Hybrid Approach for Parkinson's Disease Detection: Integrating Handcrafted and Deep Features from Handwriting Analysis Using a Voting Classifier

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***Abstract*—Parkinson's disease (PD) is a chronic and progressive neurodegenerative disorder that severely impacts motor functions, including handwriting. Early and precise detection is essential for timely intervention and effective treatment. In this paper, we propose a novel hybrid approach that integrates handcrafted and deep learning-based (DL) features extracted from handwriting samples. By leveraging both feature types, our method provides a more comprehensive analysis, enhancing the accuracy and robustness of PD detection. Indeed, Handcrafted features provide explicit, interpretable descriptors that capture domain-specific patterns while DL features encode high-level abstract representations. We first extracted DL features using a fine-tuned transfer learning model based on ResNet50 and combined them with a set of handcrafted features. Similarly, DL features were obtained using a second fine-tuned transfer learning model based on MobileNetV2, and the derived features were integrated with the same handcrafted feature set for further analysis. Afterward, a feature selection step is performed.The conducted experiments exploiting a voting classifier, demonstrates that the proposed hybrid approach achieve promising results reaching an accuracy of 91.51%.**

***Index Terms*—Parkinson disease, hybrid approach, handcrafted features, Deep features**

I. INTRODUCTION

PD is a neurodegenerative disorder characterized by both motor and non-motor symptoms [1]. The four primary motor symptoms, most noticeable in individuals, include: tremors in the hands, arms, legs, jaw, or head; stiffness in the limbs and trunk; slowness of movement; and balance problems, which can lead to falls [2]. In addition, non-motor symptoms, such as depression, anxiety, sleep disorders, and cognitive impairment, can significantly impact a patient's emotional health and daily activities [2]. Therefore, there is growing interest in developing methods for the early detection of PD, as early treatment appears to slow its progression. Moreover, recent treatments have proven effective but largely limited to patients of younger age [3].

Both slowness and rigidity in movement often occur in the early stages of PD which significantly affects the handwriting and sketching abilities. Thus, micrographia is used as an early diagnostic tool for PD detection. While handwriting is influenced by factors such as language proficiency and education, sketching shapes like spirals and waves offers a reliable, non-invasive measure for PD detection [4].

Traditional handwriting-based approaches are highly based on clinical assessment and manual scoring, making them limited in scalability.

Recent advances in artificial intelligence and machine learning (ML) have effectively addressed this limitation by enabling the automated extraction of meaningful features from handwriting samples. Conventional ML-based methods rely on handcrafted features such as contrast, correlation, and energy to analyze handwriting abnormalities. These features offer interpretability and computational efficiency, making them particularly useful for small datasets. However, their limited ability to generalize across diverse handwriting variations restricts their effectiveness. Recently, DL has emerged as a powerful approach for PD detection, capable of automatically extracting discriminative, high-level features. These deep features effectively capture complex handwriting abnormalities, improving classification accuracy and enhancing generalization across different disease stages. However, DL models particularly with small datasets, can cause overfitting, which make them struggle to generalize to new unseen data.

To tackle the challenges discussed previously, this research aims to make significant contributions, which can be summarized as follows:

- Combination of Handcrafted and DL Features: We integrate handcrafted features, which capture critical statistical and structural aspects of handwriting images, with DL features obtained through transfer learning using respectively ResNet50 and MobileNetV2. This fusion optimizes the strengths of both methods, enhancing classification accuracy and generalization across various stages of PD.
- Feature Refinement: The generated feature vector is refined by assessing the statistical relevance of each feature, ensuring that only the most impactful information

influences the classification, leading to improved model precision and efficiency.
- Voting Classifier for Improved Performance: We apply a voting classifier to combine predictions from multiple models, further enhancing classification accuracy, robustness, and overall performance in detecting PD.

The rest of the article is organized as follows: Section II reviews prior research in PD detection through handwriting analysis. Section III outlines the suggested approach. Section IV provides an overview of the experimental setup, presents the results, and discusses the insights drawn from the experimental findings. Finally, Section V provides concluding remarks and discusses potential future directions.

