42–79 (64.1 $\pm$ 8.2)	100 Hz (Accelerometer/ Gyroscope)	20-second alternating finger-tapping & rest tremor test	SMOTE oversampling on extracted time/frequency features
Handwriting Analysis	PaHaW (Parkinson's Handwriting) Database	37 PD / 38 HC	45–84 (68.0 $\pm$ 10.5)	224 $\times$ 224 normalized image matrices	Archimedes spiral drawing & repetitive loop writing	Random affine transformations (rotation $\pm 15^\circ$, contrast shift)

3.2 Data Partitioning And Availability

- **Train/Test Splitting:** The datasets have been partitioned into 80-20 splits. 80% of the data was used to train the data and rest 20% was used to test it. Data leakage also have been prevented to make the model more accurate.
- **Data Availability Statement:** The datasets are publicly available via the PhysioNet repository [25] (Gait in PD), the Synapse mPower portal, and the PaHaW repository [26]. This has been provided for complete transparency.

3.3 Gait Signal Analysis

How people walk provides indicators that are useful for identifying motor impairment in Parkinson's disease. In the gait analysis module, the system processes multi channel acceleration signals - those signals come from inertial measurement units (IMUs) that are on the lower back, thighs and ankles.

- *Data Acquisition:* The tri axial accelerometers detect how the body accelerates along three axes during walking activities. As the process continues, the subjects repeat the activity - this repetition ensures that the gait cycle is consistent instead of being an accidental occurrence. It is standard for the system to capture signals continuously at a constant sampling rate.
- *Signal Preprocessing:* The system improves the raw gait signals which are not clean in their original state. There is noise from motion artifacts and sensor drift. If the system does not address those issues, they distort the later analysis. To remove the low frequency drift and high frequency noise, a fourth order Butterworth band pass filter (0.5 - 20 Hz) is applied. With this method the signal range that is relevant to physiology remains available.

The filtered signal is z-score normalized:

$$x' = \frac{x - \mu}{\sigma} \quad (1)$$

where μ and σ is mean and standard deviation of the signal.

- *Feature Extraction:* The windows are divided and those divided windows we extract temporal and spectral features. On the statistical side, this includes mean acceleration, variance, and skewness. RMS energy determines how intense is the signal over time..

$$RMS = \sqrt{\frac{1}{n} \sum_{i=1}^N x^2} \quad (2)$$

Spectral entropy measures signal complexity:

$$SE = - \sum P(f) \log P(f) \quad (3)$$

where $P(f)$ denotes normalized power spectral density at frequency f . These features record the changes in walking rhythm and motor coordination that are important characteristics of Parkinson's disease.

- *Classification:* The features that are extracted are feeded into a Random Forest classifier. Random Forest is a best fit for biomedical time-series data as it handles nonlinear relationships well and is relatively stable to the noise inherent in physiological measurements.

3.4 Motor Task Analysis

Parkinson's disease affects not only shown in how people walk though gait is one of important and visible sign. The motor task assessment module is short and targeted activities such as finger tapping, wrist rotation, and tremor monitoring.

1. *Data Acquisition:* By using motion sensors, researchers record motor tasks. The signals are received that tell us about about motor irregularities, like the size of tremors, how much rhythm varies and how slow the movement is.
2. *Signal Processing:* The system cleans and smooths raw motor signals to remove baseline drift and it also remove noise from the sensors. When the task repeats, the system segments the cleaned signals.
3. *Feature Extraction:* The system extracts time domain and frequency domain features from each segment. There is a combination of how intense the motor movements are and how much they vary.
4. *Classification:* Feature vectors from the motor task module train a Random Forest classifier, this is the same approach as the one for gait. It is a model that identifies differences between Parkinsonian motor activity or behavior that is typical.

3.5 Handwriting Analysis

Handwriting is most common and essentially used as it provides relevant information for Parkinson's disease. Micrographia can be defined as the gradual reduction in letter size and irregular stroke patterns that are the earliest and most observable motor signs of the condition.

