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# Detection of Parkinson's Disease Through Handwriting using GLCM, HOG, and SVM

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## ABSTRACT

Parkinson's disease (PD) is a neurodegenerative disorder whose motor symptoms can affect handwriting characteristics, making handwriting images a potential source of information for computational screening. However, the performance of handcrafted features may vary according to the characteristics of handwriting patterns, and the complementary contribution of texture and structural information requires further investigation. This study aims to evaluate and compare Gray-Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradients (HOG), and their combination using Support Vector Machine (SVM) for classifying handwriting images from individuals with PD and healthy individuals. The NewHandPD dataset, comprising 594 images from 66 subjects, was divided into training and independent testing sets using a subject-level 80:20 split. Spiral, Meander, and Circle patterns were evaluated separately. Images were converted to grayscale, resized to 200 × 200 pixels, and normalized. GLCM and HOG features were extracted individually and jointly, while SVM kernel selection was conducted through five-fold Stratified Group Cross-Validation on the training data. The results showed pattern-dependent performance. For Spiral, GLCM+HOG+SVM achieved the highest accuracy of 98.2%, compared with 96.4% for HOG+SVM and 76.8% for GLCM+SVM. For Meander, GLCM+SVM and GLCM+HOG+SVM both achieved 85.7%, while HOG+SVM reached 82.1%. For Circle, HOG+SVM and GLCM+HOG+SVM achieved 100% accuracy, although the test set contained only 14 images. These findings indicate that feature fusion does not consistently improve classification across patterns. The approach shows potential for handwriting-based PD classification, further validation with larger datasets and independent subjects is needed.

## INTRODUCTION

Neurodegenerative diseases are disorders characterized by progressive damage to the nervous system, particularly the brain, which can impair cognitive, sensory, and motor functions (Hastuti et al., 2022; Safutra et al., 2023). Parkinson's disease is a progressive neurodegenerative disorder that affects the central nervous system and is characterized by various motor symptoms, including tremor, bradykinesia, muscle rigidity, and postural instability. In addition, this condition may also cause non-motor symptoms that can affect an individual's daily activities and overall quality of life (Bensefia et al., 2026). Over the past 25 years, the number of people affected by Parkinson's disease has doubled. In 2019, approximately 8.5 million people worldwide were living with the disease, resulting in 5.8 million years of healthy life lost and 329,000 deaths (World Health Organization, 2023).

Parkinson's disease diagnosis generally involves reviewing medical history and conducting several motor assessments rather than relying on a single examination (Setianto et al., 2023). Handwriting analysis has emerged as a potential approach for identifying motor impairments because changes in handwriting may reflect difficulties in fine motor control. Paper-based handwriting tests are relatively simple and quick to perform (Toffoli et al., 2023). However, visual assessment of handwriting irregularities remains subjective and difficult to quantify consistently (Saadh et al., 2025). Therefore, digital image processing and machine learning can be applied to support quantitative handwriting analysis.

Handwriting irregularities associated with Parkinson's disease include tremor-induced stroke variations and deviations in line shape and direction (Bensefia et al., 2026; Toffoli et al., 2023). These characteristics can be represented through texture, edge structure, and line orientation. Handcrafted feature extraction methods provide an alternative to computationally intensive deep learning approaches, particularly for limited datasets (Galaz et al., 2022). Furthermore, previous research has demonstrated promising classification performance using handcrafted features combined with machine learning classifiers (Reddy et al., 2025). Nevertheless, the contribution of different feature representations requires further investigation to understand their influence on classification performance.

Although previous studies have investigated GLCM and HOG for Parkinson's disease detection, their individual contributions and the effect of combining both features have not been systematically compared under the same experimental conditions using handwriting images. Therefore, this study compares GLCM, HOG, and GLCM-HOG

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feature fusion using Support Vector Machine (SVM) on the NewHandPD dataset. Three handwriting patterns, namely Spiral, Meander, and Circle, are evaluated through nine experimental scenarios. This study aims to analyze the classification performance of different feature configurations and investigate whether feature fusion provides improvements over individual feature representations.

