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Research Article

Enhancing Parkinson's Disease Diagnosis Through Image-Driven Deep Transfer Learning and Optimization

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Abstract

This research proposed a hybrid methodology that combines data augmentation approaches, feature extraction using a pretrained Convolutional Neural Network (CNN), feature selection through optimization, and classification through Machine Learning to enhance the identification of Parkinson's Disease. This research first uses six different pretrained CNN models to classify different types of handwriting images (circle, spiral, and meander). The VGG16 framework works better than the others. The second step uses Binary Grey Wolf Optimization (BGWO) to choose the best collection of features from the VGG16 network by freezing the layers. The suggested strategy gets a 99.8% accuracy rate in classification using Support Vector Machine (SVM). We used the NewHandPD benchmark dataset to test how well our technique works. The experimental results demonstrate that the proposed method diagnoses Parkinson's disease more effectively.

1 Introduction

The primary etiology of Parkinson's disease is the degeneration of neurons' regenerative capacity. As people get older, neurons start to die and can't be replaced [1]. It is hard to tell if someone has PD, especially at first when the motor symptoms are minor, like tremors in the hands, micrographia (trouble writing), and muscle stiffness [2]. The symptoms come on slowly and usually don't show up until the patient's health gets worse. Some of the signs are trouble speaking, losing balance, moving slowly, having an unstable posture, feeling stiff, having trouble sleeping, and hiding your face [3].

In the initial stage, PD symptoms usually only affect one side of the body. In the second stage, they affect both parts. In the terminal stage of the disease, movement is hard. In the last two stages, people with PD can't do everyday things without help. There are already some diagnostic techniques, such as the Mini-Mental State Examination [4] questionnaire, the UPDRS [5], and brain scans. These techniques are expensive and need a lot of skill to use. Consequently, research has transitioned towards the creation of an automated method for differentiating patients with Parkinson's Disease from healthy individuals. According to the literature, handwriting or drawing analysis is regarded as a promising deterministic method for identifying PD patients [6]. The rest of the document is set up like this. Section 2 provides a concise overview of the literature regarding PD detection. In Section 3, we show the dataset and the methodology we provide. In Section 4, you can see the setup for the experiment and the outcomes. Section 5 wraps up the work and gives ideas for what to do next.

2 Related Work

James Parkinson was the first to talk about how shaking palsy makes it hard for people to write. Since then, the pattern recognition community has been working hard to find ways to identify PD for more than 40 years [7]. It is easy and non-invasive to capture handwritten picture data with digitizing tablets. The tablets also give other vital information, such as the subjects' pace and pressure [8]. In recent years, many decision support systems have been established for the differential diagnosis of PD. These systems use speech assessment, gait tracking [9], and tremor evaluation [10]. These approaches encounter several challenges, including the necessity for high-quality, noise-free recording settings for speech evaluation. It is easy to accomplish handwriting-based PD diagnosis anywhere, and you don't need any particular equipment to get the data. To monitor gait and detect tremors, on the other hand, you need special gear like accelerometers or gyroscopes.

Handwriting modifications are difficult to detect in the initial stages of Parkinson's Disease (PD); yet, they remain a significant biomarker for PD identification [11]. The objective of this project is to develop an automated system capable of identifying the symptoms of Parkinson's disease from handwritten photographs. Literature indicates that it is feasible to automatically differentiate between unhealthy and healthy individuals by utilizing several features identified through basic handwriting exercises. The authors in [12] employed computer vision techniques to construct the HandPD dataset and utilized various ML classifiers on the retrieved characteristics. They had to sort the data by figuring out how different the Spiral Template (ST) and Handwritten Trace (HT) were. Nine features were extracted from each by considering the statistical disparity between the ST and the HT [15, 16]. The Naïve Bayes (NB) classifier achieved a maximum accuracy of 78.9%. Authors [13] examined the potential of a dynamically augmented handwriting image for diagnosing Parkinson's disease (PD). We used time-series signals from the PaHaW dataset to make static visuals that change over time.

