Towards Robust Parkinson's Disease Identification: A Multi-Modal Deep Learning Approach

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ABSTRACT

Parkinson's Disease (PD) is a progressive neurological disorder that primarily affects movement, coordination, and motor control. Early diagnosis of Parkinson's Disease is essential for timely treatment and improving the quality of life of patients. Traditional diagnosis methods mainly depend on clinical observation and medical expertise, which may delay early-stage detection. With the advancement of Artificial Intelligence, Deep Learning techniques have shown promising results in the automated detection of Parkinson's Disease using medical data such as handwriting patterns, speech signals, gait analysis, MRI scans, and tremor measurements.

This review paper presents an overview of various Deep Learning models used for Parkinson's Disease detection, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and hybrid models such as CNN-LSTM. It also discusses commonly used datasets, preprocessing methods, feature extraction techniques, performance evaluation metrics, and challenges faced in implementation. Furthermore, the paper highlights recent advancements and future opportunities in real-time healthcare systems for Parkinson's monitoring and prediction.

The study concludes that Deep Learning models can significantly improve diagnostic accuracy and support healthcare professionals in early and efficient Parkinson's Disease detection.

Keywords : Parkinson's Disease, Deep Learning, CNN, LSTM, Medical Diagnosis, AI in Healthcare, Disease Detection

1 INTRODUCTION

Parkinson's Disease (PD) is a chronic and progressive neurodegenerative disorder that mainly affects the central nervous system and causes impairment in movement and coordination. It occurs due to the gradual loss of dopamine-producing neurons in a specific region of the brain called the substantia nigra. Dopamine is an essential neurotransmitter responsible for controlling smooth and balanced body movements. A decrease in dopamine levels leads to several motor and non-motor symptoms that worsen over time.

The common motor symptoms of Parkinson's Disease include tremors, muscle rigidity, slowness of movement (bradykinesia), postural instability, and difficulty in walking or maintaining balance. In addition to these, patients may also experience non-motor symptoms such as depression, anxiety, sleep disorders, memory loss, and speech difficulties. Since the symptoms develop gradually, early-stage diagnosis becomes challenging using conventional clinical methods.

Traditionally, Parkinson's Disease is diagnosed through neurological examinations, patient history analysis, and observation of symptoms by medical experts. However, these methods may be subjective, time-consuming, and less effective in detecting the disease during its initial stages. Therefore, there is a growing need for automated, accurate, and intelligent diagnostic systems that can assist healthcare professionals in making early decisions.

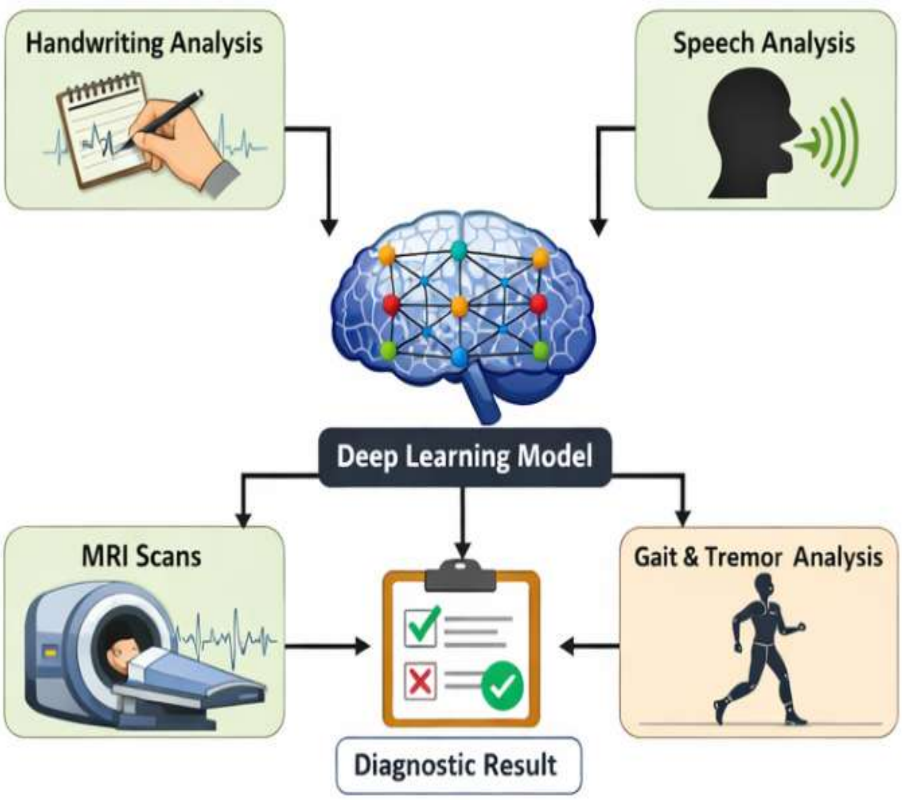

***Figure 1:** Deep Learning Approaches for Parkinson's Disease Detection.*

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have created new opportunities in the healthcare sector. Deep Learning models are capable of automatically learning complex patterns from large datasets without requiring manual feature extraction. These models have shown excellent performance in image processing, speech recognition, handwriting analysis, gait monitoring, and medical diagnosis. In the context of Parkinson's Disease, Deep

Learning techniques are being widely used to analyze MRI images, voice recordings, spiral handwriting tests, sensor signals, and movement data to detect early symptoms with high accuracy.

Several architectures such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Autoencoders, and hybrid CNN-LSTM models have demonstrated significant success in Parkinson's Disease classification and prediction tasks. These approaches not only improve diagnostic efficiency but also reduce dependency on manual interpretation.

