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A Hybrid Framework for the Diagnosis of Parkinson's Disease using Handwritten Drawings-Spiral and Wave

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Parkinson's disease is a progressive neurological disorder that significantly affects individuals worldwide. Early and accurate classification of the disease is crucial for timely intervention and improved patient outcomes. This study aims to develop an effective classification system using drawings of spirals and waves to discriminate between healthy individuals and those with Parkinson's disease, aiming to provide an early diagnostic method, leading to improved patient lifespan. The study utilizes two sets of drawings: spirals and waves. Data augmentation techniques are employed to increase the dataset size and enhance training data for deep neural networks. The Pyramid Histogram of Oriented Gradients (PHoG) algorithm is applied to compute shape descriptors from healthy and Parkinson's drawings. A Visual Geometry Group (VGG)-based deep learning model is used to extract significant features from the modified drawings, particularly from the fc6 and fc7 layers. Supervised classifiers, Support Vector Machine (SVM) and K-Nearest Neighbor (KNN), are employed individually and in combination to classify the extracted features. The results demonstrate that the fused features achieved the highest accuracy values: 98.6% for spiral drawings using SVM and 96.57% for wave drawings using KNN. These accuracy rates highlight the effectiveness of the proposed method in accurately classifying Parkinson's disease based on drawings of spirals and waves. The findings suggest that the proposed method has the potential to serve as a non-invasive and reliable tool for early diagnosis of Parkinson's disease. It can enable timely interventions and improved patient care.

Keywords: Classification, Deep learning, Non-invasive diagnosis, Shape descriptors, Supervised classifiers

Introduction

Researchers have been investigating the use of handwriting analysis in the diagnosis and monitoring of Parkinson's disease. This neurodegenerative disorder is characterized by the loss of nerve cells in the substantia nigra, resulting in reduced dopamine levels and impaired motor function.[1] It is one of the primary neurodegenerative disorders after Alzheimer's.[2] Handwriting analysis, particularly through spiral and wave drawings, can provide valuable insights into tremors and motor function associated with Parkinson's disease.[3] However, there is a need for trained medical professionals and more accurate and accessible diagnostic methods, which motivates ongoing research in this area.

Several recent studies have made significant advancements in utilizing handwritten images for the diagnosis of Parkinson's disease. Arefin *et al.*[4] achieved 92.43% accuracy using a Fully Convolutional Neural Network (FCNN). Alniemi *et al.*[5] developed a customized CNN architecture and attained 93.33% accuracy. Das *et al.*[6] integrated Discrete Wavelet Transform (DWT), Histogram Of Gradients (HoG), and Random Forest (RF) to achieve 79.7% accuracy. Chowdhary *et al.*[7] proposed a lightweight computer-vision model combining CNN and HoG mechanisms, and yielded 94% accuracy. Lamba *et al.*[8] utilized kinematic features, mutual information gain, and AdaBoost classifier, resulting in 96.02% accuracy. Kamble *et al.*[9] employed machine learning techniques and logistic regression, and achieved 91.6% accuracy. Islam *et al.*[10] developed a CNN-based architecture with 96.64% accuracy. Jahan *et al.*[11] implemented a deep CNN with transfer learning, and achieved 96.67% accuracy. The summary of recent relevant works is presented in Table 1.

Research Gaps

- From the literature mentioned above, the following issues have been observed:
- A few authors[6,7] introduced a HoG descriptor; however, it is very sensitive to image rotation.
- A few researchers[6] utilized wavelet features to analyze handwritten Parkinson's subjects. However, it cannot represent the spatial characteristics. In

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addition, it has poor dimensionality and lack of phase details.

- Most of the authors[6,8,9] employed conventional machine learning techniques. But, arises overfitting issues and sensitivity to hyperparameter tuning.
- In a few works[4,10,11] authors utilized very deep networks to predict the Parkinson's disease. However, training of such complex models is a difficult task, and sometimes prone to overfitting, which leads to poor generalization.
- To minimize the above-mentioned issues, a novel framework is presented to using Pyramid HoG (PHoG) descriptors, Visual Geometry Group (VGG) networks, and supervised learning strategies. Major

