Detecting Parkinson's Disease Through Handwriting Patterns

Reshma R. Vernekar, Sammed B. Ghattad, Ms Sheetal S. Bandekar

Department of Master of Computer Applications (MCA), KLS Gogte Institute of Technology, Belagavi. Belagavi, India

DOI: https://doi.org/10.51584/IJRIAS.2025.100700083

Received: 22 July 2025; Accepted: 28 July 2025; Published: 13 August 2025

ABSTRACT

Parkinson's disease (PD) is a gradually worsening neurological disorder that mainly affects motor functions due to the decline of dopamine-producing neurons in the substantia nigra. Early and precise diagnosis is often difficult because traditional tools like MRI, PET scans, or neurological tests tend to be costly, subjective, and not widely available. Handwriting analysis has emerged as a non-invasive, cost-efficient biomarker, capable of revealing early-stage motor abnormalities such as micrographia, tremors, and bradykinesia. This literature survey systematically reviews recent advancements in the automatic detection of PD using handwriting patterns, leveraging machine learning (ML) and deep learning (DL) algorithms. It highlights methodologies involving Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), hybrid CNN-RNN models, and transfer learning approaches applied to both static images and dynamic time-series handwriting data. The review also explores data preprocessing strategies, augmentation techniques, and handcrafted as well as learned feature extraction methods. Studies report diagnostic accuracies often exceeding 90%, with some achieving over 98% using optimized architectures. Explainable Artificial Intelligence (XAI) frameworks, such as LIME, have further improved clinical trust in model predictions. Despite these achievements, challenges remain in data diversity, generalizability, and deployment on low-power edge devices, prompting the need for future research focused on scalable and interpretable diagnostic systems.

Keywords: Parkinson's Disease, Deep Learning, Handwriting Biomarkers, Early Diagnosis, Convolutional Neural Networks.

INTRODUCTION

Parkinson's disease (PD) is a long-term degenerative condition that impacts more than 10 million individuals globally. It primarily impairs motor functions due to the gradual loss of dopamine-producing neurons in the substantia nigra region of the brain. Characteristic symptoms include resting tremors, bradykinesia, rigidity, and postural instability. Non-motor symptoms such as cognitive decline, sleep disorders, and speech impairments may also occur. Although PD typically manifests in older adults, early-stage detection remains critical for implementing timely therapeutic interventions that can delay progression and improve quality of life.

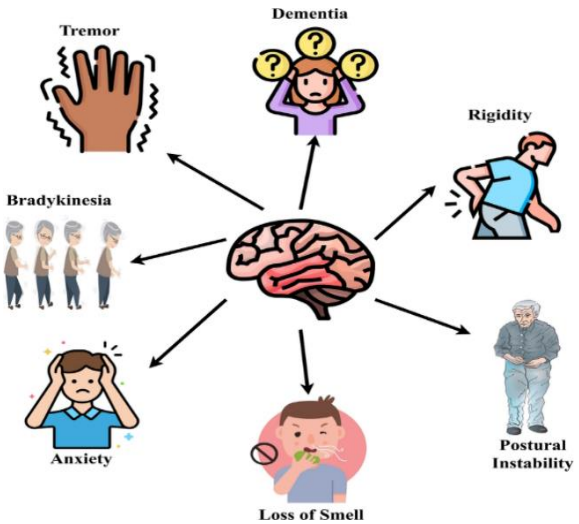

Fig. I. 1 Common Symptoms of Parkinson Disease

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VII July 2025

Diagnosis commonly involves tools like the UPDRS scale and neuroimaging techniques such as MRI, PET scans, and DaTscan. However, these methods are often costly, time-consuming, and subjective, limiting their accessibility—particularly in under-resourced healthcare systems.

In recent years, handwriting analysis has emerged as a viable digital biomarker for PD detection. The motor deficits associated with PD are often reflected in handwriting anomalies, such as micrographia, tremor-induced irregularities, and reduced pen pressure. These motor impairments can be quantified through both offline (static image-based) and online (dynamic, signal-based) handwriting data.

With the advancement of artificial intelligence (AI), machine learning (ML), and deep learning (DL), researchers have developed automated systems that analyze handwriting patterns to assist in early PD detection. These models can identify subtle variations in spatial, temporal, and kinematic features that may not be apparent to clinicians.