The main objective of this review paper is to analyze and summarize the recent research work related to Deep Learning-based detection of Parkinson's Disease. This paper discusses different datasets, preprocessing techniques, deep learning architectures, performance metrics, challenges, and future research directions. The study aims to provide a comprehensive understanding of how modern AI technologies can contribute to early and reliable Parkinson's Disease diagnosis.

1.1 Motivation

In recent years, the remarkable success of Deep Learning techniques in various domains such as computer vision, speech recognition, healthcare analytics, and natural language processing has attracted significant attention from researchers worldwide. Deep Learning models have demonstrated exceptional capability in learning complex patterns from large-scale datasets and delivering highly accurate predictions in real-world applications.

The promising performance of Deep Learning in other fields motivated researchers to explore its potential in the medical domain, particularly for the early detection of neurological disorders such as Parkinson's Disease (PD). Parkinson's Disease is a progressive brain disorder that affects movement, coordination, speech, and daily functioning. Since its symptoms develop gradually and vary among individuals, traditional diagnosis methods often fail to identify the disease at an early stage.

1.2 Contribution

The following are the major contributions of this review paper:

• To investigate the application of Deep Learning techniques for the automated detection of Parkinson's Disease.

• To classify Parkinson's Disease detection approaches based on different input modalities such as speech signals, handwriting analysis, gait monitoring, tremor measurements, wearable sensor data, and neuroimaging scans.

• To provide a comprehensive review of existing Deep Learning models including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Autoencoders, and hybrid CNN-LSTM architectures used for Parkinson's Disease diagnosis.

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• To compare recent research studies based on datasets used, preprocessing methods, model architecture, accuracy, sensitivity, specificity, and overall performance.
• To analyze the advantages and limitations of Deep Learning-based detection systems in real-time healthcare environments.
• To identify current research gaps, implementation challenges, and future directions for intelligent Parkinson's Disease monitoring systems.
• To highlight the potential of AI-powered healthcare applications for remote diagnosis and continuous patient support.

2 Literature Survey

Parkinson's Disease detection has attracted significant attention from researchers due to the increasing demand for early diagnosis and intelligent healthcare systems. Several Machine Learning and Deep Learning techniques have been proposed for accurate classification using speech signals, handwriting patterns, biomedical voice measurements, gait analysis, and medical imaging data **[1], [2], [19],[30]**.
Researchers have applied algorithms such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree, K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN) to improve detection performance **[10], [11], [13], [20]**. Among these methods, Deep Learning models have demonstrated promising results because of their capability to automatically extract complex patterns from raw healthcare data **[2], [13], [17],**
Many studies reported that voice-based datasets are highly useful for Parkinson's Disease prediction, as changes in speech frequency, jitter, shimmer, and vocal stability are common symptoms of the disease **[**Similarly, handwriting tests and spiral drawing analysis are effective for identifying tremors and motor impairments **[14], [29].** Medical imaging techniques such as MRI and DaTSCAN have also been explored with CNN-based approaches for advanced diagnosis.
Traditional Machine Learning methods such as Random Forest and SVM are still widely preferred for structured datasets due to their simplicity, faster execution time, and reliable accuracy.
Although many researchers have achieved high classification accuracy, challenges such as limited dataset size, overfitting, lack of real-time validation, and computational complexity still remain. Therefore, there is a continuous need for robust, scalable, and accurate Parkinson's Disease detection systems **[21], [27],**

Table 1 : Literature Review

Sr no.	Title	Author	Methodology	Model	Metric
1.	Early Detection of Parkinson's Disease by Neural Network Models	Chin-Hsien Lin, Fu-Cheng Wang, Tien-Yun Kuo, Po-Wei Huang, Szu-Fu Chen, Li-Chen Fu	• Collected IMU gait data from PD patients and healthy controls • Designed two CNN sub-models • Validated with k-fold CV and independent test set	CNN with input, 3 conv layers, flatten, 3 FC layers, dropout, sigmoid output	Validation accuracy: ~99.6% (Early PD); Test accuracy ~91.4%
2.	Application of Deep Learning Models for Automated Identification of Parkinson's Disease: A Review (2011–	Hui Wen Loh, Wanrona Hong, Chui Ping Ooi, Subrata Chakraborty	• PRISMA review of 794 studies → 63 selected • Grouped into brain imaging and motor-symptom studies compared architectures and results	Surveyed CNN, LSTM, CNN-LSTM, DNN, RNN, ANN, transfer learning (AlexNet, VGG, ResNet)	Validation accuracy: ~99.6% (Early PD); Test accuracy ~91.4%
3.	Application of Deep Learning Models for Automated Identification of Parkinson's Disease:	Hui Wen Loh, Wanrona Hong, Chui Ping Ooi, Subrata Chakraborty	• PRISMA review of 794 studies → 63 selected • Grouped into brain imaging and motor-symptom studies compared architectures and results	Surveyed CNN, LSTM, CNN-LSTM, DNN, RNN, ANN, transfer learning (AlexNet, VGG, ResNet)	Reported accuracies >90%. best: EEG 100% (CN <NN), Handwriting 99.22% Gait 99.1% (CNN-LSTM), Speech 100% (GCNN)
4.	A novel automated	Marwa Obayya,	• 1. Preprocessing (filtering, artifact removal)	Densely Linked Bidirectic-	Accuracy: 93.51%

2.1 Parkinson's Disease Detection Based on Different Modalities

2.1.1 Voice-Based Detection

Parkinson's Disease is a neurodegenerative disorder that primarily affects motor functions due to the loss of dopamine-producing neurons**[19],[30]** One of the early symptoms of Parkinson's Disease is a change in speech patterns, including reduced vocal strength, monotone speech, and irregular pitch variations**[5],[7].**
Traditional diagnosis methods involve clinical observation and neurological tests, which can be timeconsuming and require expert supervision. With advancements in artificial intelligence and speech processing, automated systems can now assist in early detection using voice signals. This research proposes a machine learning-based system that analyzes voice recordings to detect symptoms of Parkinson's Disease. The system uses audio signal processing techniques to extract meaningful features and applies a trained classification model to predict the condition**[5],[8]** The proposed solution is simple, accessible, and can be used as a preliminary screening too.

