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# Optimized Handwriting-based Parkinson's Disease Classification Using Ensemble Modeling and VGG19 Feature Extraction

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**Abstract.**
**Purpose:** Parkinson's is a neurological disorder that causes muscles to weaken and arms and legs to tremor over time. The discovery and identification of the stages of Parkinson's disease can substantially benefit the treatment of its symptoms. Many studies have been conducted in classifying hand-drawn -based Parkinson's disease but the resulting performance is still not optimal. The purpose of this research is to improve the performance of handwritten Parkinson's disease classification accuracy using an ensemble soft voting model.
**Methods:** The model adopted the Parkinson's Disease Augmented Data of Handwritten dataset taken from Kaggle Repository, where the dataset contains Healthy and Parkinson's classes with a total of 3264 images. Then, the dataset was augmented again, resulting in 2612 images in the training data and 652 images in the validation data. After that, the dataset was optimized with VGG19 feature extraction and fine-tuning and then modeled with the Ensemble Learning model. The model was evaluated with a confusion matrix, and the classification report was viewed.
**Results:** The results of the proposed evaluation test discovered the effectiveness of the Ensemble Learning model with Fine Tuning VGG19 feature extraction by producing an accuracy of 98.9%.
**Novelty:** This research has successfully contributed to the proposed ensemble model for Parkinson's handwriting and improved the accuracy performance of the model.

**Keywords**: Parkinson’s disease, Classification, Ensemble, VGG19
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## INTRODUCTION

Parkinson’s disease is a chronic neurodegenerative brain disorder, which affects the ability of the person to perform the regular activities [1]. Parkinson's Disease (PD) is a neurological disorder that causes muscles to weaken and arms and legs to tremor over time. Slow degeneration of neurons that produce a substance called dopamine results in aberrant brain activity and PD symptoms [2], [3]. Characterized by the degeneration of nigrostriatal dopamine neurons and the appearance of inclusion bodies containing - synuclein as a major component [4], [5]. Nerve cells gradually lose their ability to communicate with each other, resulting in depression and other nervous system disorders [6]. Early-stage symptoms include slower movements, tremors, muscle tension, decreased posture and balance, speech abnormalities, handwriting problems, and so on. People who have Parkinson's disease feel difficulty in doing activities like speaking, writing, and walking [7]. In addition to speech patterns, handwriting patterns can be used to diagnose disease by comparing the types of pictures drawn by sick and healthy people [8]–[10]. This disease reduces patients' quality of life, makes social connections more difficult, and worsens their financial situation due to high medical costs [11], [12].

Handwriting is a complex activity that involves cognitive, kinesthetic, and perceptual-motor aspects, changes which could be a promising biomarker for the evaluation of PD [13]. In addition, there is evidence that easy and simple handwriting tasks can help distinguish healthy people from unhealthy people. To date, there is no cure for the disease, and gradual deterioration of the patient's condition is only possible if the disease continues to progress. However, diagnosis of PD at an early stage can be crucial for the prospects of medical treatment and evaluation of the effectiveness of new drugs.

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One of the Parkinson's disorders is handwriting, They tend to move sequentially and are more segmented [14], [15]. Often, there are hesitations and pauses between sequence components [16]. Coordinating the movement components of a motor sequence is very difficult for PDs [17]. The discovery and identification of the stages of Parkinson's disease can substantially benefit the treatment of its symptoms [18], [19]. Machine learning and ensemble-based techniques can be used to improve the efficiency of treatment and medical facilities, and estimate the risk of Parkinson's disease.

In the process, there is research focusing on Parkinson's classification using handwritten images. Research [20] using SVM algorithm in handwriting analysis of PD patients with additional feature selection algorithm analysis of kinematic and pressure features during hand-writing with a classification accuracy of 81.3%. One recent study generated a composite score by averaging speed and pressure in the context of spiral drawing analysis for Parkinson's disease with tablets, which were used to discriminate the various stages of Parkinson's disease [21]. In addition, an entropy-based method was used to quantify temporal irregularities in limb movements of patients with Parkinson's disease (PD) [22].