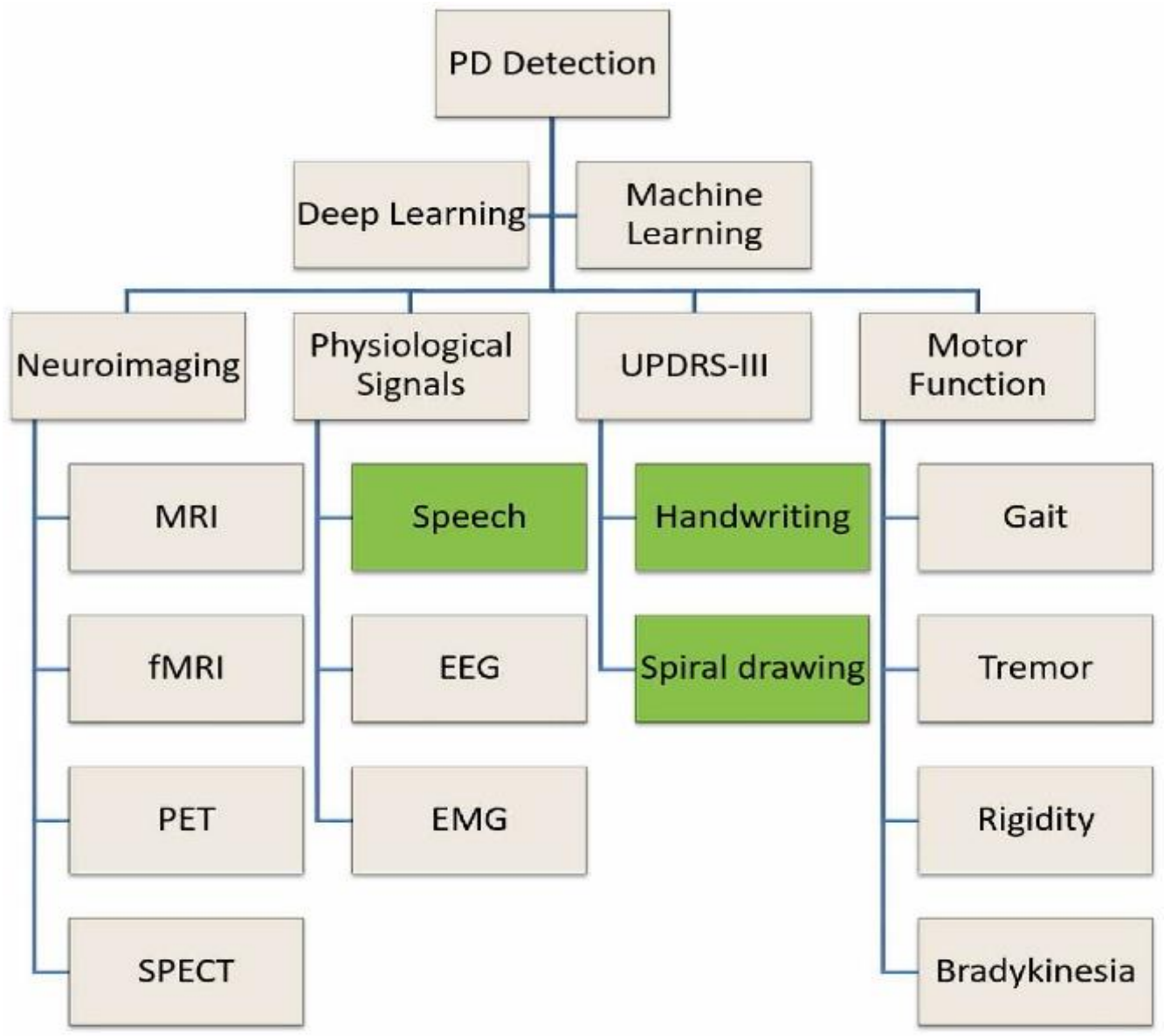

Fig. I.2 PD Detection Techniques

This literature survey seeks to bring together and analyze recent research focused on detecting Parkinson's disease using handwriting patterns. It investigates the processes followed for data gathering, preprocessing, feature selection, and classification. The review also compares machine learning and deep learning models—including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and combined approaches—and evaluates their effectiveness across multiple datasets. Additionally, it examines the influence of transfer learning, data augmentation, and explainable artificial intelligence in improving model precision and

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VII July 2025

interpretability. By outlining the advantages, drawbacks, and unresolved issues in current techniques, this review offers guidance for designing scalable, explainable, and clinically applicable tools for Parkinson's diagnosis.

RELATED WORK

The exploration of handwriting as a biomarker for Parkinson's disease (PD) has significantly advanced, transitioning from traditional machine learning (ML) methods to more sophisticated deep learning (DL) architectures. Early research efforts primarily employed manual feature engineering approaches. Features such as pen pressure, stroke velocity, acceleration, and jerk were extracted from dynamic handwriting sequences and used with classical classifiers like Support Vector Machines (SVM), Random Forest (RF), AdaBoost, and K-Nearest Neighbors (KNN). Although these approaches are fundamental, they typically lack objectivity, rely heavily on domain knowledge, and often fail to generalize well across different datasets.

The emergence of Convolutional Neural Networks (CNNs) marked a paradigm shift, enabling automatic feature learning from raw static images of handwriting. Researchers began converting temporal handwriting signals into spiral, wave, or meander patterns to leverage CNN-based models. Notably, Ranade et al. applied VGG-19 with fine-tuning strategies, achieving 88–94% accuracy on different spiral and wave datasets. Santhosh et al. introduced SpiralDrawNet, a CNN-based architecture applied to spiral drawings, achieving a validation accuracy of 84.6%.