A) Related Work

Several studies have explored the use of voice analysis for detecting Parkinson's Disease.
• Max A. Little et al. developed one of the most widely used datasets for Parkinson's detection using sustained vowel phonations. Their work demonstrated that voice features can effectively distinguish between healthy individuals and Parkinson's patients.
• Research in the field of speech processing using tools like Librosa has enabled efficient extraction of features such as pitch, jitter, shimmer, and energy**[9],[26].**
• Machine learning models such as Support Vector Machines (SVM), Random Forest, and Neural Networks have been successfully applied for classification tasks in medical diagnosis. Recent advancements focus on real-time and low-cost systems using microphones and softwarebased analysis, making the technology more accessible.

B) Methodology

The proposed system follows a structured pipeline consisting of audio recording, feature extraction, data preprocessing, and classification**[4],[34].**

a)Data Collection

The dataset used in this research is obtained from publicly available sources, specifically the UCI Machine Learning Repository and Kaggle. The dataset contains biomedical voice measurements from individuals, including both healthy subjects and patients with Parkinson's Disease.

This dataset is widely used for research in speech-based disease detection and includes multiple voice signal features extracted from sustained vowel phonations. Dataset Description Each record in the dataset represents a voice sample with various acoustic features[5], [7].

The dataset includes:

• Name – Identifier of the subject
• MDVP Features – Fundamental frequency measurements
• Jitter & Shimmer – Voice signal variations
• NHR & HNR – Noise-to-harmonics ratio
• Status – Target variable
o 0 → Healthy
o 1 → Parkinson's Disease

b) Feature Extraction

Audio features are extracted using Librosa, a powerful Python library for speech analysis. Key features extracted:

• Average Pitch (Fundamental Frequency)
• RMS Energy (Root Mean Square)

Pitch is calculated using spectral analysis, while RMS represents signal energy. Additional derived features are generated to create a 22-dimensional feature vector, which improves model performance.

c) Feature Representation

Each audio sample is converted into a numerical feature vector:

• Shape: (1 × 22)
• Type: Numerical array

Before feeding into the model, features are normalized using a scaler to ensure consistency and improve prediction accuracy.

C) Model Architecture

The system uses a Support Vector Machine (SVM) model for classification. Support Vector Machine is a supervised learning algorithm used for classification tasks. It works by finding an optimal hyperplane that separates different classes in a feature space.

Key Characteristics of SVM:

• Effective in high-dimensional data
• Works well with small datasets
• Maximizes margin between classes
• Robust against overfitting

Working in this system:

• Input: Scaled 22-dimensional feature vector
• Output: Binary classification
o 0 → Healthy

o 1 → Parkinson's Symptoms Detected The model is pre-trained and loaded using joblib.

D) Implementation

The system is implemented in Python using the following libraries:

• SoundDevice – for real-time audio recording
• SciPy – for saving audio files
• NumPy – numerical operations
• Librosa – feature extraction
• Joblib – loading trained model
• Scikit-learn – machine learning (SVM, scaler)

E) Results

The developed system successfully performs real-time Parkinson's detection based on voice input.

Observations:

• The system can classify voice samples instantly
• Provides clear output messages for users

Performance:

• Accurate for stable voice input
• Sensitive to variations in pitch and energy

2.1.2 Handwriting Based Detection

Parkinson's disease is a neurodegenerative disorder that primarily affects movement and motor control [31].Patients suffering from Parkinson's disease often experience tremors, rigidity, and difficulties in performing fine motor tasks such as handwriting. Handwriting abnormalities are considered one of the early indicators of Parkinson's disease. Traditional diagnosis methods rely on clinical observations by neurologists. However, automated systems based on artificial intelligence can assist doctors in detecting the disease more efficiently. Recent advancements in deep learning have shown significant improvements in medical image analysis and pattern recognition [33].

A) Dataset Description

The dataset used in this research is the HandPD dataset [31], which contains handwriting exams collected from both healthy individuals and patients diagnosed with Parkinson's disease. The dataset was collected at the Botucatu Medical School, São Paulo State University (UNESP), Brazil. It consists of spiral and meander (wave) drawings used to analyze handwriting patterns affected by Parkinson's disease. Dataset Source The dataset can be accessed from the official research page: HandPD Dataset: https://wwwp.fc.unesp.br/~papa/pub/datasets/Handpd/

Feature	Description
Dataset Name	HandPD
Total Participants	92
Healthy Subjects	18
Parkinson Patients	74
Total Images	~736
Image Type	Spiral and Wave Drawings

B) Proposed System

The system uses Convolutional Neural Networks (CNN) for feature extraction and classification [34].