Table 1 — Previous approaches to Parkinson's disease classification

Type of approach	Number of datasets	Samples	Technique (method)	Performance (%)	Remarks
DL[5]	1 (Hand-draw spiral images)	102 (51: Healthy, 51: Parkinson)	Useda customized CNN to classify Parkinson's disease samples from healthy	Accuracy: 93.3	The authors used only a single dataset; They have not performed any Image augmentation as the used data is limited to train a deep learning model
ML[6]	2 (Spiral-wave, cube-triangle)	Dataset-1 (102: Healthy, 102: Parkinson) Dataset-2 (166: Healthy, 166: Parkinson)	Integrated discrete wavelet transform (DWT), histogram of gradients (HoG), and random forest (RF) to classify healthy and Parkinson's subjects	Dataset-1 Accuracy: 74.70 Dataset-2 Accuracy: 96.80	Though the authors got good results, still, the results are limited to Dataset-1; Also, adding more images using any augmentation technique and employing deep learning will improve the model's performance
DL[7]	1 (Hand-draw spiral images)	102 (51: Healthy, 51: Parkinson)	Proposed a lightweight computer-vision model with CNN and HoG	Accuracy: 94	The authors used only a single dataset; They have not performed any Image augmentation as the used data is limited to train a deep learning model
ML[9]	1(Spiral drawing dataset)	40 (25: Parkinson, 15: Healthy)	Extracted the Kinematic features, and Spatio-temporal features from the images; Later, tested with Logistic regression classifier.	Accuracy: 91.6	Data imbalancing is one of the challenges of this work
DL[10]	1(Spiral drawing dataset)	660 (330: Parkinson, 330: Healthy)	ConVnet model is used	Accuracy: 96.64	The results are limited to only a single dataset
DL[11]	2 (Spiral and wave drawing dataset)	Dataset-1 102 (51: Healthy, 51: Parkinson) Dataset-2 102 (51: Healthy, 51: Parkinson)	Exploited ResNet 50 with transfer learning	Clubbed both the datasets. Accuracy: 96.67	A fixed transfer learning method is used; Performance can be improved by exploring tuning the transfer network; Images are limited
DL[12]	2 (Spiral and wave drawing dataset)	Dataset-1 102(51: Healthy, 51: Parkinson) Dataset-2 102 (51: Healthy, 51: Parkinson)	Used a pre-trained VGG-19 network	Dataset-1 Accuracy: 88.5 Dataset-2 Accuracy:88	The authors augmented images only to 400 images in total. That number is still limited in case of DL models
ML[13]	2 (Spiral and wave drawing dataset)	Dataset-1 102 (51: Healthy, 51: Parkinson) Dataset-2 102 (51: Healthy, 51: Parkinson)	Utilized HoG features and KNN classifier	Dataset-1 Accuracy: 86.67 Dataset-2 Accuracy:89.33	They have not performed any Image augmentation to train the models with different images

(*Contd.*)

Table 1 — Previous approaches to Parkinson's disease classification — (*Contd.*)

Type of approach	Number of datasets	Samples	Technique (method)	Performance (%)	Remarks
DL[14]	2 (Spiral and wave drawing dataset)	Dataset-1 102 (51: Healthy, 51: Parkinson) Dataset-2 102 (51: Healthy, 51: Parkinson)	Employed a multistage CNN. Clubbed the two datasets in multistage CNN	Accuracy: 93.3	The number of images can be increased; Different types of images can be considered along with spiral and wave shaped images
ML[15]	1 (Hand-draw wave Images)	102 (51: Healthy, 51: Parkinson)	Utilized HoG descriptor and RF classifier	Accuracy: 83	The number of images can be increased; Different types of images can be considered along with spiral and wave shaped images
Hybrid (ML+DL)[16]	1 (Hand-draw spiral Images)	102 (51: Healthy, 51: Parkinson)	Proposed a hybrid model of RESNET-50 (feature extraction) and SVM classifier for classification	Accuracy: 98.45	The authors used only a single dataset; Different types of images can be considered along with spiral and wave shaped images
DL[17]	1 (Hand-draw spiral Images)	102 (51: Healthy, 51: Parkinson)	Developed a Cosine Deep Convolutional Neural network (CosineDCNN)	Accuracy: 89.98	The major limitation of this proposed method was requirement of high computation; Different types of images can be considered along with spiral and wave shaped images
DL[18]	2 (Spiral and wave drawing dataset)	Dataset-1 102 (51 : Healthy, 51: Parkinson) Dataset-2 102 (51: Healthy, 51: Parkinson)	Applied 2D CNN and voting-ensemble classifiers. Fused both the datasets.	Accuracy: 96.67	The number of images can be increased; Different types of images can be considered along with spiral and wave shaped images
DL[19]	2 (Spiral and wave drawing dataset)	Dataset-1 102 (51: Healthy, 51: Parkinson) Dataset-2 102 (51: Healthy, 51: Parkinson)	Fused the three types of pretrained networks: VGGs, ResNets, and vision transformers.	Dataset-1 Accuracy: 87.66 Dataset-2 Accuracy: 96.67	Different types of images can be considered along with spiral and wave shaped images
DL[20]	1 (Hand-draw spiral Images)	102 (51: Healthy, 51: Parkinson)	Analyzed various DL models: VGG19, Inception, ResNet, and Densenet models; Best results achieved with Incepetion V3	Accuracy: 89	Different types of images can be considered along with spiral and wave shaped images

contributions of the suggested approach are illustrated in the subsequent section.