- a. *Image Preprocessing:* Training is the one step ahead first the handwriting samples pass through a preprocessing technique to ensure visual consistency and accurate result across the dataset:
 1. Variance-based filtering is processed to discard the images that are black or majorly empty
 2. Median filtering clean salt and pepper noise
 3. Gaussian smoothing reduces high-frequency artifacts
 4. Stroke detail become more visible by contrast normalization.
 5. Image resizing to 224×224 pixels
 6. Pixel normalization keeps neural network training stable.

Each image is normalized using:

$$X' = \frac{x - \mu}{\sigma} \quad (4)$$

where μ and σ are the mean and standard deviation of pixel intensities.

- b. *Deep Feature Extraction:* A Convolutional neural network is built on the EfficientNet architecture. Convolutional neural network handles the handwriting classification. Through the layered structure, the network picks up on fine-grained visual features such as stroke thickness, spatial irregularities, and pressure variations that are characteristic of Parkinson's-affected handwriting.

Training from scratch was not practical with the given dataset so the model is initialized with pre-trained weights and fine-tuned on the handwriting dataset leveraging on transfer learning to adapt general visual representations to this specific classification task.

3.6 Multimodal Fusion

Instead of hard yes or no the modality-specific model produces a probability score indicating how likely the input is to reflect Parkinson's disease. Here, P_g for the gait, P_m for motor and P_h for handwriting denote the respective probabilities.

The three scores are combined and represents a single diagnostic probability through weighted decision:

$$P_{fusion} = W_g P_g + W_m P_m + W_h P_h \quad (5)$$

where the weights satisfy

$$W_g + W_m + W_h = 1 \quad (6)$$

Three signals are harder to neglect as compared to single model. Weighted fusion means a weak prediction from any single modality gets offset by the other two, keeping the overall diagnosis stable.

Hyperparameter Configurations and Decision Fusion Optimization:

The optimal extraction modalities, classifiers were tuned using grid search with 5-fold cross-validation on the training set. TABLE 2 is about the specific hyperparameter that are selected for each classifier.

Table 2: Hyperparameter configurations for individual modality classifiers

Model Stream	Algorithm	Parameter Configuration
Gait Analysis	Random Forest	n_estimators = 200, max_depth = 12, min_samples_split = 5, Criterion = Gini
Motor Analysis	Random Forest / XGBoost	n_estimators = 150, learning_rate = 0.05, max_depth = 6, Subsample = 0.8
Handwriting Analysis	EfficientNetB0	Optimizer = Adam ($lr = 10^{-4}$), Batch Size = 32, Epochs = 50, Loss = Binary Cross-Entropy

3.7 Optimization of Decision Weights

The weight allocation (w_g, w_m, w_h) in Equations (5) and (6), was executed by grid search over a constrained simplex ($\Delta w = 0.05$) on the validation fold. The weights for each of the following are as follows $w_g = 0.40$ (Gait), $w_h = 0.35$ (Handwriting), and $w_m = 0.25$ (Motor). Weight allocation proportional to individual F1-scores maximized fusion accuracy (94.6%).

4. EXPERIMENTAL RESULTS

This section walks through how the NeuroInsight-PD framework held up after the experimental testing. Rather than focusing on combined system, each modality that is gait, motor task, and

handwriting experiment has been executed, after that all three are brought together through the multimodal fusion approach.

4.1 Evaluation Metrics

System performance was evaluated using four standard classification metrics. Each metric attains something different, overall, the correctness alone does not tell you much about how the model behaves on difficult or complicated cases, so precision, recall, and F1-score were included alongside accuracy to have better and more accurate results.

Accuracy tells us the share of samples that the model classified correctly:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (7)$$

Precision is basically how many of the cases flagged as positive turn out to be correct:

$$\text{Precision} = TP / (TP + FP) \quad (8)$$

Recall (Sensitivity) measures the proportion of those that are truly positive and are correctly identified:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (9)$$

F1-score is the harmonic mean of precision and recall:

$$F1 = (2 \times \text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (10)$$

Receiver Operating Characteristic (ROC) curves and Precision–Recall (PR) curves were used to evaluate the ability of each model.