II. RELATED WORK

Advancements in ML have significantly improved PD detection. Recent studies have explored various techniques, including hybrid approaches and transfer learning, to enhance diagnostic accuracy.

A. PD detection using hybrid based approaches

Hybrid-based methods for PD detection [5] [14] [9] combine conventional features with DNN classification to enhance accuracy. For example, [5] demonstrated the integration of Histogram of Oriented Gradients (HOG) with Convolutional Neural Networks (CNN), achieving an accuracy of 86.67%. Similarly, [9] combined HOG features with CNN and LSTM, resulting in an accuracy of 83.81%. In another approach, [14] proposed the fusion of synthetic features with both CNN and LSTM, reaching an accuracy of 87.66%. An overview of hybrid-Based PD detection techniques is summarized int the table I.

TABLE I
SUMMARY OF HYBRID-BASED PD DETECTION METHODS

References	Year	Method	Dataset (spiral images)	Performance
[5]	2025	HOG + CNN	data were gathered from the study by Zham et al. [6]	86.67%
[14]	2024	sythetic feature + CNN + LSTM	spiral dataset	87.66%
[9]	2023	HOG + CNN + LSTM	PD-WAVE DATASET	83.31%

These studies highlight the effectiveness of hybrid models in improving PD detection by capturing both spatial and temporal features. However, these models require significant computational resources, which may hinder real-time use. Moreover, the complexity of hybrid models increases the risk of overfitting, and their performance depends on the quality and size of the training data, making them less reliable with limited or biased datasets.

B. PD detection using Transfer learning

Using transfer learning is an effective approach to reduce overfitting, especially when working with limited training data. This section will examine different PD detection methods that leverage transfer learning. In [10], the study investigated the use of the pre-trained VGG19 model as a feature extractor for PD detection. To enhance model performance, additional layers, including a Spatial Attention Layer, were incorporated, allowing the model to focus more effectively on relevant features. The softmax function was applied to enable more nuanced decision-making. Similarly, in [11], the authors employed the InceptionV3 model for efficient PD detection. A final dense output layer comprising two neurons with softmax activation is employed for binary classification between healthy individuals and PD patients. In [13], the authors proposed the use of DenseNet201 for feature extraction, followed by a random forest classifier to perform PD detection. This combination leveraged the strengths of transfer learning and traditional machine learning techniques to improve accuracy and robustness in PD diagnosis. An overview of the mentioned hybrid-Based PD detection techniques is summarized in the table II.

TABLE II
SUMMARY OF TRANSFER LEARNING-BASED PD DETECTION METHODS

References	Year	Exploited model	Dataset (spiral images)	Performance
[10]	2024	VGG19	Data were gathered from the study by [6]	90%
[11]	2024	InceptionV3	Data was created by [22]	89%
[13]	2024	DenseNet201	Data were gathered from the study by [6]	86%

Transfer learning for PD detection provides key advantages, such as high accuracy, reduced training time, and the ability to work with smaller datasets. However, challenges include reliance on high-quality pre-trained models, the need for sufficient labeled data for fine-tuning, and the potential for overfitting.

III. PROPOSED APPROACH

We propose in this work, a PD detection framework integrating transfer learning with feature fusion. Our approach combines handcrafted features with deep features extracted using ResNet50 and MobileNetV2 respectively. The resulting features are then merged through a voting classifier to improve detection accuracy. This hybrid model balances high performance with computational efficiency, making it well-suited for real-world applications. Fig. 1 illustrates the proposed methodology.

A. Data Augmentation

Traditional image augmentation techniques remain highly relevant in computer vision, as they offer a straightforward and effective approach to expanding the size and diversity of datasets. Additionally, their ease of implementation and computational efficiency make them particularly advantageous for real-time applications. In this study, we applied a diverse set of transformation techniques, as outlined in Table III, to ensure the robustness and enhance the generalizability of our approach.