Contributions

- The significant contributions of the implemented work are as follows:
- Image augmentation was utilized to increase the model's generalizability and minimize over fitting issues.
- To discriminate Parkinson's from healthy samples, a PHoG-based shape feature descriptor was applied. This descriptor accommodates the shape details of wave and spiral sketches.
- The VGG model was employed to obtain higher-level image features such as edges, corners, and blobs.
- The concept of transfer learning was introduced into the model to accelerate the learning process and improve performance.

Methodology

Dataset

In order to evaluate the suggested model, a total of 152 spiral drawings (51 from healthy individuals and 101 from Parkinson's patients) and 102 wave drawings (51 from healthy individuals and 51 from Parkinson's patients) were collected from publicly

accessible databases, namely Kaggle[21] and UCI machine learning[22] repositories. Out of these collected images, only 50 spiral drawings were obtained from the UCI repository, while the remaining images were sourced from the mentioned alternative database. However, due to the limited data available, it was not possible to develop an effective model. To address this limitation, synthetic images were generated using an image augmentation strategy. Sample wave and spiral drawings from healthy individuals and Parkinson's subjects, obtained from the aforementioned Kaggle dataset are illustrated in Figs 1 & 2.

Model

The suggested methodology for Parkinson's disease prognosis, depicted in Fig. 3, involves several stages. These stages encompass pre-processing tasks such as image resizing, image augmentation techniques, feature engineering processes, and ultimately classification procedure.

Image Augmentation

Image augmentation is a widely employed technique in machine learning and computer vision, particularly in deep learning approaches. Its purpose is to enhance the diversity and size of the training data, thereby improving the model's performance and resilience.[23] In this work, this image augmentation is used to address the data imbalance between healthy individuals, and Parkinson's patients. To achieve this, the following range of augmentation techniques is used to artificially increase the diversity and size of the dataset.

- Flipping and Rotating: Images can be horizontally or vertically flipped and rotated at various angles to create additional variations.
- Scaling and Cropping: Images can be resized or cropped to different dimensions, simulating variations in object sizes or capturing other regions of interest.
- Translation and Shearing: Shifting an image horizontally or vertically (translation) or applying shear transformations can introduce different perspectives or simulate changes in camera angles.
- Noise Injection: Adding random noise to the image can help the model become more robust to noise in real-world scenarios.
- Brightness and Contrast Adjustment: Modifying the images' brightness, contrast, or saturation levels can account for variations in lighting conditions.
- Gaussian Blur and Sharpening: Applying blurring or sharpening filters to images can mimic variations in focus or enhance edges.

Each transformation was randomly applied during the training process, creating a wide variety of image variations, which helped prevent over fitting and improve the model's generalization capabilities. In this study, the configurations of Reddy & Dhuli (2023)[24] is followed and the final number of images for training and testing are presented in Table 2. By applying these operations, a total of 1419 spiral drawing images are used, comprising 510 healthy individuals and 909 Parkinson's patients. Similarly, 1020 wave drawing sketches, consisting of 510 healthy individuals and 510 Parkinson's subjects are obtained.