Other research that is [23] through feature engineering and machine learning classifiers (Logistic Regression, C-Support Vector Classification, K-Nearest Neighbor, and Random Forest Classifier), analysis of static and dynamic spirals drawn by Parkinson's disease (PD) patients and healthy controls using digitized tablets achieved a classification accuracy of about 91% in Logistic Regression model, demonstrating the potential of digitized spiral drawings as a supportive tool for future differential diagnosis of PD. However, the model performance results used a comparison of several individual algorithms. To improve model performance, this study took a step further by using a robust model ensemble technique. The ensemble method combines predictions from multiple models to provide more precise and consistent results [24]–[26]. The contribution of this research is to propose a soft voting ensemble model with VGG19 feature extraction and Fine tuning and successfully improve the accuracy performance. VGG-19 is well-known for its powerful feature extraction. The contribution of this research is to improve the performance of the Parkinson's disease accuracy model using image datasets that have been augmented and ensemble models, optimizing and adding VGG1 feature extraction in fine tuning.

## METHODS

The stages of the research process carried out in this study are described in a flow as shown in Figure 1.

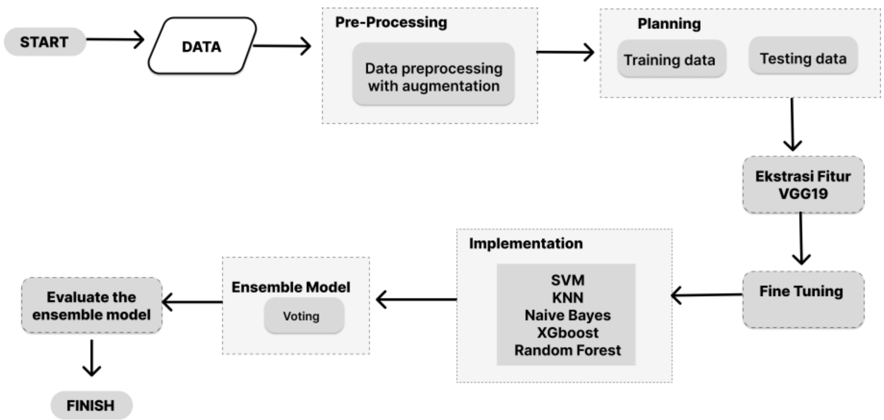


Figure 1. Research flow

### Data

Dataset in the form of Parkinson's Drawings was taken from https://www.kaggle.com/datasets/kmader/parkinsons-drawings The dataset contained the original handwritten Parkinson's disease dataset consisting of 204 images, 2 classes, namely Healthy and Parkinson's, each of which consisted of spiral images and waves images. Then, in this study, the dataset used had been augmented to increase the variety and amount of training data so that the machine learning model can recognize patterns better and increase the generalization ability of the model. https://www.kaggle.com/datasets/banilkumar20phd7071/handwritten-parkinsons-disease-augmented-data the original 204 images were increased to 3264 from 2-class. In this dataset, the images had been previously augmented to create more data by the process of adding data such as: Rotating 90°, 180°, 270°, vertically flipping 180° and converted to color images. The following is a summary of similar Parkinson's disease image research in Table 1.

Table 1. Summary of Parkinson's disease image research

| Author | Dataset | Summary |
|---|---|---|
| Kamble et al. [23] | Parkinson Disease Spiral Drawings | Applying feature engineering and four machine learning classifiers (Logistic Regression, C-Support Vector Classification (SVC), K-nearest neighbor (KNN) classifier, and Random Forest Classifier (RFC)) |
| Bernardo et al. [27] | Handwritten pattern recognition | The drawings were processed using image methods to extract 11 metrics representing relevant characteristics. Machine learning techniques, including Optimum-Path Forest, Support Vector Machine, and Naive Bayes, |
| Zham [21] | Parkinsons drawing spirals and waves | The study used the Composite Index of Speed and Pen-pressure (CISP) as a feature to analyze the severity of Parkinson's disease. Speed, pen-pressure, and CISP were measured and their correlations with PD severity were evaluated. CISP showed a stronger correlation (-0.641) compared to speed (-0.415) and pen-pressure (-0.584). CISP was able to distinguish between PD and control groups and differentiate PD severity levels 1 and 3 but not level 2. |
| Drotár et al. [20] | PaHaW Parkinson's disease handwriting database | Analyzing kinematic and pressure features during handwriting using K-nearest neighbors (K-NN), AdaBoost ensemble classifier, and support vector machine (SVM) |

**Pre-Processing**

This procedure is used to prepare the data for use with the classification model [28]. This process preprocesses the data by applying various augmentation techniques, such as rotation, width and height shift, shear, magnification, and horizontal inversion. The images are rescaled to the range of 0 to 1. Two generators, train_gen and val_gen, are created for training and validation data, respectively. The generators read images from the specified data_dir, apply the specified addition, and split the data based on the specified validation_split. For multi-class classification, class_mode should be set to 'categorical', but in this case, it is set to 'binary' since it is a binary classification problem. Figure 2 shows an example of a pre-processed image.