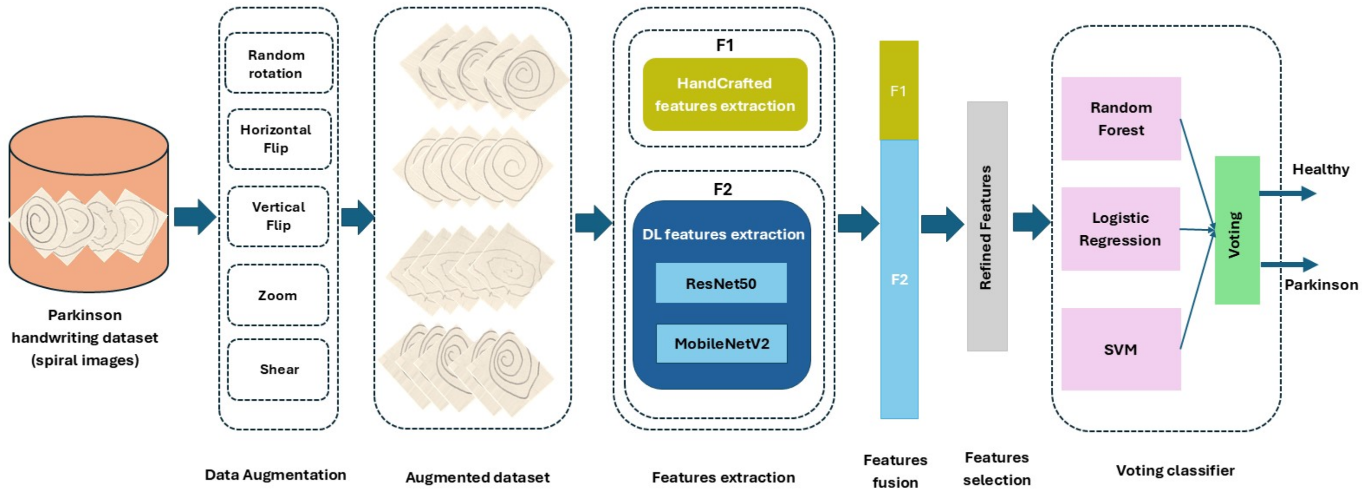

Fig. 1. Overview of the proposed approach.

TABLE III
APPLIED IMAGE AUGMENTATION TECHNIQUES AND THEIR PARAMETERS

Transformation	Value
Rotation range	±15° , ±20°
Width shift range	0.2
Height shift range	0.2
Shear range	0.1
Zoom range	0.2
Random Horizontal Flip	0.5
Random Vertical Flip	0.5

B. Feature extraction

1) Handcrafted feature extraction: Handcrafted features [7] rely on well-defined mathematical formulations, allowing clinicians to understand and validate the model's decision-making process, which is crucial for trust in medical applications [14]. Unlike DL models that require large datasets to avoid overfitting, handcrafted features enable precise extraction even with limited data, ensuring robustness and stability. In our approach, we extract seven handcrafted features from handwriting images storing them alongside their corresponding labels. These features are defined as follows:

- Contrast, which quantifies local intensity variations; correlation, which measures pixel interdependence; energy, assessing image uniformity and repetitive patterns.
- Homogeneity, evaluating the similarity of neighboring pixels.
- Mean intensity, calculating the average pixel intensity.
- Standard deviation, indicating intensity dispersion around the mean.
- Entropy, capturing the randomness in intensity distribution.

By integrating these handcrafted features with DL-based representations, our framework enhances accuracy while maintaining interpretability, making it highly suitable for PD detection.

2) Feature extraction based on DL models: DL models can automatically identify complex patterns and features that are difficult to capture through traditional methods [15]. Our approach harnesses the power of advanced neural networks like ResNet50 [16] and MobileNetV2 [17], which are highly effective at extracting relevant features. We use transfer learning with the selected pre-trained models (ResNet50 and MobileNetV2) for PD detection. This approach leverages knowledge from large datasets, eliminating the need to build a model from scratch, and is well-suited for environments with limited computational resources. Transfer learning accelerates training and ensures high performance, even with smaller PD-specific datasets.