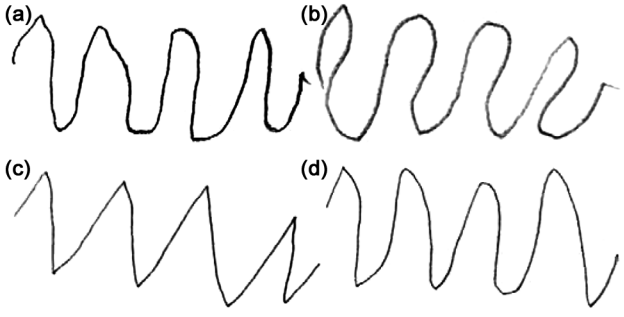

Fig. 1 — Sample wave drawings: (a) & (b) Healthy; (c) & (d) Parkinson's

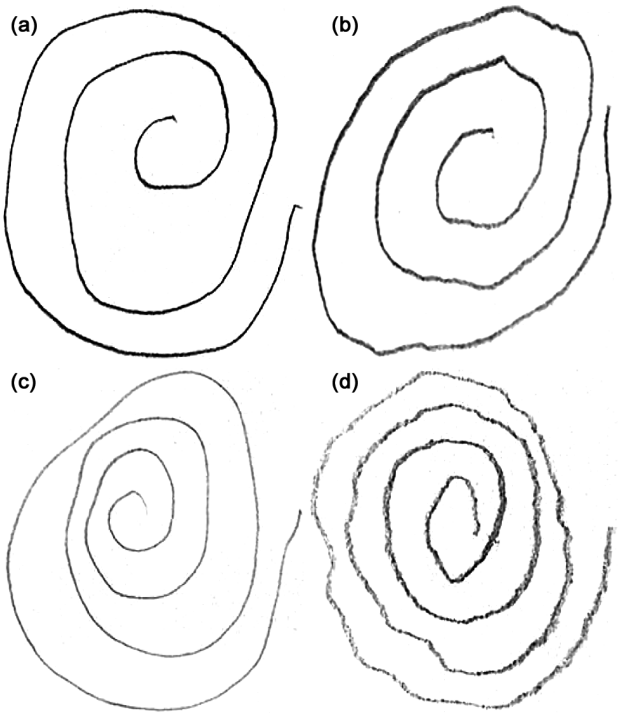

Fig. 2 — Sample spiral drawings: (a) & (b) Healthy; (c) & (d) Parkinson's

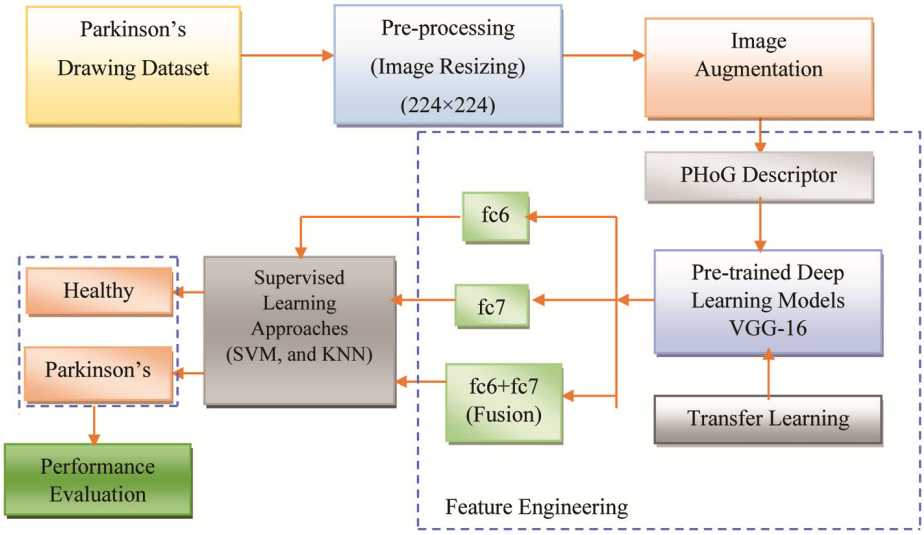

Fig. 3 — Block diagram of the suggested model

Table 2 — Data splitting proportions of spiral and wave handwritten drawings for the validation

Database	Healthy		Parkinson's		Total
	Training	Testing	Training	Testing	
Spiral Drawings	408	102	727	182	1419
Wave Drawings	408	102	408	102	1020

Feature Engineering

Pyramid HoG (PHoG) Descriptor

The Pyramid HoG (PHoG)[25] is a feature descriptor extensively utilized in computer vision and image processing to facilitate object detection and recognition tasks. Building upon the HoG method, which captures local shape and texture information from an image, the PHoG descriptor takes into account both local gradients and spatial information at various scales.

The computation process of the PHoG descriptor involves dividing the image into a pyramid of sub-regions and calculating the HoG descriptor for each of these sub-regions. These sub-regions are defined based on multiple scales and orientations. The steps included in the PHoG computation process consist of image pyramid generation, edge detection, histogram calculation, pyramid aggregation, normalization, and descriptor construction. By employing these operations, the PHoG descriptor for the entire image using the following expression can be derived:

$$N \times \sum_{n \in L} 4^n \quad \ldots (1)$$

where, N represents the number of bins and typically set to 8.