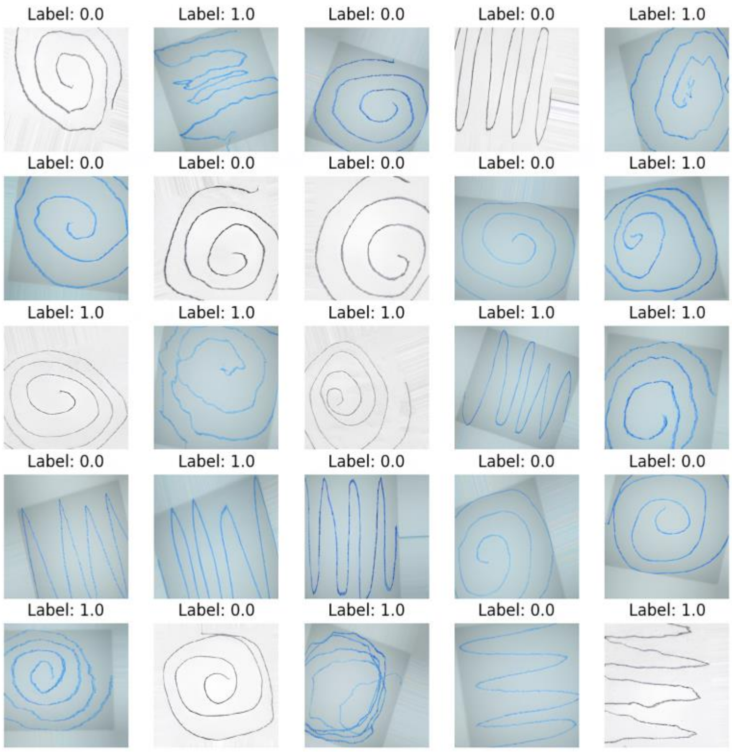


Figure 2. Example of pre-processed images

Data augmentation helps the model understands the key features of the underlying target class, so it can better generalize to data that it has never seen before. It generates variation in the training data by changing it realistically.

**Feature Extraction Using VGG19**

In supervised learning techniques, deep learning models (VGG19) and modern classifiers were used to extract and classify features. VGG-19 is a 19-layer trained Convolutional Neural Network invented by Visual Geometry Group of Oxford University [29]. VGG-19 is used for image classification and provides 1000 outputs [30]. The VGG19 image classification model has recently shown favorable results [31]. VGG19 models to extract important features from the input image and then adds a specialized layer on top to create a binary classification model for a specific task.

**Fine Tuning**

Fine-tuning in transfer learning uses pre-trained models for various tasks or data sets. This is done by slowly changing the trained model to suit the unique task at hand [32]. In the context of this research, the fine-tuning approach used a VGG19-based model. The first step was to combine the base model with specialized output layers that match the task requirements. Next, the layers in the base model, which already had pre-trained weights, were frozen. This was done so that the weights did not change during the fine-tuning process. Finally, the fine-tuning model was compiled using the Adam optimizer, with a learning rate (lr) of 0.001. The loss function used was 'binary_crossentropy', which was suitable for binary classification problems, and the model performance evaluation metric used was accurate. Thus, this fine-tuning process combined the existing model with the mentioned parameters and values to improve the performance of the model in the specific task at hand.

**Experimental result of Ensemble Model**

The ensemble method combines different sets of models to produce a more accurate model [33], [34]. The ensemble learning model is more robust and has lower generalization error than the single model [35]. In conducting model tests, splitting data with training data (80%) and validation data (20%) was used to measure model performance.

Classification models used were SVM, KNN, Naive Bayes, XGBoost and Random Forest. These models were initialized and fine-tuned with parameters such as the SVM model was initialized with the 'rbf' kernel and C = 1.0, the KNN model is initialized with n_neighbors = 5, and the Naive Bayes model uses Gaussian Naive Bayes. Then, the prediction results and model evaluation with the classification report for each model were stored. Furthermore, the individual model models were combined with the ensemble model method using voting classifier which calculated the probability of each individual model then chose the highest probability and the prediction results were evaluated.