3) ResNet50: is a deep residual network architecture that incorporates 50 layers to perform complex image classification tasks, such as detecting PD. It is based on a series of residual blocks, which allow the model to learn complex patterns by using skip connections to bypass certain layers. These skip connections help prevent the vanishing gradient problem in very deep networks, allowing the model to maintain efficient training.

To summarize, we select ResNet50 for transfer learning due to its deep residual architecture, which preserves feature integrity during training, and its pre-trained weights from large datasets, enabling effective feature extraction. By fine-tuning the model on handwriting PD data, we adapt it to detect PD-specific patterns while maintaining computational efficiency and high accuracy.

4) MobileNetV2: is a highly efficient DL architecture designed to offer a balance between performance and computational efficiency. It introduces the concept of inverted residuals, where depthwise separable convolutions are applied after expanding the input features using lightweight expansion layers. The linear bottleneck at the end of each block helps to reduce the number of parameters while retaining essential features. By utilizing depthwise separable convolutions, MobileNetV2 drastically reduces computational requirements without sacrificing feature extraction quality. This makes it ideal for tasks like Parkinson's disease detection, where both accuracy and computational efficiency are critical, especially in resource-constrained environments.

C. Feature fusion

Feature fusion [18] [19] plays a vital role in improving model accuracy and robustness by integrating diverse and complementary features into a unified representation. In our work, the integration of handcrafted and DL features into a unified vector enables the model to leverage both expert knowledge and automatically learned representations. Handcrafted features, derived from domain expertise, capture specific characteristics, while DL features learn complex patterns and high-level abstractions from the data. By combining these two types of features, the model benefits from a richer, more comprehensive feature set, improving its ability to make accurate predictions. This unified vector strengthens the model's performance, particularly in tasks like PD detection.

D. Feature selection

In our approach, we utilized Correlation-based Feature Selection (CFS) [21] to select relevant features, which rely solely on the inherent properties of the descriptors. This approach ensures the selection of the most relevant features, enhancing the model's efficiency and accuracy. CFS is a filter algorithm designed to rank feature subsets based on a heuristic evaluation function that leverages correlation metrics [20]. The algorithm prioritizes subsets where features exhibit strong correlations with the target class while maintaining low correlations with each other. Irrelevant features, which show weak correlations with the class, are disregarded. Similarly, redundant features, which are highly correlated with other features in the subset, are excluded. A feature is selected based on its ability to predict class labels in areas of the instance space not already covered by other features. The evaluation function for CFS is defined as: The Correlation-based Feature Selection (CFS) formula is defined as:

$$MS = \frac{k r_{cf}}{\sqrt{k + k(k-1) r_{ff}}} \tag{1}$$

Where:

- MS is the merit of the feature subset.
- k is the number of features in the subset.
- r_{cf} is the mean correlation between the features in the subset and the class.
- r_{ff} is the average correlation between the features within the subset.

CFS evaluates feature subsets by considering both their correlation with the target class (r_{cf}) and the redundancy among the features within the subset (r_{ff}). The objective is to identify feature subsets that are strongly correlated with the class while being less redundant among themselves. A higher MS value indicates a better feature subset in terms of both relevance and uniqueness.

E. Classification

Our method employs a Voting Classifier that integrates multiple ML models to improve classification accuracy and robustness. This ensemble method combines predictions from different classifiers, leveraging their individual strengths to make a more reliable final decision. We integrate three diverse models:

- Random Forest Classifier, which constructs multiple decision trees and selects the majority vote.
- Logistic Regression Classifier, a linear model that estimates class probabilities.
- Support Vector Machine (SVM), which finds the optimal hyperplane to segregate classes effectively.

By combining these models, the Voting Classifier improves predictive performance and generalization, making it particularly effective for PD detection. A Voting Classifier combines multiple models to make a final prediction. The decision can be based on either **hard voting** or **soft voting**.