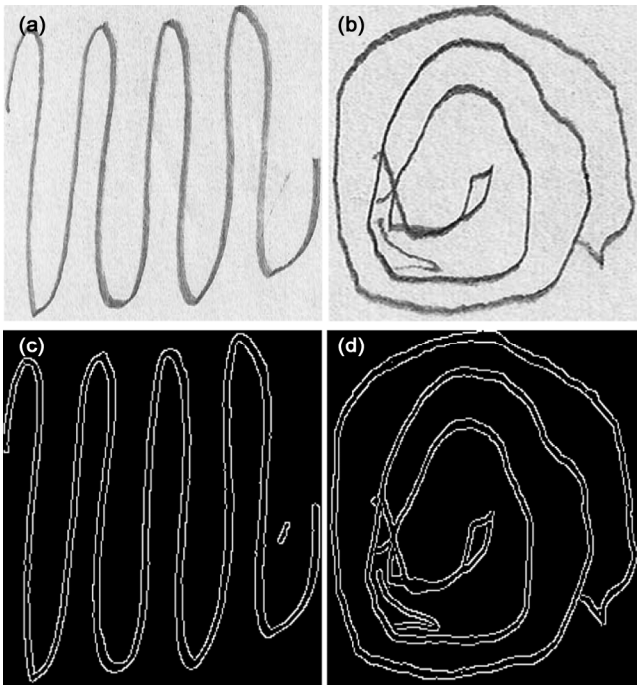

Fig. 4 — PHoG descriptors of spiral and wave drawings: (a) & (b) original images; (c) & (d) PHoG descriptors of (a) and (b)

L gives the number of cells or blocks and is given by 2^n.

Therefore, based on Eq. (1), it can be inferred that the PHoG descriptor effectively captures the spatial arrangement of gradient orientations and magnitudes at different scales. The PHoG descriptor obtained from handwritten images of spiral and wave drawings (Fig. 4) is showcasing its ability to represent the distinctive characteristics of these images.

In order to enhance the classification performance of the model, the VGG network is used to extract high-level primitive features from the PHoG descriptors. This process involved leveraging the capabilities of the VGG network to extract abstract and discriminative features that are more suitable for classification tasks.

VGG Network

The VGG-16 architecture is a CNN design developed by the visual geometry group at the university of oxford.[26] It is renowned for its straightforwardness and uniformity in structure. The VGG-16 model primarily comprises 13 convolutional layers with 3 × 3 filters, followed by Rectified Linear Unit (ReLU) activation functions. To reduce the spatial dimensions, a 2 × 2 max-pooling window with a stride of 2 is inserted after every two or three convolutional layers. The architecture concludes with two Fully Connected layers (fc6 and fc7), each containing 4096 units, and an output layer with the desired number of classes, typically activated by SoftMax for classification tasks.

The key idea behind the use of VGG is to allowing the network to learn more complex representations since it uses a series of smaller 3 × 3 convolutional filters stacked on top of each other. Therefore, it is widely used as a benchmark in various computer vision tasks and has achieved excellent performance especially in the image classification applications. However, in this application, the original VGG model cannot be directly employed since it is designed to work with thousands of categories, whereas the work dealt with only two categories (healthy vs. Parkinson's). Therefore, the concept of transfer learning is incorporated.

Transfer Learning

Transfer learning[27] is a valuable technique in deep learning that facilitates the transfer of knowledge acquired from one task or dataset to another related task or dataset. It involves utilizing a pre-trained neural network model as a starting point and subsequently fine-tuning or retraining the model on a new task or dataset. This approach offers various advantages, including reduced training time, handling limited data, knowledge transfer, and improved model performance.

In this study, a transfer learning is leveraged to address the fact that the presented CNN architectures are originally designed for multiclass classification problems with thousands of categories. However, this specific task involves binary classification, distinguishing between Parkinson's and healthy individuals. To adapt the model for this purpose, the existing classification layer is replaced with a new one that accommodates two classes instead of a thousand. By customizing the network architecture in this way, transfer learning can be effectively utilized to improve the performance of the model in the targeted binary classification task. The working of transfer learning is illustrated in Fig. 5.

Extraction of Training Features

While each layer of the VGG-16 architecture produces a response for a given input image, only a select few layers are particularly valuable for feature extraction.