Deep Learning (DL) guarantees enhanced precision in image categorization [14] owing to its resilience in autonomous feature extraction. CNNs are the most popular way to apply DL in medical imaging. Deep Learning (DL) has come a long way, and now it's possible to automatically extract features to train any network. A lot of data is needed to train a CNN model well [17]. Transfer Learning provides a robust alternative to traditional methods that mostly emphasize manual feature extraction. In [18], the authors used CNN with several image resolutions and train-to-test split ratios to get the greatest accuracy of 80.19% [19]. Authors in [20] employed the AlexNet architecture using TL to diagnose PD. They said that the AlexNet structure has the highest accuracy of 99.22 percent. The authors in [21] suggested a combination of DL architectures for detecting PD through offline handwriting [22, 23]. The method of picking features helps you get a smaller set of important features for a classification task. By getting rid of extra and unneeded features, feature selection becomes less complicated and less dimensional [24]. There is still room for more research in the area of adaptive heuristic algorithms for feature selection. There are three ways to choose features: the filter technique, the wrapper method, and the embedding method. The wrapper approach has been used in a number of studies. This strategy focuses on picking an optimization algorithm for feature identification from the three ways. Presenting a system that utilizes handwritten pictures to diagnose PD early and correctly.

1. Using the deep network that works best to get features.

2. The wrapper-based BGWO meta-heuristic method picks the best subset of features, and the Support Vector Machine helps sort them.

3. Using various data augmentation methods to expand the input space and improve classification performance.

3 Materials and Methods

This part gives a general idea of the suggested framework for PD classification. In this study, Parkinson's disease patients are categorized alongside healthy persons based on features derived from a pretrained CNN model, picked through BGWO, and subsequently classified using SVM. Figure 1 shows the block diagram for the whole system. The subsections below explain each block.

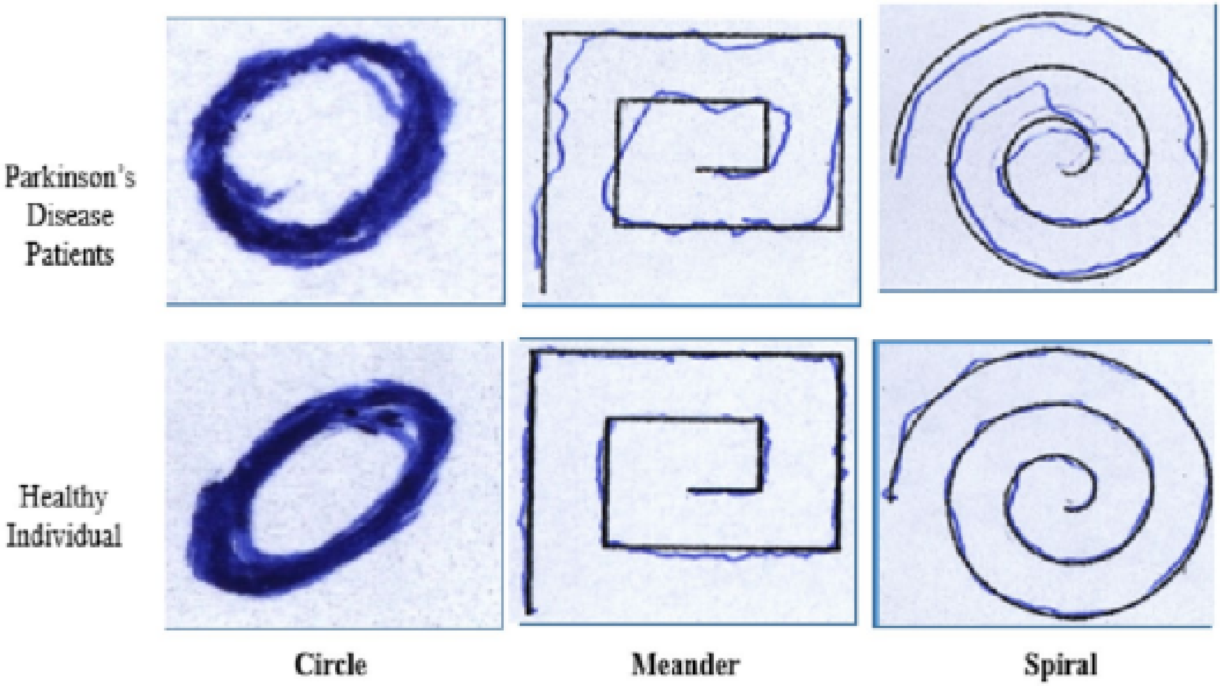

Figure 1: Images of a PD sufferer and a healthy individual written by hand.