Hard Voting: The final prediction is determined by the majority vote:

$$\hat{y} = \text{mode}\{\hat{y}_1, \hat{y}_2, ..., \hat{y}_n\} \tag{2}$$

where $\hat{y}_i$ is the prediction from classifier i, and mode represents the most frequently predicted class.

Soft Voting: The ultimate prediction relies on the averaged output probabilities of the models:

$$\hat{y} = \arg\max_c \sum_{i=1}^{n} w_i P_i(c) \tag{3}$$

where $P_i(c)$ is the predicted probability of class c from classifier i, and w_i is the weight assigned to each classifier.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

This section provides an overview of the conducted experiments. Besides, it presents the exploited database, followed by a discussion of the obtained results.

A. Conducted Experiments

In our experiments, we exploited the Spiral dataset, incorporating conventional data augmentation techniques, such as random rotation, normalization and flipping along both axes, to enhance generalization. The dataset was partitioned into 80% for training and 20% for testing, ensuring a robust evaluation framework. We implemented a Hybrid method that combines DL and handcrafted features, using ResNet50 and MobileNetV2 for DL feature extraction. The model was trained for 20 epochs using CrossEntropyLoss and Adam optimizer (lr=0.0005, weight decay=1e-4). In addition, early stopping was employed to improve training stability and mitigate overfitting.

Feature selection was performed to retain the most informative 150 features, reducing overfitting and improving computational efficiency. For classification, we employed a Voting Classifier, combining Random Forest, Logistic Regression, and SVM to leverage their complementary strengths. Hyperparameter tuning was conducted using GridSearchCV, while model evaluation was performed with StratifiedKFold (n_splits=5, shuffle=True, random_state=42) to ensure a reliable and unbiased assessment. Finally, the best-performing classifier was tested on the test set to determine its overall effectiveness in real-world scenarios.

B. Dataset description

The exploited dataset is developed by [22]. It was gathered from participants who were asked to draw spirals and waves on paper, which were then digitized. People with Parkinson's disease often produce irregular and shaky patterns, whereas healthy individuals tend to create smoother curves. The dataset contains 204 images, equally split into two categories: 102 spiral drawings and 102 wave drawings. Each image is labeled as either representing PD or Healthy. The images are divided into two sets: 72 for training and 30 for testing in each category. Fig. 2 illustrates a set of handwriting samples for from both healthy individuals and PD patients.

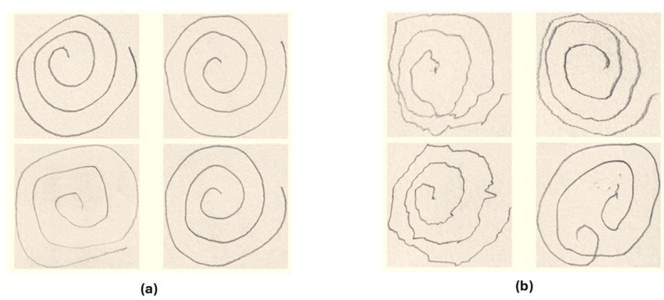

Fig. 2. Example of handwriting samples for : (a) healthy and (b) PD patients.

C. Result and discussion

This section is dedicated to compare the performance of MobileNetV2 and ResNet50 in PD detection using three key evaluation metrics: accuracy curves, confusion matrices, and loss curves. In Fig. 3 , MobileNetV2 misclassifies 24 instances of class 0 and only 4 instances of class 1, whereas ResNet50 improves classification for class 0 (reducing misclassifications to 18) but slightly increases errors in class 1 predictions (12 misclassified instances compared to 4 in MobileNetV2). This suggests that ResNet50 achieves a better balance between precision and recall.

In Fig. 4 MobileNetV2 reaches near-perfect training accuracy quickly, but its validation accuracy fluctuates slightely, suggesting potential instability in learning. In contrast, ResNet50 exhibits a more stable validation accuracy progression, indicating better generalization.