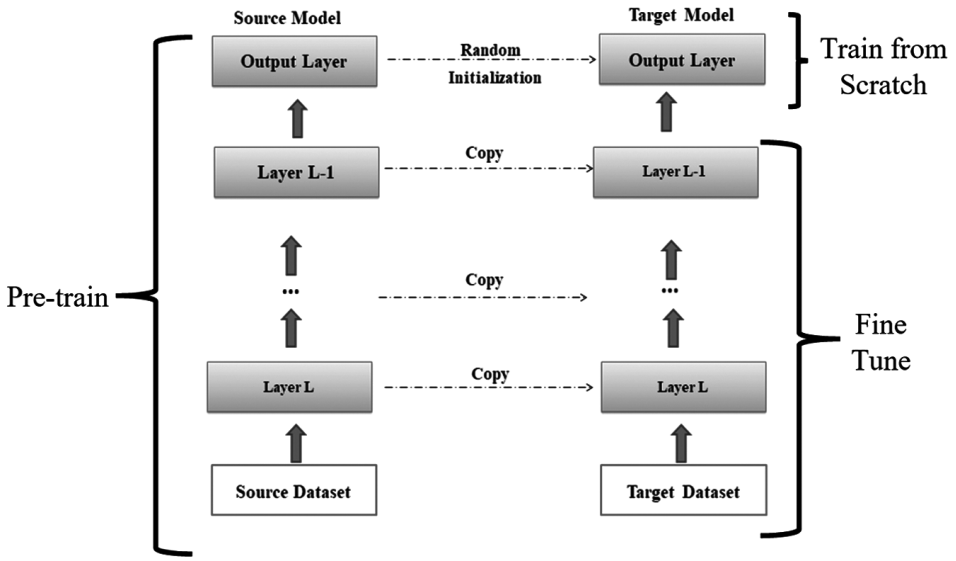

Fig. 5 — Work-flow of the transfer learning

Higher-level features play a crucial role in Parkinson's identification as they integrate various primitive elements like edges, corners, and blobs, resulting in a more comprehensive representation of the image.[28] In this approach with VGG-16, the features obtained from the dense or fully connected layers are focused, specifically fc6 and fc7, utilizing MATLAB's 'activations' function with a mini-batch size of 128. These extracted features are then employed in supervised learning techniques such as Support Vector Machine (SVM)[29] and K-Nearest Neighbors (KNN)[30] to differentiate between healthy and Parkinson's cases. By leveraging these classification methods, the proposed method aims to effectively distinguish between the two categories based on the extracted features.

Training

In order to conduct thorough validation and testing, a hold-out validation approach was utilized, which involved randomly dividing the complete dataset into two portions: 80% for training and 20% for testing. The distribution of training and testing proportions for each category of drawings can be found in Table 2, while Table 3 provides an overview of the hyperparameters used during the model training process.

Evaluation Criteria

Machine learning relies on performance metrics to assess the effectiveness of models in accomplishing specific tasks. In this study, various performance metrics were employed to evaluate the performance of the proposed model. These metrics include sensitivity (or recall), specificity, accuracy, precision, F1-score (which combines precision and sensitivity in a harmonic mean), and Area Under the Curve (AUC) a measure of the model's ability to differentiate between positive and negative samples. AUC is calculated by plotting recall against 1-specificity and determining the area under the resulting curve.

Table 3 — Hyperparameters of the classifiers

Classifier	Hyperparameters
SVM	Kernel = 'rbf', Solver = 'SMO', Kernel Scale = 'auto'
KNN	Neighbors = 5, Distance = 'Euclidean'

Results

This section showcases the simulation results of the proposed approach, as illustrated in Fig. 3, for differentiating between Parkinson's and healthy states using spiral and wave drawings. The distribution of training and testing images for wave drawings as given in Table 2 is indicating a balanced representation of Parkinson's and healthy subjects. However, a higher number of Parkinson's spiral images were utilized compared to healthy subjects. The datasets encompassed over a thousand images for each category, as outlined in the methodology. The PHoG descriptors extracted from the drawings were applied to the VGG16 deep learning model, and discriminative features were obtained from the fully connected layers (specifically fc6 and fc7). These features were then employed individually and in combination with two supervised machine learning algorithms: SVM and KNN. The performance of these features, along with the machine learning models, for both spiral and wave drawings, can be observed in Tables 4 & 5. All simulations were

Table 4 — Performance of the proposed model on spiral drawings

Feature	Classifier	Performance measures (%)					
		Recall	Specificity	Precision	F1-Score	AUC	Accuracy
fc6	SVM	98.35	97.06	98.35	98.35	97.7	97.88
	KNN	94.45	94.12	96.79	98.1	96.78	97.53
fc7	SVM	98.9	97.06	98.36	98.63	97.98	98.24
	KNN	99.45	95.09	97.31	98.37	97.27	97.88
Fused (fc6+fc7)	SVM	98.9	98.04	98.9	98.9	98.47	98.6
	KNN	99.45	96.08	97.84	98.64	97.76	98.24

Table 5 — Performance of the proposed model on wave drawings

Feature	Classifier	Performance measures (%)					
		Recall	Specificity	Precision	F1-Score	AUC	Accuracy
fc6	SVM	87.25	98.04	97.80	92.22	92.64	92.64
	KNN	96.07	95.09	95.14	95.6	95.58	95.6
fc7	SVM	88.23	97.06	96.77	92.30	92.64	92.64
	KNN	97.06	95.09	95.19	96.11	96.07	96.07
Fused (fc6+fc7)	SVM	92.15	97.06	96.90	94.46	94.6	94.6
	KNN	97.06	96.08	96.11	96.58	96.57	96.57