3.1 Dataset

People with PD have trouble controlling their bodily movements because of changes in how neurons work. This makes it challenging for them to do things that require motor skills, including writing. In this research, we utilized the NewHandPD handwriting dataset to differentiate. The present work employs a hybrid methodology integrating Deep Learning (DL) and Machine Learning (ML) as given in Table 1. In our research, we first use data augmentation methods like flipping (horizontally and vertically) and scaling the image to make the dataset bigger. Then, the data is balanced utilizing the data equalization technique. The BGWO algorithm is used to choose important features, and then the ML classifier is used to sort them. Figure 2 shows the block diagram of the proposed framework and what each block does.

Table 1: Dataset Description

Sample	**PD patients**	**Healthy Individuals**
Circle	35	35
Spiral	130	140
Circle + Spiral	165	175

3.2 Data Preprocessing

This work uses three data augmentation methods to make the dataset more diverse and less likely to overfit: rotating the image at 45 and 90 degrees, flipping it (horizontally and vertically), and scaling it. So, one original image can be used to make five other versions. After that, the data equalization process is done to make sure that the records in each class are the same as shown in Figure 2. Table 2 illustrates how many photos were made after using the data augmentation and data equalization

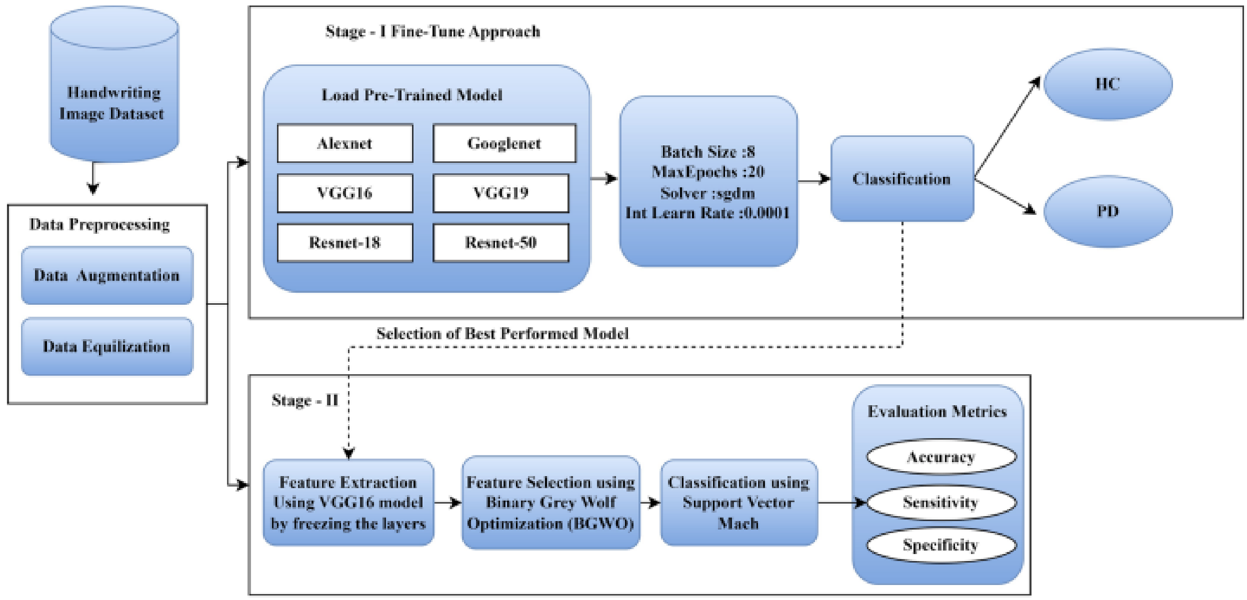

Figure 2: Block Diagram of proposed framework.

techniques. There are 3150 photos in total, and both groups will get them. This is because TL works better with smaller datasets.

3.3 Transfer learning

A CNN has a convolutional layer, a rectified linear unit (ReLU), an activation function, a pooling layer, and a batch normalization layer. The last layers are the dropout, softmax, completely connected, and categorization output layers. Table 3 shows how different testing with different values might help you find the best network parameters for PD detection. Our research indicated that the transfer learning model achieved optimal performance with a maximum of 20 epochs, a batch size of eight, and a learning rate of 0.0001.