**Model Evaluation**

Confusion Matrix can display forecasts as well as the current status of data created by machine learning algorithms [36]. True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) are the correct number of positive classes, the number of false positive classes, the correct negative class, and the erroneous negative class on the data in the Confusion Matrix. In this study, accuracy was measured by measuring the evaluation of model performance using the confusion matrix and the accuracy indicator. Accuracy was used to understand how accurate the model was in predicting/detecting Parkinson's and healthy correctly, the accuracy calculation can be seen in formula (1).

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

## RESULTS AND DISCUSSIONS

Research results is a stage based on the testing scheme mentioned in the research method. At this point, the proposed model will be tested, and the accuracy values will be compared. In addition, when comparing the model's predicted results with the actual categorization, the confusion matrix will be used as an additional source of information. The accuracy results indicated good performance.

## VGG19 and Fine Tuning Model

The VGG19 model had proven to be very effective in various image classification tasks and had been widely used in the machine learning and computer vision communities. We used the pre-trained VGG19 model by excluding the top classification layer in this study. The VGG19 model was known for its deep architecture and was often used for transfer learning in image classification tasks. The model was set to accept an image of 224 x 24 pixels with three color channels (RGB) as input.

Initially, the VGG19 model was used with its standard architecture, which included deep convolution and pooling layers. However, to meet the needs of the study, several additional layers were added on top of the basic VGG19 model. The first layer added was the GlobalAveragePooling2D layer, which served to reduce the spatial dimensionality of the features generated by the VGG19 model. This was done by taking the average across spatial units, generating global features in the image, and converting them into feature vectors with a dimension of 512. To see the layers in the VGG19 model, see Figure 3.

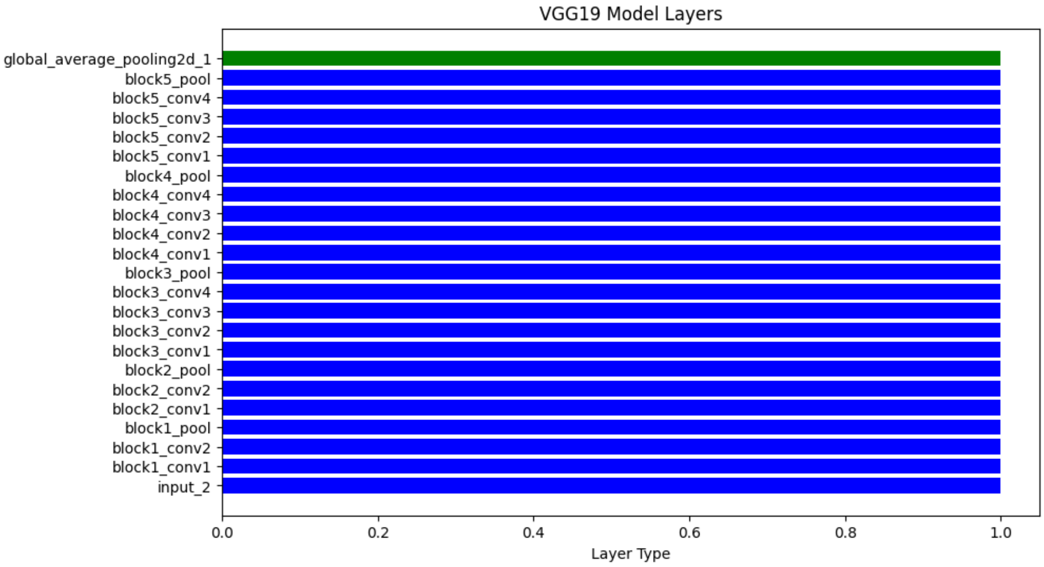


Figure 3. VGG19 model layers

Typically, simple features such as edges and lines can be captured by filters at early layers, while filters at deeper layers can capture more complex and abstract features. To understand what each filter at a particular layer of the VGG19 model learns, the following example image shows the activation of a filter at a particular layer. This is done using one of the Parkinson's images shown in Figure 4.