4.2 Gait Model Results

The gait module performed well in testing phase with the given test set of the Parkinson’s Disease (PD) patients from healthy individuals. The confusion matrix in FIGURE 2, shows that there were very few samples that were incorrectly classified, indicates reliable and accurate detection of gait abnormalities associated.

FIGURE 3 shows the precision-recall curve of the gait model. According to the precision-recall curve, the average precision score of the gait model is 0.935 and this is good as far as a classification model is concerned. It has near perfection in the low and mid-range recall values and reduces continuously in the higher recall levels. Nonetheless, this is to be anticipated of a well-calibrated classifier which is run on a moderately unbalanced dataset. This accuracy-recall curve is an indicator that it is possible to modify the gait model to achieve high recall without a loss of precision. The accuracy-recall curve also reiterates that Butterworth filter temporal features together with spectral entropy features is beneficial combination, when it comes to discriminative classification between Parkinsonian and healthy gait patterns.

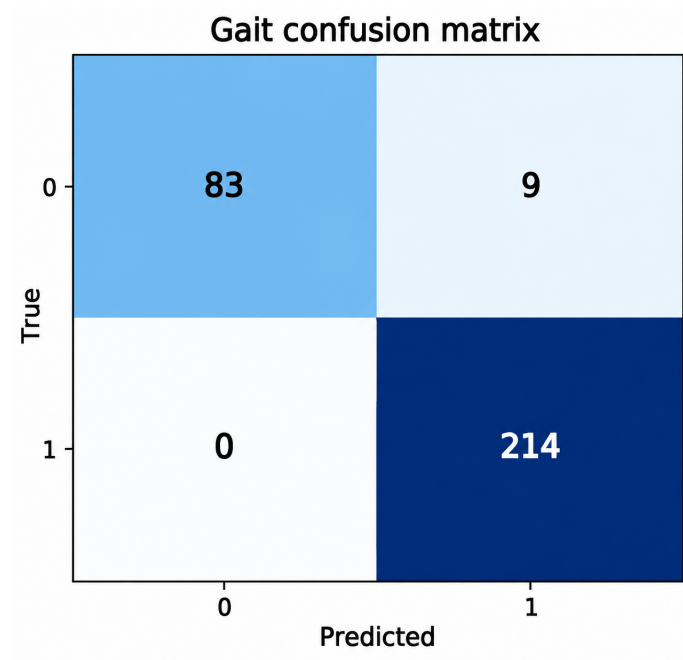


Figure 2: Confusion matrix for the gait-based classification model.