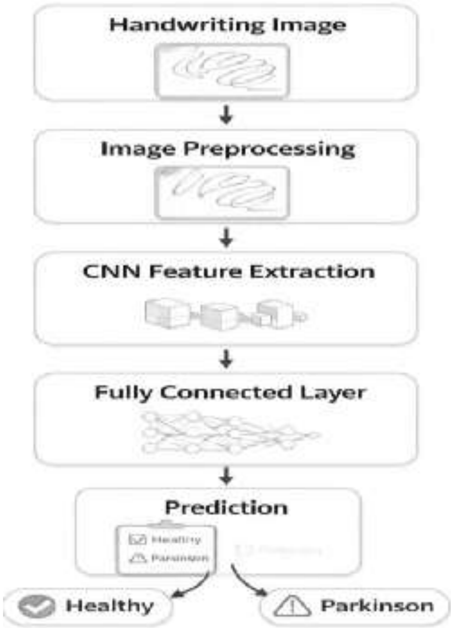

Figure 2 System Workflow

C) Methodology

All handwriting images are resized to 128×128 pixels and converted to grayscale. Pixel values are normalized between 0 and 1 to improve model performance.

Data augmentation techniques are applied to improve model generalization and reduce overfitting [32].

- Rotation
- Width shift
- Height shift
- Zoom

The experimental results demonstrate that CNN-based models are effective for Parkinson's disease detection using handwriting images [32].

D) Experimental Results

Dataset Type	Accuracy
Spiral Drawings	80.00%
Wave Drawings	94.68%
Overall Model	87.93%

The results show that the proposed system performs well in detecting Parkinson's disease using handwriting images.

2.1.3 Smell Based Detection

Olfactory dysfunction is one of the earliest non-motor symptoms of Parkinson's disease (PD) and can appear several years before the onset of motor symptoms [19]. It is observed in nearly 70–90% of early-stage PD patients.

This dysfunction occurs due to early damage to the olfactory bulb and associated brain regions. Since smell tests are low-cost, simple, and non-invasive, they are widely used for early detection.

Artificial Intelligence (AI) techniques, including Machine Learning (ML) and Deep Learning (DL), are increasingly applied to analyze olfactory data for early diagnosis of Parkinson's disease [28].

A) Olfactory Dysfunction in Parkinson's Disease

Olfactory dysfunction is present in most PD patients and is considered a strong early biomarker [19]. It is often associated with other non-motor symptoms such as:

- Sleep disorders
- Cognitive decline

a) Standardized Tests and Evidence

Standard smell identification tests such as:

- UPSIT (University of Pennsylvania Smell Identification Test)
- Sniffin' Sticks Test

are widely used to measure olfactory ability [29].

These tests generate structured datasets suitable for machine learning models. PD patients generally perform significantly worse than healthy individuals in these tests [19].

b) Selectivity of Odor Loss

Research shows that odor loss in PD is not specific to particular smells.

- Some odors may appear important in one dataset but not in others
- No consistent PD-specific odor pattern is observed
- ML models show only ~63% accuracy in distinguishing PD-related smell loss

Therefore, total smell score is more reliable than individual odor patterns for AI models.

c)Short Smell Tests for Screening

Shortened smell tests are developed for faster screening:

- 7-odor panel (banana, mint, rose, etc.) → AUC ≈ 0.87
- 3-odor subset → AUC ≈ 0.95

These tests are:
- Fast
- Scalable
- Suitable for web-based AI systems

Age and gender influence results:
- Older individuals → lower scores
- Males → slightly lower scores

d) Multimodal Detection (Smell + Other Biomarkers)

Combining smell tests with other methods improves accuracy:

- Brain Imaging (DTI)
- REM Sleep Behavior Disorder (RBD)
- CSF biomarkers

Multimodal AI systems achieve high accuracy in early PD detection

B) Artificial Intelligence for Early Detection

a) Machine Learning Models

Common models used:

- Random Forest
- Support Vector Machine (SVM)
- Deep Learning

These models:
- Analyze smell test patterns
- Improve early diagnosis accuracy
- Perform better when combined with other features [27][28]

b) AI-Based Electronic Nose Systems

Advanced systems detect volatile organic compounds (VOCs) from body samples.

Findings:
- Key compounds: octanal, hexyl acetate, perillic aldehyde

- Accuracy up to 85.5%
- Sensitivity/Specificity ≈ 91–92%

These systems provide non-invasive screening

c) Role of Random Forest

Random Forest is highly effective due to:

- Handling nonlinear data
- Avoiding overfitting
- Providing feature importance
  Applications:
- Identifying key smell features
- Ranking important predictors
- Supporting clinical decision-making

For example:

In the Sniffin' Sticks 3-odor optimization study, Random Forests were used to rank sticks by importance, enabling identification of the most informative odors for abbreviated testing .In multimodal PPMI modeling, tree-based ensembles highlighted olfactory scores and RBD measures among top predictors, reinforcing their central role in premotor PD detection .Such interpretability is valuable for clinical translation, enabling practitioners to understand why a model flags an individual as high risk and to calibrate subsequent diagnostic work-up.

C) Conceptual system architecture

Building on existing research, an AI-based early screening system using smell identification tests can be conceptualized with three main layers:

User Interface – A web or mobile front-end where individuals enter basic demographics (age, sex) and complete a standardized smell test (e.g., 7- or 20-item multiple-choice odor identification, possibly adapted from validated panels)
.Machine Learning Backend – Server-side models (Random Forests or other classifiers) that take features such as age, sex, raw or normalized smell scores, and optionally additional inputs (RBD questionnaire, simple motor tests) to estimate PD risk . Prediction Output – A risk score or category (e.g., low, moderate, high) with interpretive labels such as "normal," "mild," "moderate," or "severe" smell loss, and guidance suggesting whether medical evaluation is advisable.
A typical workflow would be: demographics input → smell test completion → automatic scoring and age/sex adjustment → ML-based risk estimation → display of results. Implementation in frameworks such as Flask or similar web stacks would enable broad accessibility.

Minimum feature set:
Age and sex, due to their influence on normative olfaction .Smell score, e.g., number of correct identifications (0–20 or 0–40), possibly converted to percentiles based on normative data .