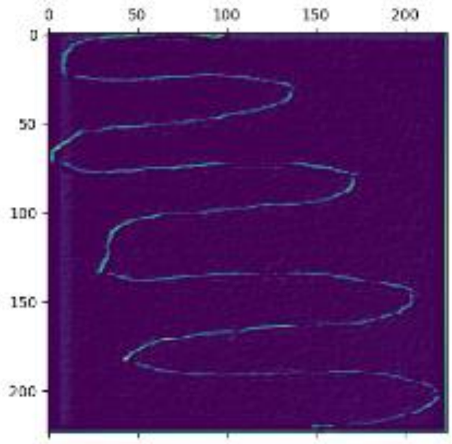


Figure 4. Example of block1_conv1 layer on VGG19

The pre-trained VGG19 model was input without a final classification layer, and then two dense layers were added to extract additional features. The model was used to predict the image class after loading the example image. After retrieving the output feature map from the last convolution layer, the next step was to compare the gradient of the predicted class with the feature map. Then, these gradients were "polled" to obtain information about important areas in the image. These important areas were indicated by connecting the pixels in the image that contributed most to a particular classification. This was done using a heatmap, as shown in Figure 5.

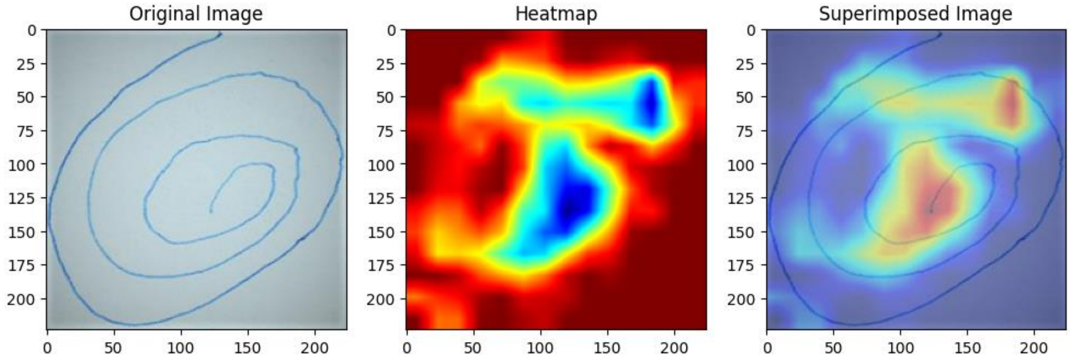

Figure 5. Gradient weighted class activation mapping example

In the context of VGG19, fine-tuning involves taking a pre-trained VGG19 model that has been trained on a large dataset (e.g., ImageNet) and adjusting its parameters to better suit the new dataset or task. This is done by replacing the last fully connected layer of the VGG19 model with a new layer that corresponds to the number of classes in the new data set. The weights of the previously trained layers are frozen, and only the weights of the new layer are updated during training [37]. Fine-tuning allows for better generalization and better performance on tasks by utilizing information obtained from pre-trained models.

**Implementation Ensemble Model**

After the Parkinson drawing, data was pre-processed and feature extracted. The process continued by extracting features on the base model. Various learning techniques have been developed, including supervised, unsupervised, and reinforcement learning [38]. Algorithm models used for ensemble models were Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naïve Bayes, Xgboost, and Random Forest which were initialized by fine tuning then the model was evaluated with an ensemble model using the voting Classifier technique.

This confusion matrix showed that the model performs very well because it had a low number of False Positive (false predictions for positive classes) and False Negative (false predictions for negative classes). The high number of True Positive (correct prediction for positive class) and True Negative (correct prediction for negative class) also indicated that the model can well distinguish between healthy patients and Parkinson's patients. The confusion matrix compares the model's predictions and the actual values to evaluate the model's performance, which can then be used to see the model's accuracy performance. which can be seen in Table 2.

Table 2. Confusion matrix for ensemble model

| | Healthy | Parkinson |
|---|---|---|
| Healthy | 325 | 1 |
| Parkinson | 4 | 322 |

Before using the ensemble model, several single models were tested, namely SVM with 85% accuracy, KNN 84%, Naïve Bayes 96% and 100% for XGBoost and Random Forest. Although these single models had good performance, the model will be improved by combining the results of several models. The individual model test results are shown in Figure 6.