## LITERATURE REVIEW

Previous studies have investigated handcrafted feature extraction methods for Parkinson's disease detection using various data modalities and classification algorithms. Gray-Level Co-occurrence Matrix (GLCM) represents local texture characteristics by analyzing spatial relationships between pixel intensity pairs (Lubis & Sundari, 2025; Immanuel et al., 2025). However, its statistical texture representation may limit its ability to capture global shape and directional information (Kalbhor & Shinde, 2023). In contrast, Histogram of Oriented Gradients (HOG) represents edge structures and line orientations through gradient distributions (Veza & Arifin, 2025). These characteristics provide complementary information to GLCM, particularly for handwriting patterns containing variations in stroke direction and shape (Kalbhor & Shinde, 2023). Consequently, combining GLCM and HOG provides a potential approach to representing both texture and structural characteristics of handwriting images.

The application of GLCM and HOG has been explored in several Parkinson's disease detection studies. GLCM combined with convolutional neural networks achieved 97.02% accuracy using spiral and wave images (Verma, 2026), while GLCM combined with Random Forest achieved 90.05% accuracy using MRI images (Tomer et al., 2022). HOG combined with Random Forest achieved 86.67% accuracy on spiral images and 76.67% on wave images (Nagamani et al., 2024), whereas Weighted Random Forest obtained accuracies of 92% and 93%, respectively (Abdullah et al., 2024). These findings demonstrate the potential of both feature extraction methods, although their performance varies according to the dataset, modality, and classification algorithm. Furthermore, previous studies have reported promising results using handcrafted features and SVM, including 95% accuracy on spiral images, 93.3% on meander images (Elbarawy et al., 2023), and 90.01% on the NewHandPD dataset (Rabie & Akhloufi, 2025). (Reddy et al., 2025) also reported average accuracies of 98.24% on spiral images and 93.29% on wave images using feature fusion and SVM. However, these results cannot directly establish the superiority of a particular feature configuration because the studies employ different experimental settings.

Despite the promising results of GLCM, HOG, and SVM, the contribution of individual feature representations and their combination remains insufficiently compared under consistent experimental conditions using handwriting images. In particular, the extent to which combining texture information from GLCM with structural information from HOG improves classification performance across different handwriting patterns requires further investigation. Therefore, this study evaluates GLCM, HOG, and GLCM-HOG feature fusion using SVM on the NewHandPD dataset under the same experimental framework. The comparison includes Spiral, Meander, and Circle patterns, providing a systematic evaluation of nine experimental scenarios to examine the contribution of each feature configuration to Parkinson's disease detection.

## METHOD

This study employs a systematic research methodology to investigate the application of GLCM, HOG, and their combination for Parkinson's disease detection based on handwriting images. The research consists of several stages, including dataset preparation, preprocessing, feature extraction, feature fusion, dimensionality reduction, classification, and model evaluation. The overall research pipeline is illustrated in Figure 1.

As illustrated in Figure 1, the research pipeline begins with dataset preparation, followed by image preprocessing and subject-level stratified splitting into training and testing sets. GLCM and HOG features are then extracted separately from the training and testing images. For the feature fusion configuration, the extracted GLCM and HOG features are combined after standardization and PCA-based dimensionality reduction of HOG features. Subsequently, five-fold Stratified Group Cross-Validation is performed on the training data for model selection and hyperparameter optimization using SVM with Linear, RBF, and Polynomial kernels. The best-performing configuration is then retrained on the entire training set to obtain the final classification model. Finally, the model is evaluated once using the independent testing set across three feature configurations and three handwriting patterns. The classification performance is assessed using accuracy, precision, recall/sensitivity, specificity, and F1-score.