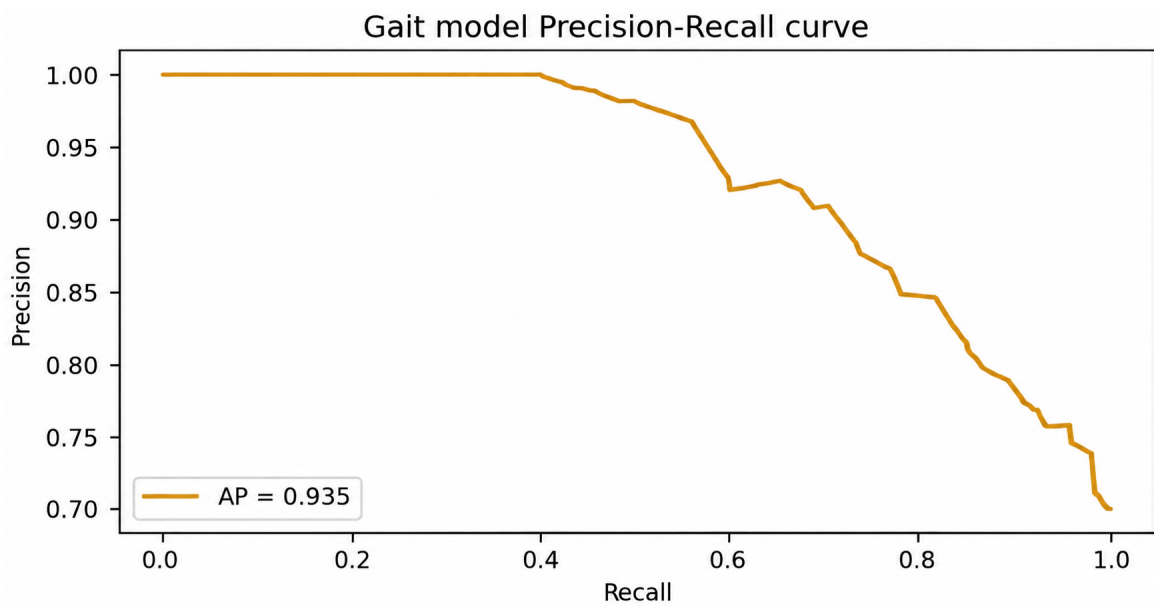


Figure 3: Precision–Recall curve for the gait analysis model.

The ROC curve shown in FIGURE 4 gives an AUC of 0.852 Further confirms the consistency of model.

4.3 Motor Task Model Results

The motor task module looks at short and it target physical actions such as finger tapping and tremor patterns to find out the characteristic of Parkinson's Disease.

As shown in FIGURE 5, the model predictions are right and which proves it accuracy

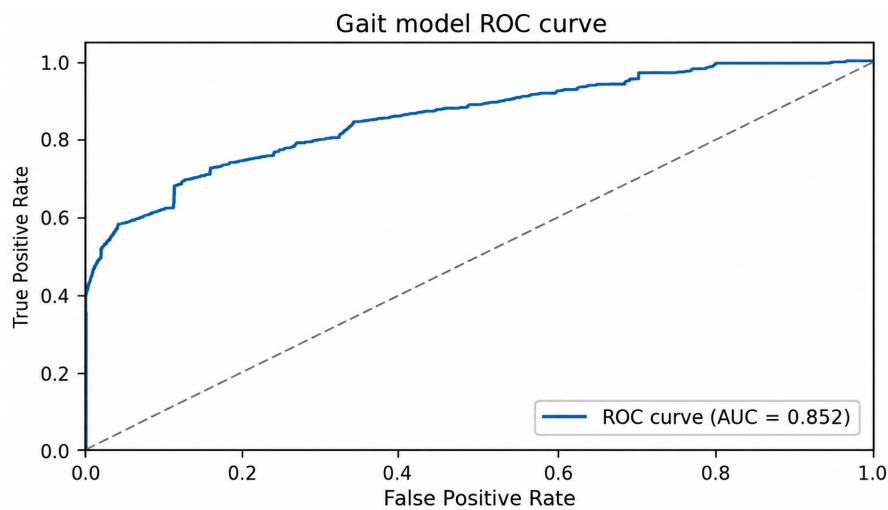


Figure 4: ROC curve gait-based classification model.