Performance on small datasets has been notably improved through the use of transfer learning approaches. Saravanan et al. proposed a VGG19-Inception hybrid model achieving 98.45% accuracy while integrating LIME for explainable AI (XAI). Huang et al. extensively tested VGG, ResNet, and ViT models using AugMix and PixMix augmentations, reporting up to 96.67% accuracy on spiral and wave drawings. Wachiracharownong et al. compared pretrained networks like EfficientNetB0, InceptionV3, and ResNet50 on spiral drawings, confirming EfficientNetB0's superior performance at 89% accuracy.

For dynamic handwriting analysis, where pen movement, timing, and pressure are recorded, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have proven effective. Wang et al. introduced a lightweight LSTM-CNN hybrid with just 0.084M parameters, achieving 96.2% accuracy on the DraWritePD dataset while maintaining real-time inference efficiency. Allebawi et al. combined BLSTM with beta-elliptical feature extraction and fuzzy perceptual detectors, demonstrating over 93% accuracy across multiple datasets. Diaz et al. and Kasab et al. also contributed with Convolutional Autoencoders and GRU-based systems targeting sequential handwriting features.

Explainability, a growing concern in clinical AI, is addressed in several works. LIME was employed by Saravanan et al. and others to improve model interpretability and facilitate clinician trust. Additionally, Bhat and Szczuko analysed the impact of preprocessing techniques like Canny edge detection, revealing it could reduce model performance—underscoring the need for thoughtful pipeline design.

Collectively, this body of work demonstrates the efficacy of deep neural models, augmented by transfer learning, data augmentation, and interpretability techniques, in detecting early PD symptoms from handwriting. However, the limited size and diversity of available datasets remain a constraint. These insights lay the groundwork for future multi-modal, explainable, and deployable PD diagnostic tools.

METHODOLOGY

Identifying Parkinson's disease (PD) using handwriting relies on a systematic workflow that includes data collection, preprocessing, feature extraction, selecting and training models, and interpreting results. The specific methods vary among studies depending on the nature of the data (online or offline), the chosen architecture (conventional ML or deep learning), and the intended purpose—such as classification, predicting severity, or enabling real-time use.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VII July 2025

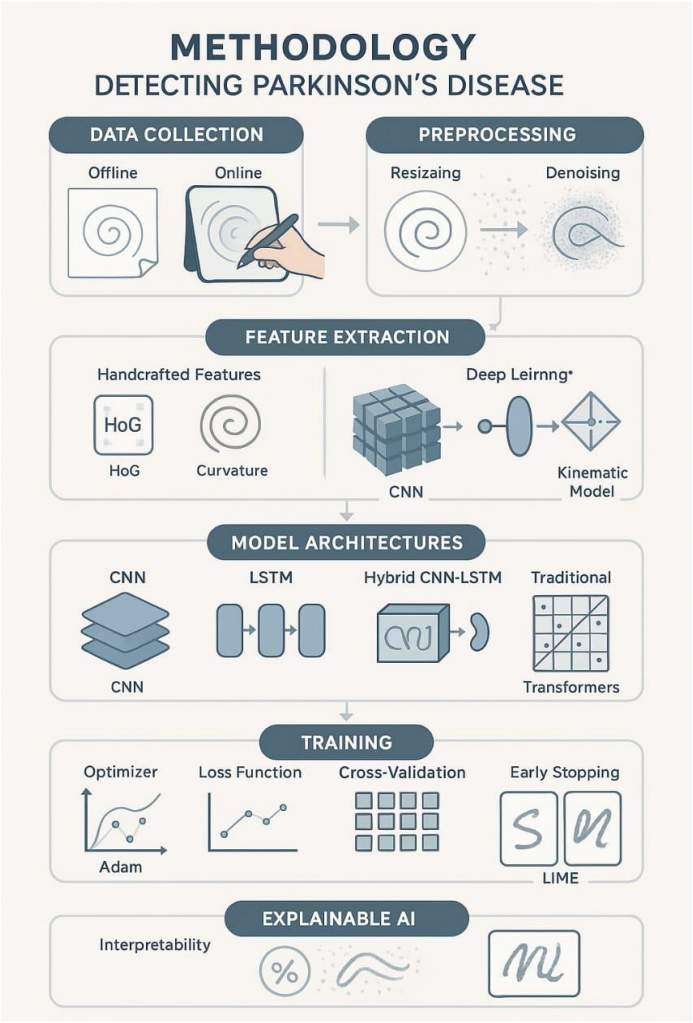

Fig. III. Methodology Pipeline for Parkinson's Disease Detection via Handwriting Analysis

Experimental Setup

The experimental procedures referenced in the reviewed studies were typically executed on computational environments equipped with high-performance configurations. A standard setup includes an Intel Core i7 CPU, 16GB of RAM, and an NVIDIA GTX 1080Ti GPU, enabling efficient training of deep learning models. The development platforms primarily involved Python 3.8, utilizing popular machine learning libraries such as TensorFlow, Keras, and scikit-learn. Execution was carried out using Jupyter Notebook on a Windows 10 operating system. To enhance computational speed**,** CUDA and cuDNN were employed for GPU-accelerated operations, which is essential for training deep neural networks on large handwriting datasets.