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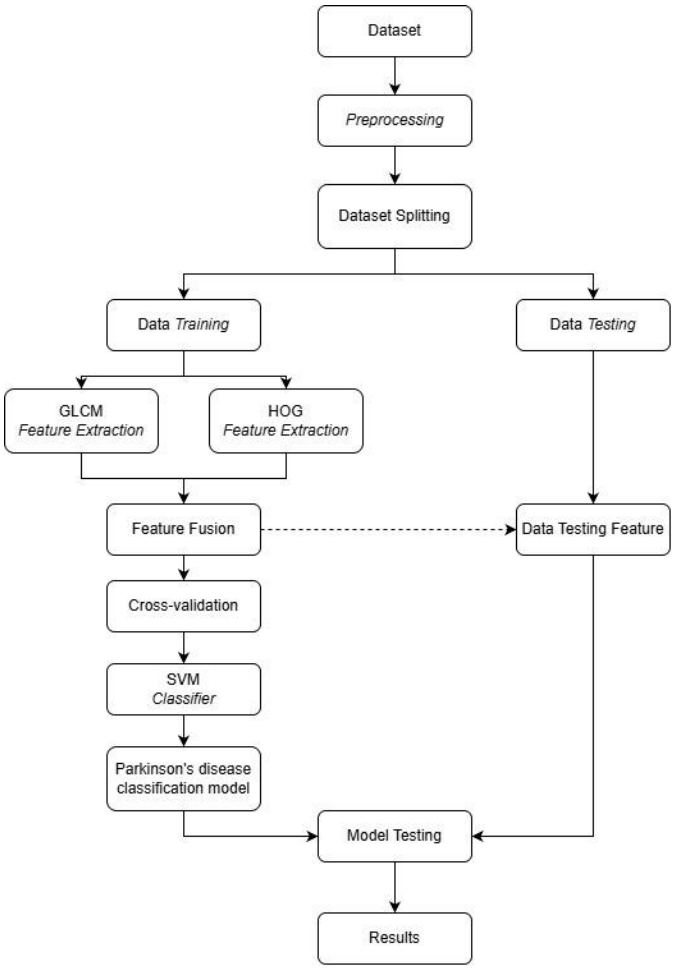



Figure 1. Research Pipeline

**Dataset Preparation**

This study utilized the NewHandPD dataset, consisting of handwriting images collected from healthy individuals and Parkinson's disease (PD) patients. The dataset contains three handwriting patterns: spiral, meander, and circle. A total of 66 subjects were included, comprising 35 healthy individuals and 31 PD patients. The dataset distribution is presented in Table 1.

Table 1. Distribution of NewHandPD Dataset

| Pattern | Healthy | PD | Total |
|---|---|---|---|
| Spiral | 140 | 124 | 264 |
| Meander | 140 | 124 | 264 |
| Circle | 35 | 31 | 66 |
| **Total** | **315** | **279** | **594** |

Examples of handwriting from patients with Parkinson's disease (PD) in the form of spirals, meanders, and circles can be seen in Figure 2. These examples illustrate the handwriting characteristics used as input for the classification process.

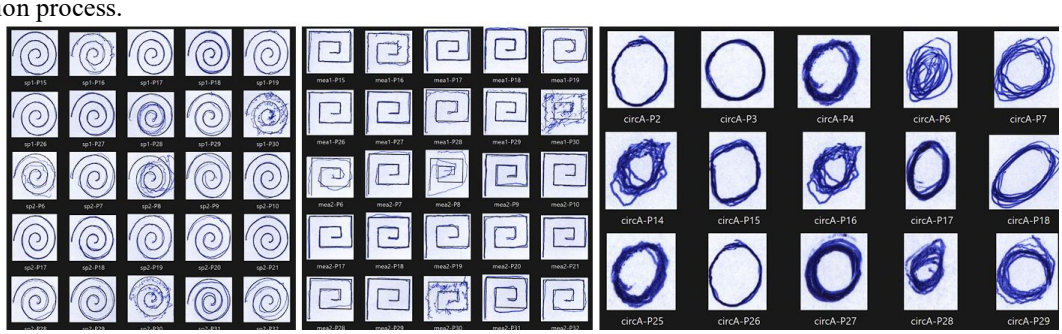


Figure 2. Handwriting samples for spiral, meander, and circle patterns

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**Image Preprocessing**

The handwriting images were preprocessed through grayscale conversion, resizing to 200 × 200 pixels, and min-max normalization to the range of 0–255. These steps were performed to ensure consistent image representation before feature extraction.