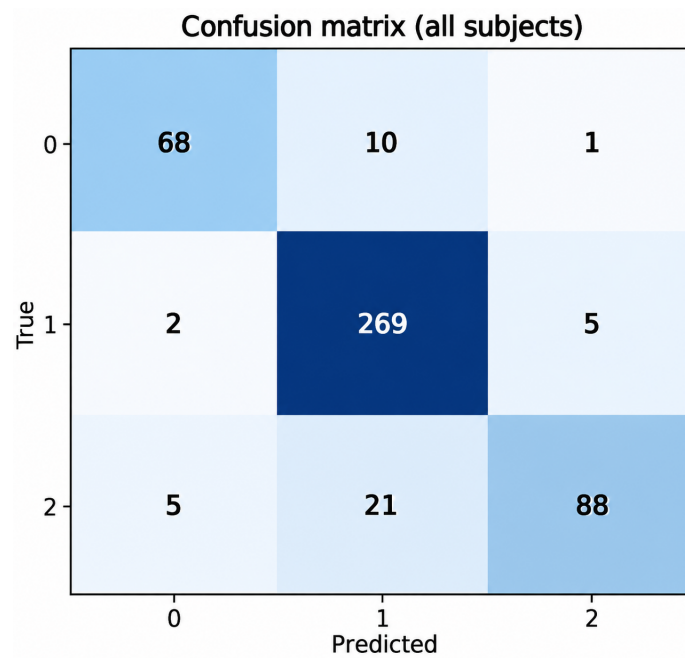


Figure 5: Confusion matrix motor task classification model.

The precision–recall curve in FIGURE 6 shows stable classification performance with maintained high precision for PD detection.

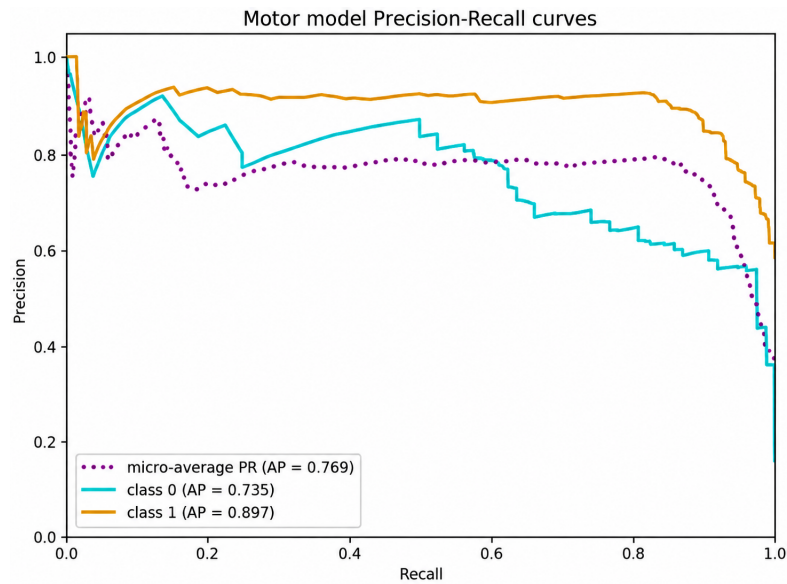


Figure 6: Precision–Recall curve motor task model.

FIGURE 7 displays the characteristic curves for the motor task model in all three categories. In those results the area under the curve is 0.887, which is a value that indicates the classification is effective. Due to the data the separation between individuals with Parkinson’s Disease and healthy participants is distinct because the area under the curve values are 0.951 and 0.901 but the intermediate category is characterized - overlapping data points. As this outcome was anticipated, it is consistent with expectations. For the who perform Parkinson’s Disease staging, it is known that the middle stage is difficult to distinguish from other groups. And those results verify that the middle category is not isolated from the others.

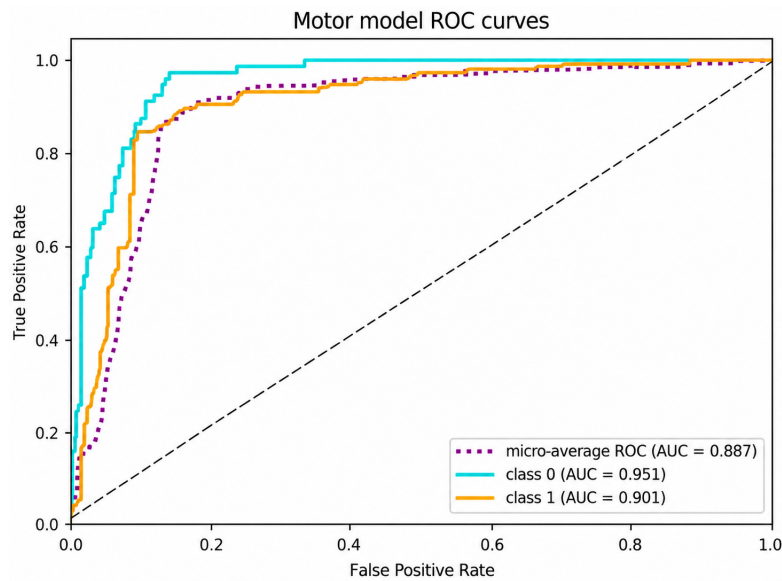


Figure 7: ROC curve for the motor task classification model.