Data Collection and Sources

Data is sourced in two primary forms:

- Datasets like NIATS and the Kaggle Parkinson's Drawings consist of scanned static spiral and wave drawings created manually by participants.
- Online datasets like PaHaW, DraWritePD, and NewHandPD, which collect time-series signals (x-y coordinates, timestamp, pressure, azimuth, and altitude) using digitising tablets or smart pens.

These datasets capture both motor impairments and temporal variations indicative of PD symptoms.

Benchmark Datasets

The literature references both offline and online benchmark datasets specifically designed for Parkinson's disease detection through handwriting analysis. Offline datasets generally comprise scanned images of spiral or wave

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VII July 2025

drawings collected from diagnosed individuals, available through public repositories like Kaggle or NIATS. In contrast, online datasets—such as PaHaW, NewHandPD, and DraWritePD—contain temporal handwriting data recorded via digital tablets or smart pens. These datasets include variables such as spatial coordinates (X, Y), pen pressure, speed, and timestamp sequences.

Each dataset is annotated with binary labels distinguishing Parkinson's patients from healthy control participants. These publicly accessible datasets have been widely adopted as standard benchmarks, enabling consistent evaluation and comparison across different experimental frameworks. Their inclusion supports the reproducibility and generalizability of model performance metrics, thus validating the diagnostic effectiveness of the proposed methodologies.

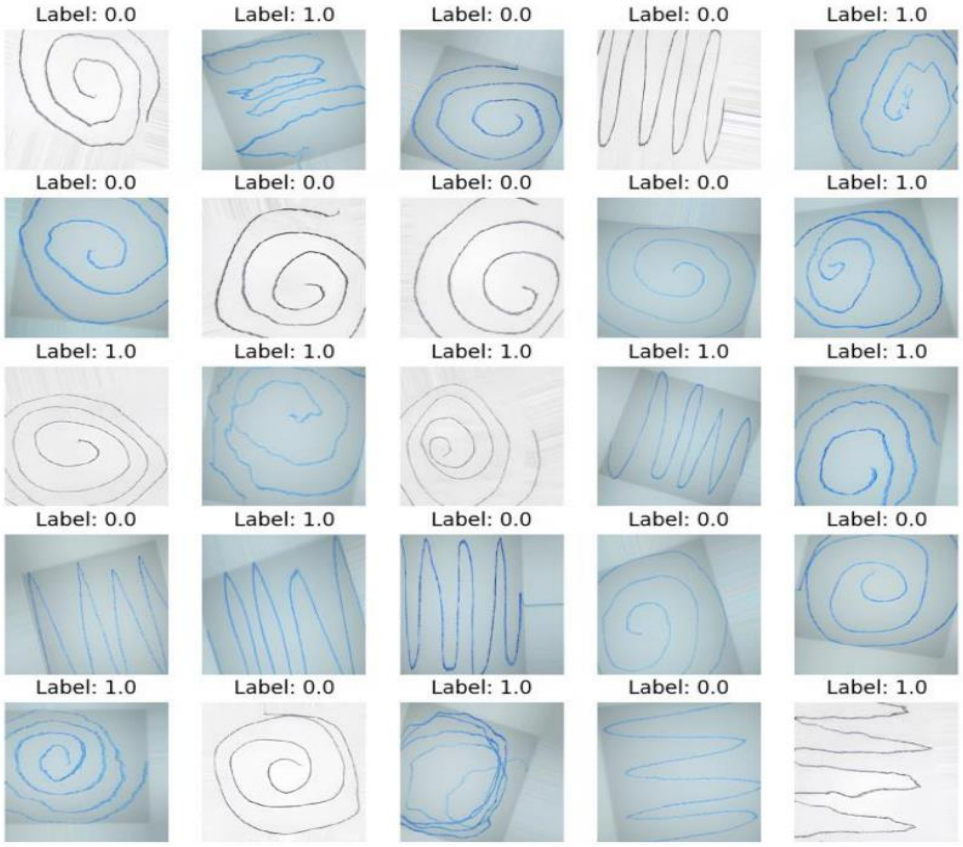

Fig. 3.1.1 Spiral and wave samples from healthy and PD subjects

Preprocessing and Augmentation

Preprocessing standardises data to improve model performance:

- Resizing (e.g., to 128×128 or 224×224),
- Grayscale conversion (removing color artifacts),
- Normalisation (0–1 pixel scaling or Min-Max for signals),
- Filtering (e.g., Chebyshev type II for denoising),
- Forward difference operations and velocity/acceleration derivation enhance motion pattern analysis for online data.