**Feature Extraction**

Gray-Level Co-occurrence Matrix (GLCM) was employed to extract texture characteristics from handwriting images. Six statistical features, namely contrast, correlation, energy, homogeneity, dissimilarity, and entropy, were calculated using four directional angles (0°, 45°, 90°, and 135°) with a pixel distance of 1 (Verma, 2026).

Histogram of Oriented Gradients (HOG) was utilized to capture handwriting shape and directional gradient information. The extraction process employed nine orientation bins, 10 × 10 pixel cells, and 2 × 2 cell blocks, resulting in a 12,996-dimensional feature vector for each image (Agarwal et al., 2024).

The GLCM and HOG features were combined through feature fusion. StandardScaler was applied to standardize the features, while Principal Component Analysis (PCA) reduced the dimensionality of HOG to 20 components. The fused representation consisted of six GLCM features and 20 PCA-reduced HOG components. Standardization and PCA were fitted exclusively using training data to prevent data leakage.

**Data Splitting and Cross-Validation**

The dataset was divided into training and testing sets using an 80:20 subject-level split, stratified by class. This approach ensured that images from the same subject were not distributed across both sets. The same testing subjects were maintained across the three handwriting patterns to ensure fair comparisons.

Five-fold Stratified Group Cross-Validation was performed on the training set for model selection and hyperparameter optimization. In each fold, four subsets were used for training and one subset for validation. StandardScaler, PCA, and SVM were fitted within each training fold, while validation data were only transformed and evaluated. The independent test set was excluded from cross-validation and used only for final evaluation (Franko & Alamsyah, 2026).

**Support Vector Machine Classification**

Support Vector Machine (SVM) was employed to classify handwriting images into healthy and PD categories. Three kernel functions were investigated: Linear, Radial Basis Function (RBF), and Polynomial (Bernando et al., 2021). The classification models were developed using GLCM, HOG, and GLCM-HOG fused features.

Hyperparameter optimization was conducted using GridSearchCV within the training cross-validation process. The investigated hyperparameters are presented in Table 2.

Table 2. SVM Hyperparameter Configuration

| Parameter | Candidate Values |
|---|---|
| Kernel | Linear, Polynomial, RBF |
| C | 0.1, 1, 10, 100 |
| Gamma | Scale, Auto |
| Degree | 2, 3 |

As presented in Table 2, three SVM kernel functions, namely Linear, Polynomial, and Radial Basis Function (RBF), were investigated to identify the most suitable classification configuration. The regularization parameter (C) was evaluated using values of 0.1, 1, 10, and 100 to control the trade-off between classification errors and model complexity. The Gamma parameter was tested using Scale and Auto settings for the RBF and Polynomial kernels, while the Degree parameter was evaluated at values of 2 and 3 for the Polynomial kernel. These candidate values were explored through GridSearchCV with five-fold cross-validation on the training data to determine the optimal hyperparameter configuration for each experimental scenario.

**Experimental Scenarios**

The experiments were designed to investigate the influence of handwriting patterns and feature extraction configurations on SVM classification performance. Three handwriting patterns (spiral, meander, and circle) were evaluated using three feature configurations that is GLCM, HOG, and GLCM-HOG fusion. Therefore, nine experimental scenarios were established, as presented in Table 3.