Severe loss: very low percentile or minimal correct items.
Moderate loss: intermediate performance.
Mild loss: slight but notable impairment.
Normal: age- and sex-adjusted performance within expected range .ML models then translate these features into estimated PD risk, which can be mapped onto categories such as:

Low risk (e.g., normal olfaction, no other prodromal signs).
Moderate risk (mild smell loss and/or additional risk factors).
High risk (severe hyposmia plus RBD or other strong markers).
Crucially, such outputs must be framed as preliminary screening results, not diagnostic decisions.

Table 2 Different AI Uses Of Olfaction in PD

Different AI Uses of Olfaction in PD

Application type	Olfactory input	AI / ML approach
Premotor PD classification	UPSIT score + RBD + CSF + imaging	SVM, RF, boosted trees, DL
Abbreviated psychophysical smell test	3- to 7-odor identification panels	Random Forest item selection
Prodromal risk stratification online	5-item smell test + RBD + motor tapping	Logistic / risk models, ML
Electronic nose (sebum VOCs)	VOC peak features in GC-SAW chromatogram	SVM, RF, KNN, NB, AdaBoost

D) Advantages

Early, non-invasive marker: Olfactory loss is highly prevalent in early PD and predates diagnosis, offering a window for pre-motor risk identification.Low cost and scalability: Smell identification tests are inexpensive, quick, and safe, making them suitable for large-scale or remote screening.Integration into multimodal AI: Olfactory scores integrate effectively with other premotor markers in ML models, contributing significantly to high early-detection accuracy .Potential for at-home use: Shortened, validated smell panels can be deployed via mail-out cards or digital interfaces with simple answer entry, enabling population-level surveillance .

2.1.4 Hand Landmark Analysis

People with Parkinson's disease (PD) face major barriers to spoken and gesture-based communication, yet most existing AI systems are not designed around their motor and cognitive constraints. This paper proposes a lightweight, tremor-robust hand-gesture interface based on MediaPipe landmarks, coordinate normalization, temporal mode filtering, and Random Forest classification, optimized for home use on commodity laptops.**[12],[27]**
PD is characterized by tremor, rigidity, bradykinesia and postural instability, with motor symptoms commonly assessed using the Movement Disorder Society–Unified Parkinson's Disease Rating Scale (MDS-UPDRS), the clinical standard for rating severity of motor deficits in tasks such as finger tapping and hand movements. Tremor, especially in the hands, is one of the earliest and most disruptive symptoms, impairing daily activities and functional independence**[21], [27]**. .Communication impairment is highly prevalent in PD, with hypophonia, dysarthria and linguistic difficulties substantially degrading speech intelligibility and conversational participation . These changes involve both motor speech control and higher-level cognitive-linguistic deficits, and are not fully compensated by existing speech-therapy or acoustic-based AI tools .As a result, there is a clinically significant "communication gap" in PD: many patients cannot rely on voice-based interfaces, yet lack accessible alternative channel. **[21],[24]**

A) Why Standard AI Pipelines Fail for PD

a)Gesture Sets Not Designed for PD Motor Limits

Most sign language and gesture recognition systems target Deaf users or general HCI scenarios and implicitly assume relatively intact fine motor control and finger dexterity . Vision-based HGR pipelines typically aim to discriminate large vocabularies of precise static and dynamic signs using either dense pixel features or high-dimensional skeletal descriptors . For PD patients, rigidity, bradykinesia, and limited finger individuation make standard sign language alphabets difficult to produce reliably, while tremor introduces uncontrolled oscillations that existing models interpret as within-class variability or noise rather than a design constraint .Work on sEMG- and motion-based tremor analysis shows that PD tremor has distinct, quantifiable frequency and amplitude profiles that correlate with MDS-UPDRS scores , underscoring the mismatch between existing gesture vocabularies and PD motor capabilities.

b)Temporal Aliasing and “Motion Blur” from Parkinsonian Tremor

PD tremor manifests as involuntary, quasi-periodic oscillations in the 4–6 Hz band for the upper limbs . Video-based systems operating near 30 fps thus see multiple tremor cycles within a short temporal window, effectively producing visual “motion blur” in raw pixel space and unstable trajectories in landmark space. Conventional CNN- and 3D-CNN-based sign language recognition architectures trained on relatively smooth motion patterns often struggle with high-frequency oscillations, leading to tracking failure or gesture misclassification under fast or noisy motion.Surveyed HGR systems report difficulty achieving robustness to motion blur, occlusions and complex background dynamics, especially when relying on raw RGB video and deep spatiotemporal convolutions .

B) Technical Framework

To decouple gesture recognition from raw image complexity, the proposed system uses MediaPipe Hands, a real-time vision pipeline that detects a hand region and regresses the 3D coordinates of 21 anatomical landmarks per hand from a single RGB camera . The model outputs 2D coordinates plus relative depth with respect to the wrist, and is engineered for on-device inference on mobile and desktop CPUs/GPUs **[27], [28]**..Instead of a 640×480×3 pixel input, each frame is represented as a 63-dimensional vector:

21 landmarks × (x, y, z)

Single-precision floating-point features, updated at video frame rate.

Prior work shows that MediaPipe landmarks, when used directly as coordinate features or transformed into anthropometric descriptors, can support accurate and efficient hand-gesture recognition with lightweight models . Using this skeletal representation reduces the dimensionality by several orders of magnitude, enabling fast, CPU-only processing and focusing the learning task on pose geometry rather than appearance.