Data augmentation methods help to overcome limited dataset sizes and enhance the model’s ability to generalize.

- Basic techniques include rotation, flipping, shifting, and zooming.
- Advanced methods like AugMix and PixMix probabilistically combine transformed samples to enhance diversity.
- Online-specific augmentations involve manipulating writing angle, magnitude ratio, and baseline inclination to simulate motor variability.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VII July 2025

Feature Extraction

Feature engineering follows two major approaches:

- Handcrafted features (mainly in ML-based methods): Statistical attributes (mean, RMS, skewness), Histogram of Oriented Gradients (HoG), and curvature-based indicators are extracted from static drawings.
- Model-derived features (in DL-based methods): CNNs automatically learn spatial hierarchies; for sequential data, techniques such as the Beta-elliptical model (combining geometric and kinematic analysis) and fuzzy perceptual detectors effectively characterise motor dynamics.

Model Architectures

A variety of models are employed:

- Convolutional Neural Networks (CNNs) like VGG16/19, ResNet (18/50/101), EfficientNet, and SpiralDrawNet process image data.
- Recurrent architectures (RNNs, LSTM, BiGRU, BLSTM) handle temporal sequences in dynamic handwriting.
- Hybrid models, such as LSTM-CNN, merge spatial and temporal features, achieving superior accuracy with reduced complexity.
- Autoencoders (CAE) are utilised for unsupervised dimensionality reduction, followed by classification layers.
- Vision Transformers (ViT) segment drawings into patches for global attention-based learning.
- Traditional ML classifiers (e.g., RF, SVM, Adaboost, XGBoost) serve as baselines or in ensemble frameworks.

Transfer learning—especially with pre-trained models from ImageNet—remains critical in low-data scenarios, with some studies performing “multi-stage fine-tuning” (e.g., VGG19 on MNIST before PD-specific tasks).

Training and Optimisation

Training configurations vary:

- Loss functions include Binary Cross-Entropy (for classification) and MSE (for reconstruction tasks).
- Optimisers: Adam and RMSprop dominate, often used with Cosine Annealing Schedulers for dynamic learning rates.
- Validation strategies: K-fold stratified cross-validation (typically 5- or 10-fold) ensures performance robustness.

Batch sizes range from 32 to 128, and early stopping is applied to mitigate overfitting.

Explainable AI (XAI)

To foster interpretability, LIME (Local Interpretable

Model-agnostic Explanations) is applied. It highlights superpixels or data segments influencing decisions, enhancing clinical trust in the diagnostic outcome. This step is crucial to overcome the "black box" limitation of DL models and supports regulatory transparency in medical applications.

EXPERIMENTAL RESULTS

Experimental assessments are essential in measuring the diagnostic capabilities of both machine learning (ML) and deep learning (DL) approaches applied to handwriting-based Parkinson’s disease (PD) identification. This section provides a comparative synthesis of empirical findings from recent studies involving both offline (static) and online (dynamic) handwriting data sources.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VII July 2025

The evaluated models range from traditional supervised algorithms to sophisticated deep learning frameworks, including CNNs, RNNs, LSTMs, and integrated CNN-LSTM architectures. Many recent investigations employed transfer learning by fine-tuning pretrained architectures such as VGG19, ResNet, and EfficientNet to improve performance on Parkinson-specific datasets with limited samples.

These models are typically evaluated using common performance metrics, including classification accuracy, validation accuracy, and the Area Under the ROC Curve (AUC). Researchers further examined how advanced augmentation methods (such as AugMix and PixMix), optimization algorithms, and adaptive learning rate strategies like cosine annealing influence the model performance. Evaluation protocols like k-fold cross-validation were also used in several studies to ensure robustness and generalizability of results.

Furthermore, the reported outcomes reflect not only model architecture but also training conditions, dataset characteristics, and preprocessing strategies, all of which collectively contribute to the observed variances in diagnostic accuracy. Cross-dataset evaluations—including those on PaHaW, DraWritePD, NewHandPD, and Kaggle spiral drawing sets—demonstrate that diagnostic accuracy is influenced by both the format and complexity of the input data, especially when distinguishing early-stage PD from control samples.

To strengthen reproducibility, several studies documented experimental configurations including hardware setups, software frameworks, and training epochs. In addition, explainability tools such as LIME were integrated to interpret classification decisions, which is vital for clinical applicability.

Table I offers a consolidated presentation of findings from ten pivotal studies focusing on PD detection through handwriting. It outlines key details such as the year, contributing authors, applied methodologies, and the performance outcomes of each approach. This table enables quick comparison across methods and highlights promising directions for future research. By bridging algorithmic advancements with dataset-driven evaluations, the section aims to facilitate the identification of reliable diagnostic pipelines suitable for real-world deployment.