Each scenario was evaluated using Linear, RBF, and Polynomial SVM kernels. The optimal kernel and hyperparameters were selected through five-fold cross-validation, resulting in the best configuration for each experimental scenario.

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Table 3. Experimental Scenarios

| Scenario | Handwritten Pattern | GLCM | HOG |
|---|---|---|---|
| 1 | Spiral | ✔ | - |
| 2 | Meander | ✔ | - |
| 3 | Circle | ✔ | - |
| 4 | Spiral | - | ✔ |
| 5 | Meander | - | ✔ |
| 6 | Circle | - | ✔ |
| 7 | Spiral | ✔ | ✔ |
| 8 | Meander | ✔ | ✔ |
| 9 | Circle | ✔ | ✔ |

**Evaluation Metrics**

The final evaluation was performed exclusively on the independent test set at the image level. Classification performance was assessed using Accuracy, Precision, Recall, Specificity, F1-score, and Specificity as shown in (1), (2), (3), (4), and (5) (Eilleen et al., 2025; Saied et al., 2023).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall/Sensitivity = \frac{TP}{TP + FN} \quad (3)$$

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

$$Specificity = \frac{TN}{TN + FP} \quad (5)$$

## RESULT

**Preprocessing Result**

The preprocessing stage was applied to the handwriting images in the NewHandPD dataset to prepare the data for feature extraction. Each image was converted into grayscale, resized to 200 × 200 pixels, and normalized using min-max normalization within the 0–255 intensity range. These preprocessing operations were performed to maintain a consistent image representation before extracting handwriting features. Figure 3 presents representative examples of handwriting images after preprocessing for the Spiral, Meander, and Circle patterns.

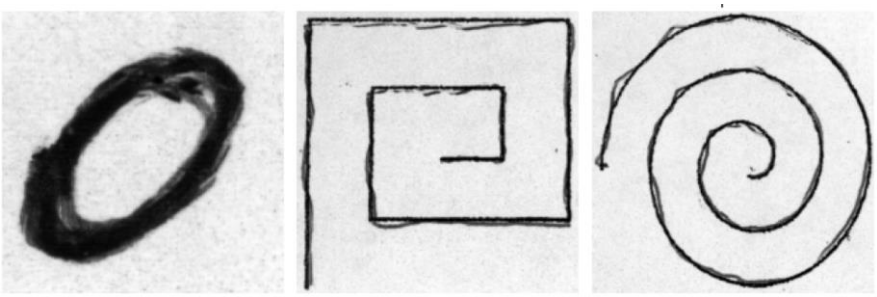


Figure 3. Examples of handwriting images after preprocessing

**Dataset Splitting Results**

Table 4. Distribution of handwriting images in the training and testing sets

| Handwritting Pattern | Healthy Training | Healthy Testing | PD Training | PD Testing | Total Training | Total Tesing |
|---|---|---|---|---|---|---|
| Spiral | 112 | 28 | 96 | 28 | 208 | 56 |
| Meander | 112 | 28 | 96 | 28 | 208 | 56 |
| Circle | 28 | 7 | 24 | 7 | 52 | 14 |
| **Total** | **252** | **63** | **216** | **63** | **468** | **126** |

The dataset was divided into training and testing sets using subject-level stratified splitting. This strategy ensured that images belonging to the same subject were not distributed across both sets, thereby preventing subject overlap

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between training and testing data. Table 4 presents the distribution of handwriting images according to their patterns and subject categories.

As presented in Table 4, the training set consisted of 468 handwriting images, while the testing set contained 126 images. The training set included 252 images from healthy subjects and 216 images from subjects with Parkinson's disease. Meanwhile, the testing set consisted of 63 images from each class. The Spiral and Meander patterns contributed 56 testing images each, whereas the Circle pattern consisted of 14 testing images. This distribution was maintained across the three feature configurations to ensure a consistent comparison of classification performance.