4.4 Handwriting Model Results

Among the three modalities tested, handwriting is best for identifying Parkinson's Disease. The confusion matrix in FIGURE 8 shows the correctly identified PD samples by handwriting model, demonstrating its effectiveness in detecting handwriting irregularities associated with the disease.

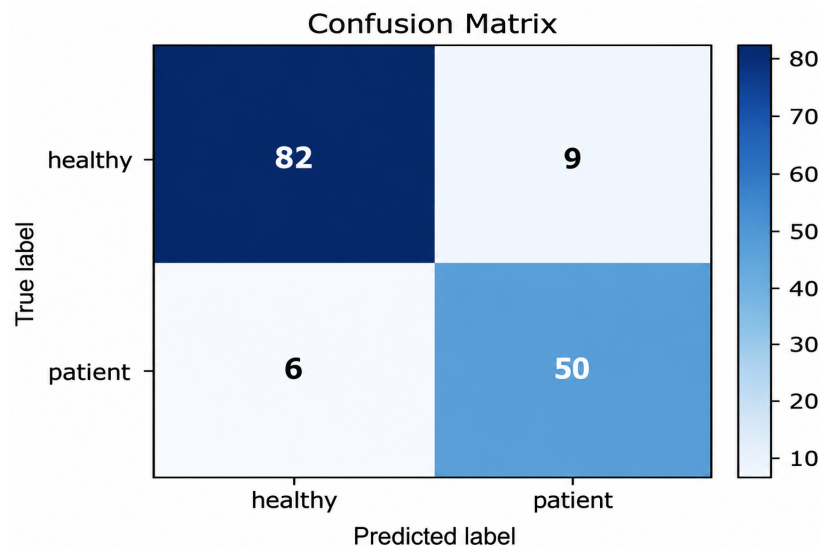


Figure 8: Confusion matrix handwriting classification model.

The training accuracy and validation loss curves illustrated in FIGURE 9 and FIGURE 10 demonstrate consistent learning and convergence of the handwriting model, with the increase in epochs the accuracy is also improving while validation loss decreases which indicates effective generalization without overfitting.