TABLE I

Year	Author(s)	Model / Method Used	Accuracy / AUC
2023	A. Malathi et al.	Adam – EfficientNet	98.3%
		CNN-BLSTM	89.4%
		BiGRU	93.3%
		Optimum-path forest + K-means	98%
		EfficientNetB3	99.03%
		CNN, SVC, KNN, EML, RFC	91%
2023	M. Kasab et al.	CAE + supervised classifier	73.83% (val), 60% (overall)
2023	S. Saravanan et al.	VGG19 + GoogleNet Hybrid	98.45%
		ResNet-50 + diff. learning rates	98.3%
2023	Wachiracharownong et al.	InceptionV3 (pretrained CNN)	82%
		EfficientNetB0 (pretrained CNN)	89%
		VGG16 (pretrained CNN)	72%
		ResNet50 (pretrained CNN)	61%
2023	Atharva Ranade et al.	VGG-19 (Set-1, fine-tuned)	88%
		VGG-19 (Set-2, fine-tuned)	89%
2023	X. Wanga et al.	LSTM-CNN on DraWritePD	96.2%
		LSTM-CNN on PaHaW	90.7%
2023	Thakur et al.	Restricted Boltzmann Machine	95.32%
2024	Dr. Santhosh S et al.	SpiralDrawNet (CNN)	84.6% (val)
2024	Yingcong Huang et al.	VGG19 + CosineAnneal	96.67%
		VGG19 (Wave, aug.)	96.67%
		VGG19 (Spiral, aug.)	90%
		ResNet18 (aug. wave)	92.67%
		ResNet50 (aug. wave)	87.33%

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VII July 2025

		ResNet101 (aug. wave)	94%
		ViT (PixMix, spiral)	86.67%
2024	M.F. Allebawi et al.	BLSTM + ellipse detector	93.33%
2025	Sameer Bhat et al.	DT + AdB on DS0	AUC 0.92
		RF, XGB, SVM on DS2	AUC 0.97
		KNN on DS2	92%
		KNN on DS1	82%

DISCUSSION

The application of artificial intelligence (AI) in neurodegenerative disease diagnostics has opened new avenues for early-stage identification of Parkinson's disease (PD). This discussion distills key observations from reviewed literature focused on the analysis of handwriting to detect PD symptoms using machine learning (ML) and deep learning (DL) algorithms. It provides insight into data types, modeling techniques, performance metrics, and the current challenges that influence the deployment of these systems in practical settings.

Handwriting Input Types and Their Implications

The structure and modality of handwriting datasets—whether static or dynamic—play a decisive role in determining the choice of models and the granularity of captured features. Static data typically includes scanned images of hand-drawn spirals or waveforms. These are compatible with visual processing networks, primarily convolutional neural networks (CNNs). However, such datasets do not capture the temporal dynamics like stroke velocity or pressure variations, which are vital indicators of motor dysfunction in PD.

Dynamic or online datasets, collected using digital tablets or smart pens, provide time-stamped records of motion including pen trajectory, speed, tilt, and pressure. These richer datasets are better suited for time-sequence models such as Long Short-Term Memory (LSTM) networks or Gated Recurrent Units (GRUs). As a result, online handwriting enables a more nuanced interpretation of motion-related anomalies, leading to improved model accuracy in real-time symptom tracking.

Modeling Approaches and Evaluation

Convolutional models have dominated image-based handwriting analysis due to their strength in identifying spatial hierarchies. Pretrained CNN architectures, including VGG19, ResNet-50, and EfficientNetB3, achieved classification accuracies well above 95%, with some approaching 99%, especially when data augmentation and transfer learning were applied. The use of hybrid models, combining CNNs with LSTM layers, was particularly effective in processing dynamic handwriting signals by capturing both spatial and temporal aspects. One such example is a low-resource CNN-LSTM model that attained 96.2% accuracy on the DraWritePD dataset and 90.7% on PaHaW, while consuming minimal computation, proving its suitability for embedded systems.

In contrast, some studies utilized autoencoder-based architectures, such as convolutional autoencoders (CAEs), which, while useful for unsupervised feature learning, faced issues of overfitting. These findings suggest that careful architecture design, regularization methods like dropout or batch normalization, and model complexity control are necessary to maintain generalizability.

Preprocessing Techniques and Augmentations

Preprocessing and augmentation strategies significantly affect model robustness. Standard techniques such as resizing, rotation, and contrast normalization were frequently employed to make models invariant to writing variations. More advanced techniques like PixMix and AugMix allowed for blending of multiple augmentations to introduce statistical variability while preserving label consistency.

For temporal handwriting data, augmentations such as random noise injection in stroke trajectory, speed warping, and pressure scaling helped mimic natural variability observed among PD patients. On the other hand, some

image-processing techniques, like Canny edge detection, degraded model performance by eliminating subtle stroke deformations that carry diagnostic value, as evidenced in certain comparative studies.