Table 2: Images of handwriting taken after data pre-processing

Sample	**Patient**	**Control Group**
Circle	275	275
Spiral	900	900
Circle + Spiral	1175	1175

3.4 Feature Selection

After feature extraction, feature selection is used to cut down on the number of dimensions in the feature space as given in Table 3 . This makes the process more accurate and takes less time. There has been a big rise in research on meta-heuristic and evolutionary algorithms lately. Some of these algorithms are the binary bat method, the crow search algorithm, the ant colony optimization algorithm, and the chaotic mapped bat algorithm. The present work utilizes an innovative bio-inspired optimization method known as the Grey Wolf Optimizer (GWO), derived from the hunting behavior of wolves as given in Table 4. The Binary Grey Wolf Optimization (BGWO) technique is utilized in our study to identify the most pertinent features for categorization. The BGWO algorithm was chosen because its best attributes made it more accurate than the other three optimization methods mentioned. Grey wolves hunt in three different stages: encirclement, pursuit, and attack. Equations 1 and 2 show how to use the encircling strategy in math:

Table 3: Hyperparameter Summary

Hyperparameters(HYP)	**Value**
Batchsize	16
Learnrate	0.00001
Optimizer+No of epoch	Sgdm+50

Table 4: Parameter for Grey wolve optimization Approach

Srno	**Parameter(PARM)**	**Value(VAl)**
1	No of search gray wolves	20
2	No of Loop	150
3	FeatureDimension(Dim)	1500
4	SearchDomain	[1,0]
5	Parameter	0.01

$$\vec{X}(t+1) = \vec{X}_p(t) + \vec{A} \cdot \vec{D} \tag{1}$$

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \tag{2}$$

4 Results

The initial step is to put the augmented handwriting images into the AlexNet, Googlenet, VGG16, VGG19, Resnet-18, and ResNet-50 networks. Table 5 shows the result of this method. Using the best pretrained network, the features are retrieved. To assess the classification parameters, a comparative analysis of both the holdout and cross-validation methods is conducted. For holdout, the training and test datasets are divided in the proportions of 70:30, 80:20, and 90:10. To minimize overfitting, both fivefold and tenfold cross validation are utilized. The experiment is conducted several times to find the average classification accuracy, sensitivity, specificity, and precision. Table 6 displays the outcome derived from feature extraction using VGG16, selection via the BGWO algorithm, and classification through SVM. Evaluation metrics are used to judge how well a classifier works. This study calculates three performance evaluation measures. In this case, True Positive (TP) and True Negative (TN) show how many positive and negative records were accurately detected. False positive (FP) and false negative (FN) figures show how many records belong to the wrong positive and negative classifications, respectively. Accuracy, Sensitivity, and Specificity [35] are calculated to assess the model's performance,

Table 5: Average Classification Approach using Fine Tuned Models

Img Type	**Alexnet**	**Googlenet**	**Vgg16**	**Resnet**	**Vgg19**
Circle	91.7741	90.3123	86.9966	87.3256	90.3205
Spiral	90.5252	92.0903	86.2145	89.9999	89.3654
Circle +Spiral	94.3265	93.6514	97.3258	96.3898	91.2689

Table 6: Mean Classification Results obtained from feature extraction using the VGG16 model (frozen approach), supplemented by feature selection via BGWO and SVM.

Img Type	**Accu(%)**	**Sensitivity**	**Specifity**
Circle	85.3265	86.3324	91.2635
Spiral	92.6539	93.2651	94.2145
Circle+ Spiral	96.6788	95.3296	93.9855

with their corresponding formulas denoted by Equations 3 - 5.

$$\text{Accuracy (ACC)} = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{3}$$

$$\text{Sensitivity (Sens)} = \frac{TP}{TP + FN} \tag{4}$$

$$\text{Specificity (Specf)} = \frac{TN}{TN + FP} \tag{5}$$

Identifying essential traits makes things more accurate and takes less time to compute. The time is 3.21 seconds with feature selection and 14.265 seconds without it. Figure 3 displays the ROC figure for the linear SVM classifier following feature selection. Numerous studies have been undertaken with transfer learning and convolutional neural networks (CNN). This section compares our suggested method to other methods that have already been published. The suggested strategy compares to other studies that used the same dataset. Our proposed method exhibits a slight advantage over alternatives, maybe indicating a new direction for the field of study.

5 Conclusion

The current study aimed to distinguish Parkinson's disease patients from healthy controls through the examination of handwritten graphics. Then, SVM is used to group them. A linear kernel SVM classifier gets the most accurate results, with an accuracy of 99.8%. The findings are clearly demonstrated with several shapes, such as a circle, a spiral, and a meander. The combination of these four sketches produced the most accurate result. The study finds that BGWO finds the best subset of features, which limits the number of features while increasing accuracy and cutting down on the time it takes to run the SVM classifier. This hybrid approach that combines deep learning and machine learning could be useful for automatically finding Parkinson's illness.

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