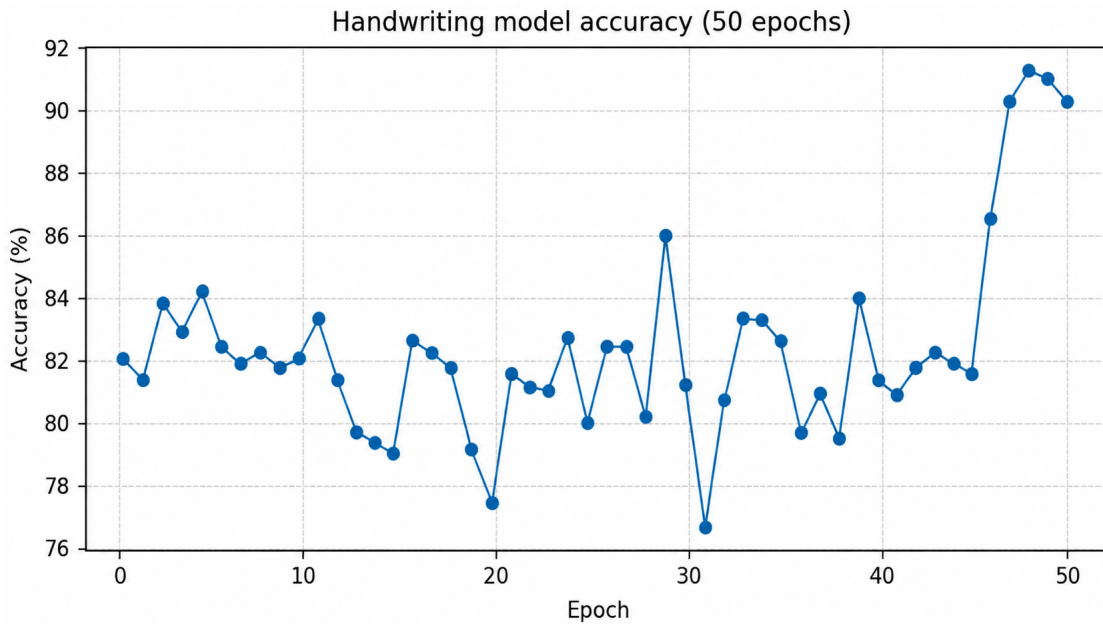


Figure 9: Training accuracy curve handwriting model.

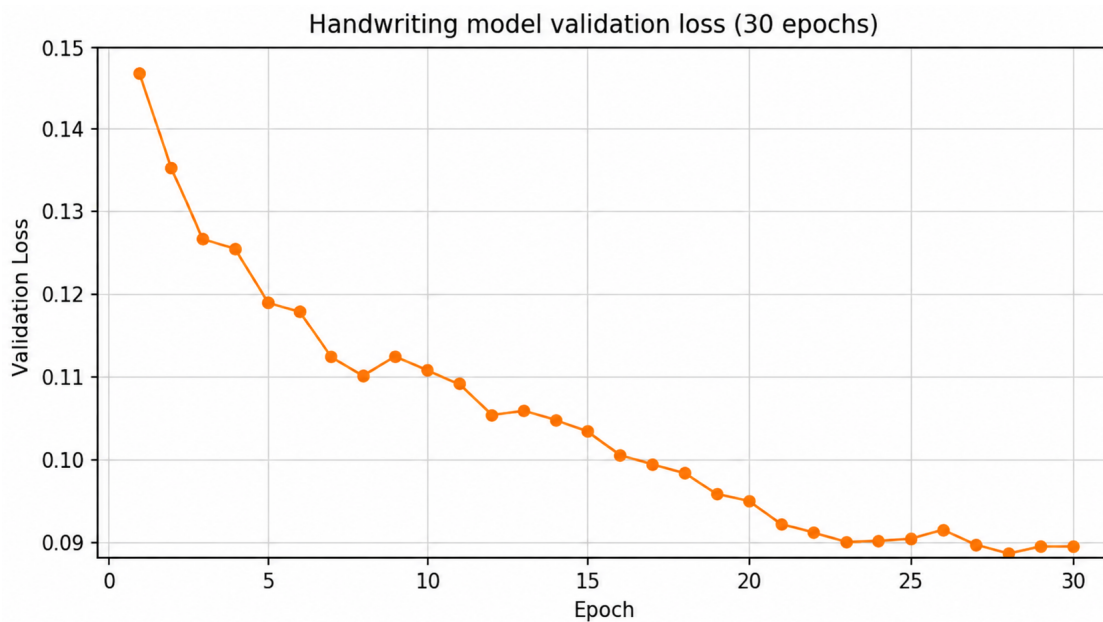


Figure 10: Validation loss curve for the handwriting model.

4.5 Multimodal Performance Comparison

The final evaluation compares the performance of individual modalities and also the multimodal framework. The classification results of all three modalities (gait, motor, and handwriting) are combined together in TABLE 3.