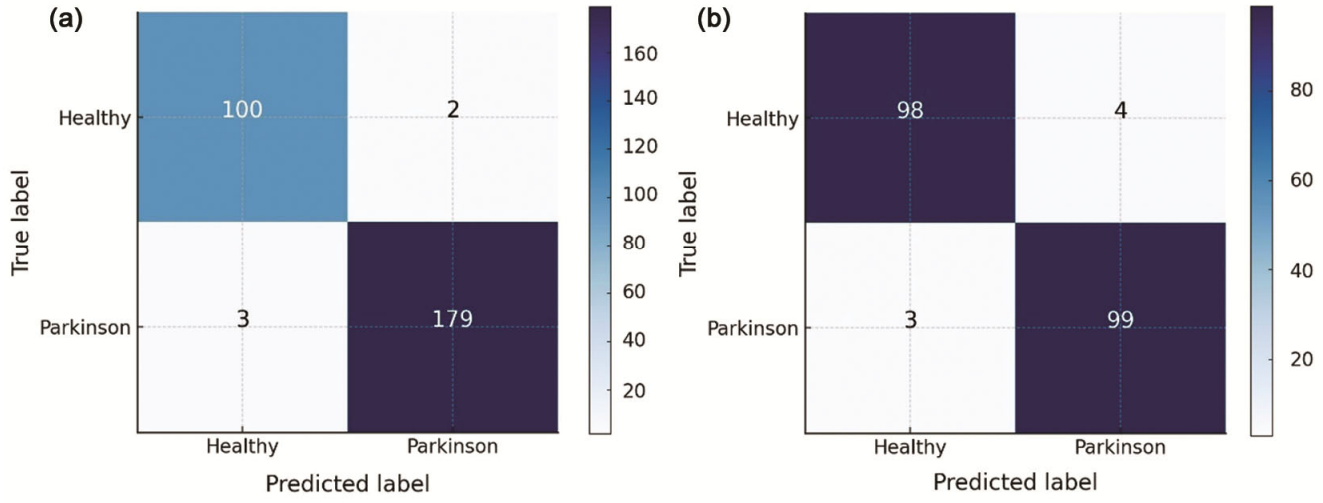

Fig. 6 — Confusion matrix of: (a) spiral images test data using fused features and SVM classifier, (b) wave images test data using fused features and KNN classifier

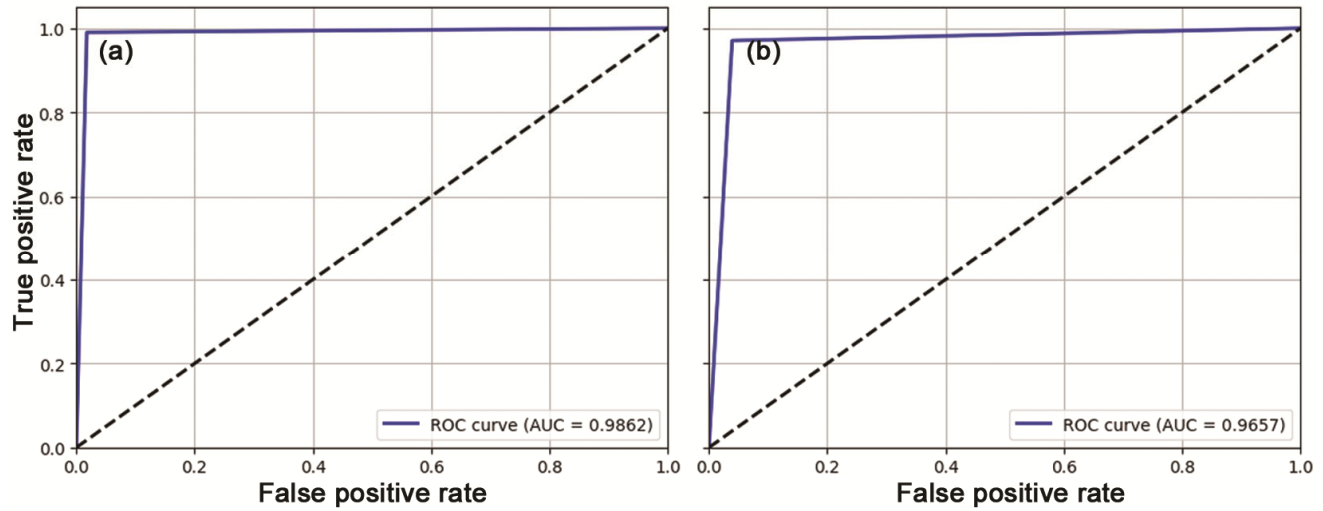

Fig. 7 — ROC of images: (a) spiral image test data using fused features and SVM classifier, (b) wave images test data using fused features and KNN classifier

conducted using MATLAB 2022b on an Intel (R) Core (TM) i3-5005U CPU @ 2 GHz.