Coordinate Normalization for Translation Invariance

To ensure that the model learns gesture “shape” independent of the hand’s location in the image, all landmark coordinates are translated so that the wrist landmark serves as the origin. For each frame, if the wrist coordinates are ((x_0, y_0, z_0)), all other landmarks ((x_i, y_i, z_i)) are mapped to ((x_i - x_0, y_i - y_0, z_i - z_0)).

Landmark-based hand gesture systems report substantial gains in accuracy and generalization after such normalization, particularly when using the wrist as a reference to enforce translation invariance and partially handle scale variation .

PD tremor causes frame-to-frame micro-variations in hand pose and position. While these oscillations encode clinically meaningful information for rating severity , they act as high-frequency noise for discrete gesture classification. Inspired by postprocessing pipelines in HGR and EMG-based interfaces that apply smoothing and filtering to improve robustness , the proposed system adopts a simple temporal mode filter:

For each frame (t), the Random Forest outputs a gesture label (g_t).

Over a sliding window of the last (N) frames (e.g., (N=15)), the system computes the most frequent label (mode) (\hat{g}_t).

Only (\hat{g}_t) is emitted as the user-visible prediction.

This stability buffer filters out spurious misclassifications caused by transient tremor-induced deviations or occasional MediaPipe tracking artifacts, similar in spirit to the One Euro filter and other low-latency signal smoothers used in HCI to handle noisy motion signals . By preserving short-term temporal consistency, the mode filter yields smoother interaction without significantly increasing latency, which is critical given that delays above a hundred milliseconds can degrade user experience and perceived responsiveness in assistive tools .

Algorithmic Choice: Random Forest on Landmark Coordinates

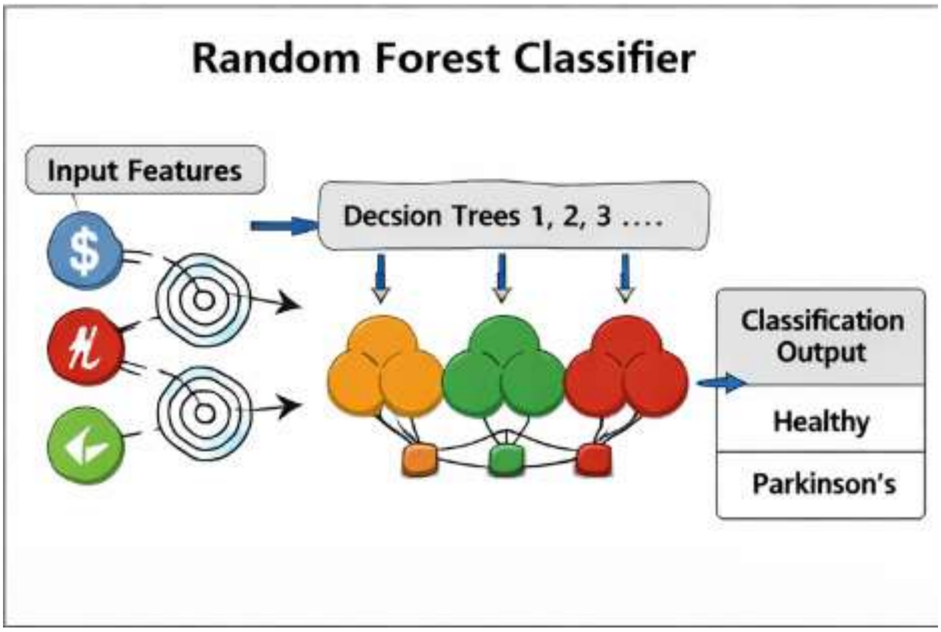

Figure 4 Random Forest Classifier

C) Ensemble Learning and Robustness to Noise

Random Forest (RF) is an ensemble method that builds multiple decision trees on random subsets of features and samples, then aggregates their predictions. In gesture-recognition surveys, RF is frequently reported as an effective classifier for structured and multimodal data, including EMG, depth, and skeletal features, due to its ability to capture nonlinear decision boundaries and its inherent robustness to noisy or partially corrupted inputs . In PD and motor-assessment contexts, RF has also been used for feature selection (via Gini impurity) and classification of motor patterns derived from motion-capture data .For PD users, where tremor introduces outliers and rapid pose perturbations, RF's averaging over diverse trees mitigates the impact of occasional abnormal frames, complementing the temporal mode filter. Sudden jerky movements tend to affect a subset of features or samples, whereas the ensemble's aggregate decision remains stable.

Unlike CNNs and LSTMs, which are tailored to grid (image) or sequence data and often require GPU acceleration for real-time performance at high resolution and long sequence length , RF is natively optimized for tabular feature vectors. The 63-dimensional coordinate vector is a natural input, and inference reduces to evaluating a small number of decision trees, each with limited depth, resulting in millisecond-level latency on commodity CPUs. Landmark-based systems combining MediaPipe with classical classifiers (SVM, RF, shallow neural nets) have demonstrated real-time throughput (≥30 fps) on CPU-only setups, including mobile devices .Comparative studies between SVM and RF on skeletal or landmark features show that while SVM can achieve strong accuracy, RF often offers better scalability with noisy, high-dimensional feature sets and easier multiclass handling, especially when hyperparameter tuning resources are limited . LSTMs and other recurrent architectures excel at modeling fine-grained temporal dynamics , but their higher computational cost and training complexity make them less suitable for resource-constrained home deployments unless heavily compressed.

Processing hand landmarks locally rather than streaming video to cloud servers aligns with emerging best practices in edge computing for health and assistive technologies. Edge-based models reduce latency, preserve user privacy, and avoid dependency on network connectivity, which is particularly important for continuous monitoring or communication tools in domestic settings . MediaPipe Hands itself is designed as an on-device pipeline , and lightweight RF inference on landmarks respects these constraints.