Table 3: Performance comparison of modality-specific models

Model	Accuracy	Precision	Recall	F1-Score
Gait Model	91.2%	95.8%	94.9%	95.3%
Motor Model	88.9%	90.1%	87.2%	88.6%
Handwriting Model	92.1%	93.2%	91.0%	92.1%
Multimodal Fusion	94.6%	94.9%	93.8%	94.3%

Table 4: Ablation study of the proposed framework

Configuration	Accuracy	Precision	Recall	F1-Score
Full Model (Proposed)	94.6%	94.9%	93.8%	94.3%
Without Hard Negative Mining	92.7%	92.1%	91.8%	91.9%
Without Threshold Optimization	91.9%	93.5%	88.4%	90.8%
Without Fusion (Best Single Modality)	91.8%	92.4%	90.6%	91.5%

TABLE 4 validates how much each architectural component contributes, by testing what happens when individual elements are taken out one at a time. When the model combines it has the best result of 94.6% accuracy and 93.8% recall. The sharpest decline comes after dropping threshold optimization.

The recall falls to 88.4%, suggesting that without this tuning, the model tends to overlook PD-positive cases that fall near the classification cutoff. When single modality is used the overall accuracy falls down to 91.8%, which makes it clear that full integrated pipeline is preferred over single modality. Across all evaluated configurations, recall is the most sensitive metric to component removal, which is clinically significant, as each component of the proposed architecture contributes to reducing missed detections rather than merely improving overall precision.

4.6 Benchmark Validation

The NeuroInsight-PD is by far one of most accurate in terms of performance, here the results show how our model is outperforming the baseline and the already published models.

TABLE 5 shows three different individual modules and how they are more precise than the other models.

Table 5: Individual model comparison against published models

Modality	Architecture / Reference	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Gait	Support Vector Machine (Baseline)	86.4%	88.0%	85.1%	86.5%
	Gait Module (Proposed RF)	91.2%	95.8%	94.9%	95.3%
Motor	Decision Tree (Baseline)	82.1%	83.5%	80.2%	81.8%
	Motor Module (Proposed RF)	88.9%	90.1%	87.2%	88.6%
Handwriting	Standard 2D CNN (Baseline)	87.3%	88.5%	86.0%	87.2%
	Handwriting Module (Proposed EfficientNetB0)	92.1%	93.2%	91.0%	92.1%

Statistical Significance

The model is being not test once rather the data split into 10 chunks so by using 10-fold cross-validation, then we had a two-tailed paired -test comparing the top-performing single modality (Handwriting, 92.1%) with the weighted decision fusion ($94.6\% \pm 0.8\%$) which yielded us $p=0.012$ ($p < 0.05$). The repeated testing with different datasets proved its status significance testing.

5. CONCLUSION

The research provides a viable solution to detecting Parkinson Disease by use of a multi-modal methodology that could potentially be used in detecting Parkinson Disease, besides the conventional tests. All three modalities (gait, motor tasks, and handwriting) present specific and valuable data about the condition of the patient and the development of the Parkinson Disease. The combination of them is effective as the system combines the advantages of each modality: high levels of sensitivity using gait, motor severity using motor tasks, and sensitivity of handwriting to motor impairments. This will reduce the risk of misclassification and enhance the quality of early detection, which is very vital in such an occasion.

A combination of classic machine learning models and deep learning models depict promising results in the performance results of the system. The previous sources of disadvantage (access to limited data in handwriting, the lack of differentiation in severe motor impairment, etc.) can be mitigated in future research by augmenting data and transfer learning and a more heterogeneous dataset sample. The strength of the models of this system is also supported by ROC AUC, precision-recall curves, and results of confusion matrices. Future studies will potentially involve more modalities such as speech recognition, facial expression recognition, or wearable sensors which will eventually detect more Parkinson's Disease features, resulting in improved sensitivity as well as specificity. Moreover, if this system is implemented on a wearable device, it can potentially allow real-time monitoring, which can help doctors remotely monitor patients' health as well as make more proactive treatment decisions.

Overall, this multi-modal system has shown promising results regarding Parkinson's Disease diagnosis and has moved a step closer to non-invasive, personalized, and more accessible treatment options for patients affected by Parkinson's Disease through a promising integration of cutting-edge AI technology along with valuable features.

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