**Results of All Scenarios**

The classification performance of the nine experimental scenarios was evaluated using the independent test set at the image level. Each scenario represents a combination of handwriting pattern (Spiral, Meander, or Circle) and feature configuration (GLCM, HOG, or GLCM+HOG), with SVM as the classifier. The evaluation metrics included accuracy, precision, sensitivity, specificity, and F1-score. The results are presented in Table 5.

Table 5. Classification performance across all scenarios

| Scenario | n | Accuracy | Precision | Sensitivity | F1-Score | Specificity |
|---|---|---|---|---|---|---|
| 1 | 56 | 0.768 | 0.759 | 0.786 | 0.772 | 0.750 |
| 2 | 56 | 0.857 | 0.857 | 0.857 | 0.857 | 0.857 |
| 3 | 14 | 0.857 | 0.857 | 0.857 | 0.857 | 0.857 |
| 4 | 56 | 0.964 | 1.000 | 0.929 | 0.963 | 1.000 |
| 5 | 56 | 0.821 | 0.909 | 0.714 | 0.800 | 0.929 |
| 6 | 14 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| 7 | 56 | 0.982 | 1.000 | 0.964 | 0.982 | 1.000 |
| 8 | 56 | 0.857 | 0.917 | 0.786 | 0.846 | 0.929 |
| 9 | 14 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

As shown in Table 5, for the Spiral pattern, GLCM+HOG+SVM achieved the highest accuracy of 0.982, as can be seen in Scenario 7, followed by HOG+SVM with 0.964 in Scenario 4 and GLCM+SVM with 0.768 in Scenario 1. For the Meander pattern, GLCM+SVM and GLCM+HOG+SVM obtained the same accuracy of 0.857, as can be seen in Scenario 2 and Scenario 8, respectively, while HOG+SVM achieved 0.821 in Scenario 5. For the Circle pattern, HOG+SVM and GLCM+HOG+SVM achieved 1.000 accuracy, as can be seen in Scenario 6 and Scenario 9, respectively, whereas GLCM+SVM obtained 0.857 in Scenario 3.

**Confusion Matrix Results**

Confusion matrices were generated for all nine experimental scenarios to examine the classification outcomes on the independent test set. Parkinson's disease was considered the positive class, while healthy subjects represented the negative class. The confusion matrices distinguish true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. The results are presented in Figure 4.

For the Spiral pattern, GLCM+HOG+SVM produced one false negative, as can be seen in Scenario 7, while HOG+SVM produced two false negatives in Scenario 4. GLCM+SVM produced seven false positive and six false negative predictions in Scenario 1.

For the Meander pattern, HOG+SVM produced eight false negative and two false positive predictions, as can be seen in Scenario 5. GLCM+HOG+SVM produced six false negative and two false positive predictions in Scenario 8, while GLCM+SVM produced four false positive and four false negative predictions in Scenario 2.

For the Circle pattern, HOG+SVM and GLCM+HOG+SVM correctly classified all testing images, as can be seen in Scenario 6 and Scenario 9, respectively. Meanwhile, GLCM+SVM produced two false positive and two false negative predictions in Scenario 3.

The confusion matrix results correspond to the classification metrics reported in Table 5 and provide a detailed representation of the prediction outcomes for each experimental scenario.