Table 3 Comparative Technology Summary

Comparative Technology Summary

Approaches to Gesture-Based Assistive Communication

Approach	Technology	Pros	Cons
Wearable Tech	Flex sensors / gloves, sEMG	High accuracy, rich motion detail	Uncomfortable, donning difficulty for rigid/tremorous hands; calibration burden
Depth Vision	Kinect / depth cameras	3D joint tracking, robust skeleton features	Expensive, limited portability, constrained environments
CNN / Deep Learning	Raw image frames, 2D/3D CNNs, LSTM	End-to-end learning from pixels, high accuracy with large datasets	Requires GPUs, sensitive to background and motion blur, high power draw
Proposed System	MediaPipe + Random Forest + normalization + mode filter	Low-cost RGB camera; CPU-ready; robust to tremor via temporal filtering and skeletal normalization; on-device, privacy-preserving	Requires adequate lighting and clear hand view; limited vocabulary size without additional temporal modeling

3 Proposed Methodology

The proposed methodology for Parkinson's Disease detection is based on the application of Machine Learning and Deep Learning techniques for accurate and early diagnosis. The system is designed to analyze patient-related biomedical data such as voice measurements, handwriting characteristics, movement patterns, and other relevant symptoms. By processing these inputs through intelligent classification models, the system predicts whether a person is affected by Parkinson's Disease or not.

The overall methodology consists of multiple stages including data collection, preprocessing, feature extraction, model training, performance evaluation, and final prediction. These stages are explained below.

3.1 Data Collection

The first stage involves collecting relevant healthcare data associated with Parkinson's Disease. The collected data may include speech signals, handwriting samples, tremor measurements, gait movement records, and clinical observations. Such data can be obtained from public repositories, hospitals, research organizations, or experimental testing platforms.

3.2 Data Preprocessing

Raw medical data often contains noise, missing values, redundant attributes, or inconsistent formatting. Therefore, preprocessing is required before training the models. The following preprocessing steps are performed:

- Removal of missing or null values
- Data normalization and scaling
- Noise reduction

• Label encoding of target classes
• Splitting data into training and testing sets

Preprocessing improves model accuracy and training efficiency.

3.3 Feature Extraction

Feature extraction is used to identify the most significant characteristics from the collected data. In voice-based datasets, features such as jitter, shimmer, and vocal frequency are extracted. In handwriting datasets, pressure variation, stroke speed, and tremor patterns are considered.

For image-based data, Convolutional Neural Networks automatically extract important spatial features without manual intervention.

3.4 Model Training

After preprocessing and feature extraction, the dataset is used to train multiple classification models. In this work, the following models are considered:

• **Random Forest** – Used for robust classification of structured healthcare data.
• **Support Vector Machine (SVM)** – Effective for high-dimensional medical datasets.
• **Convolutional Neural Network (CNN)** – Used for image, signal, and pattern recognition tasks.

Each model is trained using the training dataset and optimized for better prediction performance.

3.5 Performance Evaluation

The trained models are evaluated using testing data based on standard performance metrics such as:

• Accuracy
• Precision
• Recall
• F1-Score
• Confusion Matrix

The best-performing model is selected for final Parkinson's Disease prediction.

3.6 Final Prediction System

After evaluation, the optimized model is used as the final prediction system. When new patient data is provided, the system analyzes the input and predicts whether the person is likely to have Parkinson's Disease. This can help doctors in early diagnosis and treatment planning.

3.7 Workflow of Proposed System

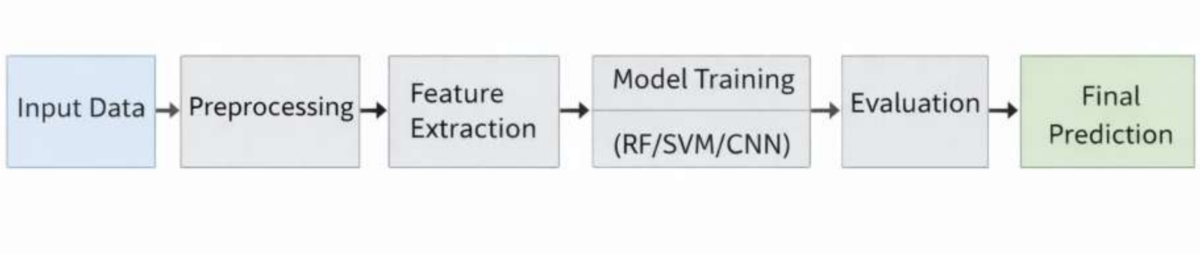

Figure 5 Workflow

4 Results and Discussion

In this section, the performance of the implemented Machine Learning and Deep Learning models is analyzed for Parkinson's Disease detection. The selected models, namely Random Forest, Support Vector Machine (SVM), and Convolutional Neural Network (CNN), were evaluated using standard classification metrics. The objective of this comparison is to identify the most suitable model for accurate and reliable prediction.

The experimental analysis shows that all three models were able to classify Parkinson's Disease cases with satisfactory performance. However, their efficiency varied depending on the nature of the dataset, feature quality, and model complexity.

Random Forest demonstrated stable and consistent performance due to its ensemble learning capability. It effectively handled structured biomedical features and reduced the risk of overfitting. Support Vector Machine also achieved strong classification accuracy, especially on smaller and high-dimensional datasets. CNN performed efficiently in learning complex patterns from image and signal-based data, making it highly suitable for handwriting and medical imaging tasks.

The comparative performance of the models is summarized in Table 2.