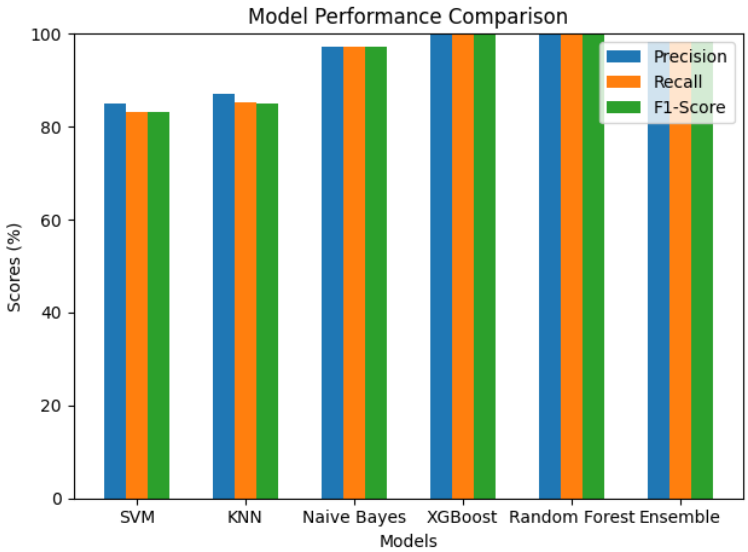


Figure 6. Model performance comparison

Additionally, ensemble model with Voting Classifier technique was performed to improve the accuracy and stability of prediction. Each model has different weaknesses and advantages, so using an ensemble model can reduce the risk of overfitting and provide better performance. The results of the single and individual model accuracy evaluation are shown in Table 3.

Table 3. Evaluation of different methods

| Algorithm | Accuracy (%) | Precision(%) | Recall(%) | F1-score(%) |
|---|---|---|---|---|
| XGBoost | 100 | 100 | 100 | 100 |
| KNN | 84 | 87 | 85 | 85 |
| Random Forest | 100 | 100 | 100 | 100 |
| SVM | 85 | 85 | 83 | 83 |
| Naïve Bayes | 97 | 97 | 97 | 97 |
| Ensemble Model | 98.9 | 98 | 98 | 98 |

The voting technique used was soft voting where the single model was taken on average the probability of prediction, the high probability value determined the final result where in this study it reached an accuracy value of 98.9%. This showed that the ensemble technique used successfully improved the performance of the model. This also proved that the approach used was useful in improving classification tasks and better accuracy than previous studies. The comparative performance of the proposed method with existing methods can be shown in Table 4.

Table 4. Performance of proposed method in comparison to current similar works

| Author | Data Used | Algorithm | Accuracy (%) |
|---|---|---|---|
| Kamble et al.[23] | Parkinson-disease-spiral-drawings | Logistic Regression | 91.6 |
| Drotár et al.[20] | Parkinson Disease Spiral Drawings Using Digitized Graphics Tablet | K-nearest neighbors (K-NN), ensemble AdaBoost classifier, and support vector machines (SVM) | 81.3 |
| Mucha et al.[39] | Parkinsons handwriting | random forests + 5 kinematic features | 90 |
| Proposed Method | handwritten-Parkinson’s-disease-augmented-data | Ensemble Voting Classifier | 98.9 |

The results showed that an ensemble model combining several machine learning algorithms achieved a high accuracy of 98.9% in Parkinson's disease classification based on handwriting data. This study surpassed the results of previous studies and demonstrated that an ensemble approach can significantly improve model performance. In addition, the use of the VGG19 model with fine-tuning provided insight into the importance of effective feature extraction from handwritten image data, while soft voting techniques in the ensemble model helped to improve the stability of the predictions. This research makes a positive contribution to the improvement of Parkinson's disease classification and the utilization of deep learning models in transfer learning tasks.

## CONCLUSION

This research used an optimized soft voting ensemble model using Random Fores, XGBoost, Naïve Bayes, KNN, and SVM algorithms. The model also used the VGG19 feature extraction method which was fine-tuned. The study showed good performance in using the ensemble soft voting model in classifying Parkinson's disease images that had been augmented. Using VGG19 feature extraction and fine-tuning involved using VGG19 for feature extraction, and refinement involved using the capacity of pre-trained networks to understand complex visual features, and then adapted them to the characteristics of Parkinson's Disease classification. The evaluation test results showed better classification accuracy by performing soft voting and the ensemble algorithm model gets an accuracy of 98.9%. In future research, it can be further developed by performing on more varied datasets and comparing various dataset models and refining new models with better performance.

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