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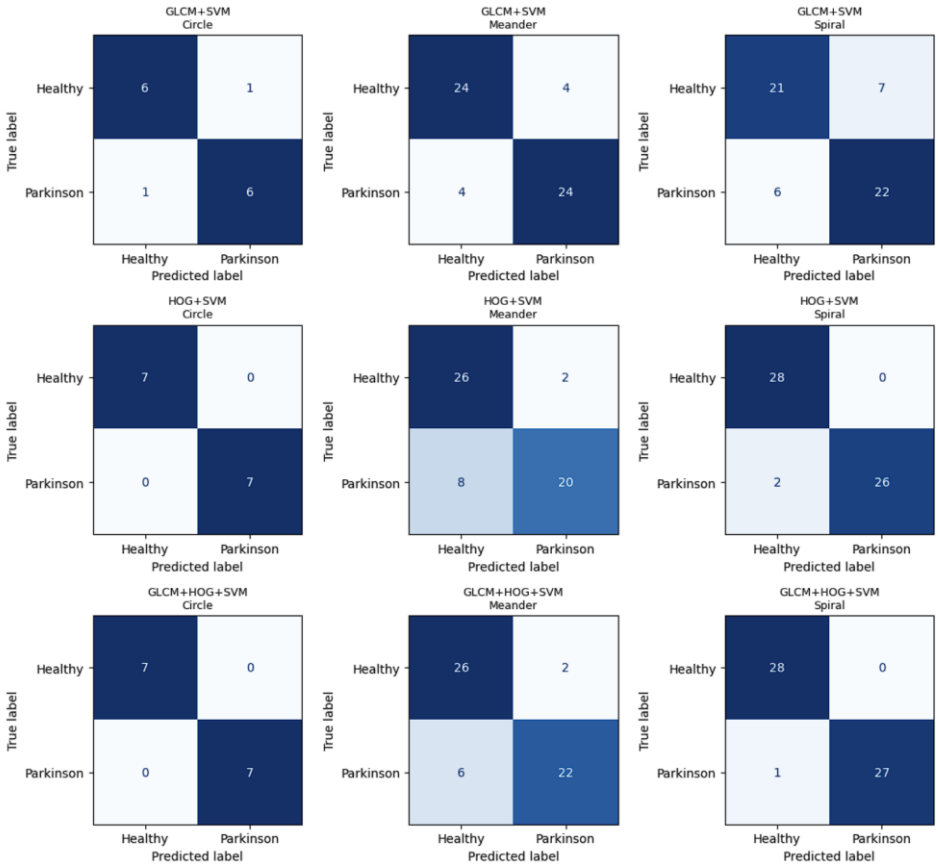


Figure 4. Confusion matrices of the nine experimental scenarios

## DISCUSSION

The experimental results demonstrate that the classification performance of GLCM, HOG, and GLCM+HOG varies across handwriting patterns. For the Spiral pattern, GLCM+HOG+SVM achieved the highest accuracy of 98.2%, as can be seen in Scenario 7, followed by HOG+SVM with 96.4% in Scenario 4. In contrast, GLCM+SVM obtained 76.8% in Scenario 1. This difference indicates that structural and directional information represented by HOG provides more discriminative information for Spiral handwriting classification than texture information represented by GLCM alone. The improvement obtained by combining both features suggests that texture information can complement the structural characteristics captured by HOG in this pattern.

For the Meander pattern, GLCM+SVM and GLCM+HOG+SVM achieved the same accuracy of 85.7%, as can be seen in Scenario 2 and Scenario 8, respectively. Meanwhile, HOG+SVM obtained 82.1% in Scenario 5. Although feature fusion achieved the highest precision of 0.917 in Scenario 8, its sensitivity was 0.786, compared with 0.857 in Scenario 2. This indicates that the combination of GLCM and HOG did not consistently improve classification performance across all evaluation metrics. The difference in sensitivity and specificity also demonstrates that the feature configurations produced different classification error distributions for Meander handwriting.

For the Circle pattern, HOG+SVM and GLCM+HOG+SVM achieved 100% accuracy, as can be seen in Scenario 6 and Scenario 9, respectively, whereas GLCM+SVM obtained 85.7% in Scenario 3. These results indicate that HOG-based configurations were able to correctly classify all images in the Circle testing set. However, the Circle pattern contained only 14 testing images, which is considerably smaller than the Spiral and Meander testing sets. Therefore, the perfect classification results should be interpreted cautiously, as the limited number of testing images may not adequately represent the variability of handwriting characteristics across subjects.