Feature Representation and Explainability

Deep models, by contrast, learned representations directly from raw inputs. In CNNs, early layers captured edge-like features, while deeper layers identified complex textures and structural anomalies. In online handwriting analysis, Beta-elliptical curve fitting and fuzzy perceptual modeling were used to quantify curvature and irregularity patterns in handwriting loops and arcs, offering robust descriptors of neuromotor dysfunction.

Interpretability remains crucial in medical applications. Tools like Local Interpretable Model-Agnostic Explanations (LIME) have been integrated to visualize which handwriting regions most influenced classification outcomes. These tools promote clinical transparency and facilitate trust in AI-generated decisions.

Practical Challenges in Clinical Settings

Although model performance has significantly improved, various real-world barriers still hinder implementation. Many systems demonstrate high sensitivity for early PD stages but show limited effectiveness in detecting advanced conditions or differentiating PD from other motor disorders. This limits their diagnostic scope.

Furthermore, sophisticated models such as ResNet101 and Vision Transformers (ViTs) demand large memory and computational resources, which pose a barrier to deployment in mobile or low-resource environments. Lightweight models, although more efficient, may compromise on accuracy if not optimized carefully.

Dataset limitations are another concern. Most studies rely on relatively small, demographically narrow datasets, often sourced from single institutions. This lack of diversity may introduce bias and restrict generalizability across populations with different linguistic and cultural handwriting characteristics.

Toward Generalization and Future Integration

The absence of rigorous cross-dataset validation is a recurring limitation. While many models perform well within their training sets, they struggle to maintain accuracy on external datasets due to differences in data acquisition tools and protocols. This highlights the importance of building large-scale, standardized benchmark datasets with diverse demographic representation and handwriting conditions.

Another promising direction lies in the fusion of handwriting with other modalities such as speech analysis, gait assessment, or neuroimaging. This multi-modal integration could enhance sensitivity to both motor and non-motor symptoms, offering a more holistic assessment of PD.

Longitudinal analysis—tracking handwriting over time—could further assist in understanding disease progression and the impact of therapeutic interventions. Additionally, models that adapt to variations in symptom expression and severity grading will be essential for personalized care and continuous monitoring.

CONCLUSION

Using Machine Learning (ML) and Deep Learning (DL) to analyze handwriting and sketches has demonstrated strong potential for early identification of Parkinson's Disease (PD). Multiple studies highlight that both traditional ML and advanced DL models are effective in identifying motor symptoms caused by PD, while also exposing critical limitations and offering valuable guidance for future research.

Summary of Key Findings

The reviewed studies demonstrated high diagnostic performance and computational efficiency across multiple modeling approaches:

- The VGG19-INC hybrid model achieved a peak classification accuracy of 98.45%, demonstrating the effectiveness of transfer learning combined with data augmentation and scheduling techniques.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VII July 2025

- ResNet-50 exhibited similarly strong results with an accuracy of 98.3%, confirming the robustness of residual learning architectures.
- A compact LSTM-CNN framework achieved an accuracy of 96.2% on DraWritePD and 90.7% on PaHaW, while maintaining low computational demand (0.084M parameters, 0.59M FLOPs), making it well-suited for deployment in real-time clinical environments.
- In the case of Arabic handwriting tasks, the model achieved 93.33% accuracy in ellipse tracing, outperforming conventional methods in motor control-sensitive tasks.
- Spiral drawings consistently provided higher predictive value than wave or meander patterns across datasets.
- The application of mediator datasets, such as MNIST for pretraining, significantly improved fine-tuning results on smaller PD datasets.
- Explainable AI (XAI) tools like LIME played a vital role in enhancing model interpretability, identifying critical regions in handwriting patterns that influenced classification outcomes.
- Random Forest (RF) maintained a consistent memory footprint (61 KB), whereas complex models like SVM and KNN exhibited increased memory and computational demands with larger datasets.

Identified Limitations

Despite promising advancements, several challenges persist:

- **Data Limitations:** The small size of publicly available handwriting datasets limits model generalization and increases the risk of overfitting. In some cases, augmenting the data led to only marginal improvements.
- **Overfitting Concerns:** Deep models like CAE and VGG19 showed signs of overfitting, with low training loss but significantly higher validation loss, highlighting the importance of regularization and architectural tuning.
- **Preprocessing Pitfalls:** Contrary to expectations, Canny edge detection with Hessian filtering consistently degraded model accuracy, raising questions about universally applied preprocessing pipelines.
- **Symptom Variability:** The reliance on handwriting alone may not capture the full spectrum of PD symptoms, especially non-motor symptoms and late-stage variations. Additionally, symptom overlap with other conditions complicates differentiation.
- **Stage Sensitivity:** Several models demonstrate improved performance in detecting early Parkinson's cases (Hoehn and Yahr stages 1–2) or differentiating them from healthy subjects, but show reduced effectiveness when applied to later disease stages.
- **Bias-Variance Trade-off:** Balancing generalization and complexity remains a key challenge, especially when working with augmented or noisy datasets.