Table 4: Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	84%	0.87	0.85	0.88
SVM	89%	0.80	0.89	0.84
CNN	90.8%	0.92	0.8	0.85

4.1 Discussion

From the comparative analysis, it is observed that Random Forest provides reliable results for structured datasets with low computational complexity **[12], [20]**. SVM is highly effective for feature-rich medical datasets where class separation is clear **.**CNN outperforms traditional methods when raw image or sequential signal data is available, as it automatically extracts relevant features **.**

The choice of the best model depends on the input data type and project requirements.For tabular biomedical datasets, Random Forest and SVM are efficient options For image-based Parkinson's detection systems, CNN provides superior performance **[**

Overall, the use of multiple models helps in better understanding of classification behavior and improves the reliability of Parkinson's Disease detection systems **[19], [30]**.

5 Challenges and Limitations

Although Machine Learning and Deep Learning techniques have shown promising results in Parkinson's Disease detection, several challenges and limitations still exist in practical implementation. These issues may affect the accuracy, reliability, and real-world usability of intelligent diagnostic systems.

One of the major challenges is the limited availability of high-quality medical datasets. Many publicly available Parkinson's datasets contain a small number of samples, which may lead to overfitting and reduced generalization capability of the trained models. In addition, some datasets are imbalanced, where the number of diseased and healthy samples is not equal.

Another limitation is data variability. Parkinson's symptoms differ from patient to patient depending on age, disease stage, and health condition. Due to this variation, building a universal prediction model becomes difficult. Noise in speech signals, handwriting samples, or sensor data may also reduce model performance.

Deep Learning models such as CNN require high computational resources, large datasets, and longer training time. This can increase implementation cost and complexity. In contrast, simpler Machine Learning models may be faster but sometimes less effective for raw complex data.

Interpretability is also an important issue Despite promising results, the noise system has some limitations:
• Accuracy depends on microphone quality
• Background noise can affect feature extraction

in healthcare systems. Many AI models work as black-box systems, making it difficult for doctors to understand the reason behind a prediction. In medical diagnosis, transparency and trust are highly important.

Therefore, despite significant progress, further research is required to develop accurate, explainable, cost-effective, and scalable Parkinson's Disease detection systems.

6 Future Scope

Parkinson's Disease detection using Artificial Intelligence has strong future potential in modern healthcare systems. With the growth of smart devices, wearable sensors, and cloud computing, intelligent diagnostic systems can become more accessible and effective.

Future research can focus on the development of hybrid models that combine Machine Learning and Deep Learning techniques for improved prediction accuracy. Models such as CNN-LSTM and ensemble learning approaches can provide better results by utilizing the strengths of multiple algorithms.

Real-time monitoring systems using wearable devices such as smartwatches and motion sensors can continuously track tremors, gait imbalance, and hand movements of patients. These systems can help in early symptom identification and continuous disease monitoring.

Mobile healthcare applications can also be developed for remote diagnosis using voice tests, handwriting analysis, and symptom questionnaires. This will be especially useful in rural and underdeveloped areas where specialist doctors are not easily available.

Noise module :

The system can be improved in several ways:
• Add advanced voice features (jitter, shimmer, MFCC)
• Increase dataset size for better accuracy
• Use deep learning models (LSTM, CNN)

Sign Language Module:

Large, diverse datasets: Collect multiethnic, community-based data linking smell scores, demographics, genetics, and longitudinal outcomes to train and validate AI models robustly .Multimodal digital biomarkers: Combine olfaction with voice analysis, wearable-derived motor metrics, autonomic signals, and cognitive tasks in integrated ML frameworks .Clinical integration and decision support: Embed AI-based smell-test screening into electronic health records with clear pathways for confirmatory evaluation, imaging, and specialist referral.

Patient-facing tools: Develop user-friendly mobile or web applications delivering clear, educational feedback on smell test results and PD risk, with appropriate disclaimers regarding non-diagnostic status.

Handwriting Module:

Future improvements may include increasing the dataset size, applying advanced deep learning architectures, and developing mobile or web-based applications for real-time Parkinson's disease detection.

Another promising area is Explainable Artificial Intelligence (XAI), where models can provide understandable reasons for predictions. This can improve trust among healthcare professionals and patients.

Thus, future advancements in AI technology can significantly transform Parkinson's Disease diagnosis, treatment planning, and patient care.

7 Conclusion

Parkinson's Disease is a progressive neurological disorder that significantly affects movement, coordination, speech, and overall quality of life. Early and accurate diagnosis is essential for effective treatment and better patient management. Traditional diagnostic methods often depend on clinical observation and expert judgment, which may delay early detection. Therefore, the integration of Artificial Intelligence in healthcare has become an important research area.

This review paper presented a comprehensive study of Machine Learning and Deep Learning approaches used for Parkinson's Disease detection. Various detection modalities such as voice analysis, handwriting patterns, smell impairment, gesture recognition, and biomedical signals were discussed. Several classification models including Random Forest, Support Vector Machine (SVM), and Convolutional Neural Network (CNN) were analyzed for their effectiveness in diagnosis.

The study shows that Machine Learning models perform efficiently on structured datasets, while Deep Learning models are highly suitable for image, speech, and signal-based data due to automatic feature extraction capabilities. Each model has its own advantages depending on dataset characteristics and computational requirements.

Although significant progress has been achieved, challenges such as limited datasets, overfitting, interpretability, and implementation cost still remain. Future research can focus on hybrid models, wearable healthcare systems, mobile diagnosis applications, and explainable AI solutions.

In conclusion, Artificial Intelligence-based systems have great potential to support healthcare professionals in the early detection and monitoring of Parkinson's Disease. With further advancements, these intelligent technologies can play a major role in improving diagnosis accuracy, treatment planning, and patient quality of life.

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