The findings of this study can also be compared with previous research investigating HOG-based feature extraction for Parkinson's disease detection. A previous study employing HOG with Random Forest reported accuracies of 86.67% for Spiral and 76.67% for Wave handwriting patterns (Nagamani et al., 2024). Another study using HOG with Weighted Random Forest achieved accuracies of 92% and 93% (Abdullah et al., 2024). In comparison, the HOG+SVM configuration in this study achieved an accuracy of 96.43% for Spiral in Scenario 4 and 82.14% for Meander in Scenario 5. Furthermore, GLCM+HOG+SVM achieved 98.21% for Spiral in Scenario 7. These findings indicate promising classification performance using HOG combined with SVM, particularly for Spiral handwriting. Nevertheless, direct comparisons should be interpreted cautiously because the datasets, handwriting patterns, classification algorithms, and evaluation procedures may differ across studies. The present study provides an additional

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comparative evaluation by investigating GLCM, HOG, and their combination under the same experimental conditions using the NewHandPD dataset.

Overall, the findings demonstrate that the contribution of feature fusion depends on the handwriting pattern being analyzed. GLCM represents local texture characteristics, whereas HOG captures edge structures and gradient orientations. Their combination achieved the highest accuracy for Spiral in Scenario 7 and maintained the same accuracy as GLCM+SVM for Meander in Scenario 8. For Circle, the fusion configuration achieved perfect classification in Scenario 9, although HOG alone produced the same result in Scenario 6. These findings indicate that combining GLCM and HOG does not universally improve classification performance across all handwriting patterns. Instead, the contribution of each feature representation depends on the characteristics of the input handwriting images.

Several limitations should be considered when interpreting the findings of this study. First, the Circle pattern contained only 14 testing images, which limits the reliability of its classification results. Although HOG+SVM and GLCM+HOG+SVM achieved 100% accuracy in Scenario 6 and Scenario 9, respectively, this result may not represent performance on a larger and more diverse sample. Second, the evaluation was conducted at the image level rather than the subject level. Although the dataset was split based on subjects to prevent data leakage between training and testing sets, the reported metrics represent image classification performance and do not directly indicate the accuracy of subject-level PD identification. Third, the evaluation relied exclusively on the NewHandPD dataset, meaning that the generalizability of the models to other datasets and populations remains uncertain. Finally, classification performance varied across handwriting patterns, indicating that the effectiveness of each feature configuration may depend on the characteristics of the input images.

These findings highlight the potential of handcrafted feature extraction combined with SVM for handwriting-based Parkinson's disease classification. However, further validation using larger datasets, additional independent subjects, and external datasets is necessary to assess the robustness and generalization capability of the proposed approach. Future research may also investigate alternative feature fusion strategies and additional classification methods to improve the consistency of classification performance across different handwriting patterns.

## CONCLUSION

This study investigated the application of GLCM, HOG, and their combination with SVM for Parkinson's disease detection based on handwriting images from the NewHandPD dataset. Nine experimental scenarios were evaluated using three handwriting patterns (Circle, Meander, and Spiral) and three feature configurations. The image-level testing results demonstrated that the classification performance varied across handwriting patterns and feature configurations. The GLCM+HOG+SVM configuration achieved the highest accuracy of 98.2% for the Spiral pattern, while HOG+SVM and GLCM+HOG+SVM obtained 100% accuracy for the Circle pattern. For the Meander pattern, GLCM+SVM and GLCM+HOG+SVM achieved the same accuracy of 85.7%. These findings indicate that combining GLCM and HOG can improve classification performance for certain handwriting patterns, although the improvement is not consistent across all patterns.

For future research, the evaluation should be extended using larger and more diverse handwriting datasets to improve the reliability of classification performance. Further studies may also investigate alternative feature fusion strategies, feature selection techniques, and additional classification methods. Moreover, subject-level evaluation and validation using independent datasets could provide a more comprehensive assessment of the model's generalization capability and its potential application in Parkinson's disease screening.

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