From the above tables it is evident that combining features through feature fusion improves the performance of the models across multiple performance measures, with a notable impact on accuracy. Notably, the combination of features with SVM achieves an outstanding accuracy of 98.6% for spiral drawings. Similarly, the fusion of features with KNN yields the highest classification accuracy of 96.57% for wave drawings. These results are calculated using confusion matrices, where the diagonal entries represent the correct diagnosis for healthy and Parkinson's, and the anti-diagonal values denotes the false predictions. In Fig. 6(a) the confusion matrix of spiral drawing images (test set) using fused features and SVM is presented. Similarly, Fig. 6(b) presents the confusion matrix of wave drawing images (test set) using fused features and KNN.

As mentioned early, the AUC values are computed using the area under the Receiver Operating Characteristic (ROC) curve. It represents the relation between the True Positive Rate (TPR) and False Positive Rate (FPR). If a higher TPR at lower FPR is obtained that presents the good model's performance. Figs. 7(a) and 7(b) presents the ROC graphs of the best performed results of spiral (feature fusion and

Table 6 — Comparison of the proposed and existing models

Method	Drawings	Accuracy (%)
FCNN[4]	Spiral and Wave	92.43
Customized CNN[5]	Spiral	93.33
	Wave	90
DWT-HoG-RF[6]	Spiral	82.7
	Wave	76.7
HoG–CNN[7]	Spiral	94
AdaBoost[8]	Spiral	96.02
Logistic Regression[9]	Spiral	91.6
CNN[10]	Spiral	96.64
ResNet 50[(11)]	Spiral	89.99
VGG-19[(12)]	Spiral	88.5
	Wave	88
HoG- KNN[13]	Spiral	89.33
HoG- Gradient Boost[13]	Wave	86.67
CNN[14]	Spiral and Wave	93.3
HoG-RF[15]	Wave	70
ResNet-50 + SVM[16]	Spiral	98.45
CosineDCNN[17]	Spiral	89.98
2D CNN and voting-ensemble classifiers[18]	Spiral and Wave	96.6
Fusion of VGGs, ResNets, and vision transformers[19]	Spiral	87.66
	Wave	96.67
Incepetion V3[(20)]	Spiral	89
PHoG+VGG-16 + SVM (The Proposed)	Spiral	98.6
PHoG+VGG-16 + KNN (The Proposed)	Wave	96.57

SVM) and wave (feature fusion and KNN) images, respectively.

From the Fig. 7, it is observed that, the area under the curve values is optimistic and represents the better classification performance.

Finally, these results highlight the effectiveness of feature fusion in enhancing the overall performance of the models.

Discussion

A state-of-the-art comparison with the proposed work is presented in Table 6. The table is demonstrating the better performance of the proposed approach on both spiral and wave drawings. As a result, the presented framework holds potential as a decision-support tool for radiologists in diagnosing Parkinson's disease. From the analysis of the suggested model, the following observations were made:

- Previous works primarily focused on spiral drawings and reported their performance based on those alone.
- The combination of PHoG descriptors and deep neural networks in the proposed model leads to improved results. However, simple PHoG parameters are susceptible to geometric image transformations. In contrast, deep models often incorporate image augmentation as a preprocessing step, which addresses these geometric transformations.
- The proposed method capitalizes on the advantages of PHoG descriptors while employing less complex machine learning models for drawing classification, instead of directly utilizing CNNs. This approach surpasses the accuracy achieved by all existing methods for both spiral and wave drawings.

These observations highlight the effectiveness and superiority of the proposed model in comparison to the state-of-the-art techniques.

Conclusions

This study has presented a novel, effective approach to classifying Parkinson's disease based on drawings of spirals and waves, employing a combination of deep learning and traditional machine learning techniques. By integrating shape descriptors (PHoG) with VGG-based feature extraction from the fc6 and fc7 layers, and subsequently classifying with SVM and KNN models, high classification accuracies of 98.6% for spiral drawings with SVM and 96.57% for wave drawings with KNN was achieved respectively. These results indicate that the propsoed method is both accurate and reliable, highlighting its potential as a non-invasive diagnostic tool for early Parkinson's detection.

The implications of this research are substantial in the field of Parkinson's disease diagnosis. The non-invasive nature of drawing-based classification offers a convenient and accessible means for early detection, enabling timely interventions and improved patient outcomes. Moreover, this approach has the potential to serve as a cost-effective screening tool, facilitating widespread implementation for individuals at risk of Parkinson's disease. It is recommended that further validation and enhancement of the proposed classification system be conducted by conducting additional research on larger and more diverse datasets. These enhancements could ultimately

support widespread clinical implementation and contribute to better patient outcomes through early intervention.

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