Fig. 5 illustrates loss curves, showing that MobileNetV2

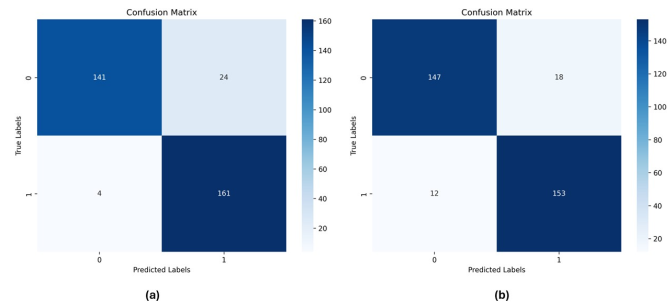

Fig. 3. Confusion matrices of the proposed hybrid model combining handcrafted features with: (a) MobileNetV2 , (b) ResNet50.

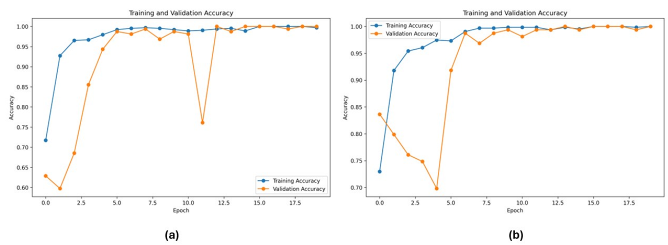

Fig. 4. Accuracy curves of the proposed hybrid model combining handcrafted features with: (a) MobileNetV2 , (b) ResNet50.

experiences multiple spikes in validation loss, reflecting unstable learning, while ResNet50 stabilizes more quickly and converges to a lower validation loss, indicating improved robustness.

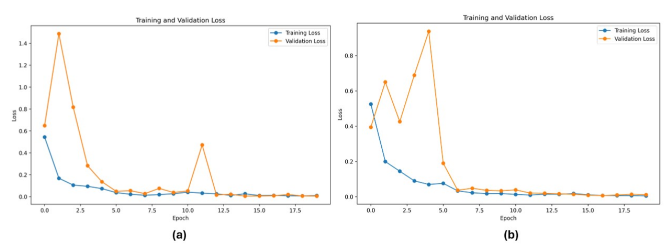

Fig. 5. Loss curves of the proposed hybrid model combining handcrafted features with: (a) MobileNetV2 , (b) ResNet50.

Both MobileNetV2 and ResNet50 combined with hand crafted features perform well in PD detection, but a detailed analysis of their accuracy curves, confusion matrices, and loss curves highlights ResNet50's superiority. ResNet50 outperforms MobileNetV2 by offering superior generalization, more stable learning dynamics, and a more balanced classification performance, making it perfect for real-world applications that demand reliability and consistency.

According to Table IV, our proposed hybrid approach achieves the highest accuracy, highlighting the advantage of integrating handcrafted features with deep characteristics. Notably, MobileNetV2 DL features combined with handcrafted features (91.51%) outperforms ResNet50 DL features integrated with handcrafted features (90.90%).

TABLE IV
ASSESMENT OF THE PROPOSED APPROACH'S PERFORMANCE COMPARED TO EXISTING STATE-OF-THE-ART EXISTING METHODS

Reference	Method	Accuracy
[5]	HOG + CNN	86.67%
[9]	HOG + CNN + LSTM	83.31%
[10]	VGG19	90%
[11]	InceptionV3	89%
[13]	DenseNet201	86%
[14]	sythetic feature + CNN + LSTM	87.66%
Proposed Hybrid Approach	**MobileNetv2 + handcrafted features**	**91.51%**
	ResNet50 + handcrafted features	**90.90%**

V. CONCLUSIONS

This paper introduces a robust hybrid framework for PD detection using handwriting analysis, combining handcrafted features with DL characteristics. The fusion of interpretable, domain-specific descriptors and abstract, high-level DL features enables a more comprehensive characterization of PD-related motor impairments. Leveraging a voting classifier, the proposed approach achieves a high classification accuracy of 91.51%, confirming its effectiveness. For future work, expanding the dataset to include more diverse subjects and handwriting conditions could improve generalizability.Additionaly, integrating additional modalities such as voice or gait data may further boost diagnostic performance.

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