Scope for Future Work

To overcome these limitations and enhance the clinical utility of AI-based PD detection systems, future work should focus on the following areas:

Model Optimization

- Incorporate regularization methods (e.g., dropout, L1/L2) to reduce overfitting.
- Explore hybrid architectures, such as combining Autoencoders with Transformers or attention mechanisms.
- Improve fine-tuning strategies and leverage multi-step transfer learning for better adaptation to domain-specific data.
- Investigate emerging theoretical approaches, including Hamilton-Jacobi-Bellman (HJB)-based optimization.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VII July 2025

Data and Feature Expansion

- Develop or integrate larger, more diverse datasets that represent various languages, age groups, and PD stages.
- Future tools should integrate handwriting data with other sources such as gait analysis, speech signals, or MRI scans to form a more comprehensive diagnostic system.
- Examine the impact of higher feature counts on memory usage and inference speed.

Clinical Implementation

- Develop real-time mobile or web-based platforms that can be easily deployed within standard clinical routines.
- Conduct longitudinal studies to monitor handwriting changes over time, improving disease staging and progression modeling.
- Ensure scalability and cross-cultural validation across diverse populations.

Advanced Evaluation

- Analyze model behavior through bias-variance trade-offs, prediction calibration, and per-patient longitudinal analysis.
- Reassess preprocessing assumptions by exploring why certain filters degrade performance, guiding better feature preservation methods.

By addressing these gaps, the next generation of AI-driven diagnostic tools can move closer to real-world deployment, enhancing early detection capabilities and ultimately improving patient outcomes in Parkinson's Disease care.

REFERENCES

1. A. Malhotra, R. Ramalakshmi, and V. Gandhi, "Detection of Parkinson disease for handwriting dataset using deep learning algorithms," Proc. 3rd Int. Conf. Adv. Comput. Innov. Technol. Eng. (ICACITE), pp. 1595–1598, 2023.
2. M. Kasab, N. Al Masri, and R. Al Moghrabi, "Detection of Parkinson's disease through spiral drawings using convolutional autoencoders," Proc. 3rd Int. Conf. Adv. Comput. Innov. Technol. Eng. (ICACITE), pp. 1695–1701, 2023.
3. S. Saravanan, K. Ramkumar, K. Narasimhan, S. Vairavasundaram, K. Kotecha, and A. Abraham, "Explainable artificial intelligence (EXAI) models for early prediction of Parkinson's disease based on spiral and wave drawings," IEEE Access, vol. 11, pp. 68366–68378, Jul. 2023.
4. A. Wachiracharownong, P. Sri-iesaranusorn, D. Surangsrirat, P. Leelaprute, P. Panyakaew, and Bhidayasiri, "Parkinson's disease classification from scanned images of spiral drawings," unpublished.
5. A. Ranade, J. Sisodia, S. Sawant, D. Kalbande, and R. Sodha, "Parkinson's disease diagnosis using deep convolutional neural networks," Proc. IEEE Int. Conf. Contemp. Comput. Commun. (InC4), pp. 116–146, 2023.
6. Y. Huang, K. Chaturvedi, A.-A. Nayan, M. H. Hesamian, A. Braytee, and M. Prasad, "Early Parkinson's disease diagnosis through hand-drawn spiral and wave analysis using deep learning techniques," Information, vol. 15, no. 4, pp. 220, Apr. 2024.
7. M. F. Allebawi et al., "Parkinson's disease detection from online handwriting based on beta-elliptical approach and fuzzy perceptual detector," IEEE Access, vol. 12, Apr. 2024.
8. X. Wang, J. Huang, S. Nõmm, M. Chatzakou, K. Medijainen, A. Toomela, and M. Ruzhansky, "LSTM-CNN: An efficient diagnostic network for Parkinson's disease utilizing dynamic handwriting analysis," submitted for publication, Nov. 2023.
9. S. Bhat and P. Szczuko, "Impact of canny edge detection preprocessing on performance of machine learning models for Parkinson's disease classification," Springer Nature, accepted for publication, Apr. 2025.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VII July 2025

10. S. Santhosh, K. J. Poojitha, S. C. M, K. S. Shetty, M. Navyasree, and M. Dwivedi, “SpiralDrawNet: CNN-driven early detection of Parkinson's disease using spiral drawings for accessible healthcare solution,” Proc. 3rd Int. Conf. Adv. Comput. Innov. Technol. Eng. (ICACITE), 2023.
11. M. A. Islam, “A review of machine learning and deep learning algorithms for Parkinson’s disease diagnosis using voice, handwriting, and wave spiral datasets,” Heliyon, vol. 10, no. 3, art. e04517, Mar. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405844024015007.
12. Northwestern Medicine, “Parkinson’s Disease Signs and Symptoms [infographic],” HealthBeat, Northwestern Medicine, Jan. 2020. [Online]. Available: https://images.app.goo.gl/5W4ed5W3aQWXnrR8A.