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# A Hybrid Approach based on Machine Learning Classifiers and Harris Hawk Optimization for Parkinson Disease Classification

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ABSTRACT

The rapid advancements in artificial intelligence (AI) and data analytics have created significant opportunities in fields such as healthcare and intelligent transportation. As the volume of complex data continues to grow, there is an increasing demand for analytical models capable of extracting meaningful patterns and generating accurate predictions. This study focuses on enhancing Parkinson's disease (PD) detection by using the Harris Hawk Optimization (HHO) for feature selection to improve classifier performance on the UCI Parkinson's disease dataset. We evaluated four classifiers: Decision Tree (DT), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF), under two scenarios: without feature selection and with HHO-based feature selection. The results reveal substantial performance improvements with HHO, with RF achieving the highest accuracy of 98.33%. Comparisons with recent studies highlight the effectiveness of our approach, establishing it as a new benchmark in PD detection accuracy. This research underscores the essential role of optimized feature selection in enhancing classifier accuracy and reliability, especially for early diagnosis through voice-based data.

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## 1.Introduction

Parkinson's disease (PD) is a neurodegenerative disorder that progresses slowly and, therefore, results in the loss of dopaminergic neurons in the brain. Common symptoms of PD include tremors, slowed movement, speech difficulties, and challenges in keeping one's balance. Because the disease generally affects older people, the ever-increasing rate of the aged population means PD is widespread in the world; it is the second most frequent neurodegenerative disorder after Alzheimer's disease, with millions of cases per year [1,2].

Within the last years, machine learning (ML) and deep learning (DL) became increasingly important in many disciplines because of their accuracy, flexibility, and good performance on big data problems. Their applications also involved several modules on intelligent transportation systems, vehicle detection, and classification for identifying and categorizing a vehicle with high accuracy for better traffic management and improving safety accordingly [3,4]. The systems will also revolutionize the field of medical diagnosis in the early detection of neurological conditions

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such as PD [5] and arrhythmia [6]. All these examples show the effectiveness that ML and DL have in different areas, assurance of their use in decision-making developments across different industries, from transport infrastructure to critical health interventions.

These ML/DL models enable the doctors in the clinical domain by giving an improved early-stage diagnosis that usually is not that sensitive. After collecting the data, the selection of the best ML algorithm is indispensable for reliable results. Some popular classifiers, such as Artificial Neural Networks (ANN) [7] and multilayer perception (MLP) [8], have become very efficient in handling the analysis of PD-related datasets and, as a result, have improved classification accuracy along with diagnostic reliability. In consequence, these strengths make ML and DL irreplaceable in health care and transportation, where speed and preciseness are complementary for any type of analysis.

This study employs Harris Hawk Optimization (HHO) to improve accuracy and reliability through feature selection for a machine learning classifier on the Parkinson's Disease dataset. Feature selection carried out with the use of HHO enhances model performance by giving greater significance to the most relevant data attributes, especially for such high-dimensional voice data. Classifiers, in our work, include Decision Tree (DT), Random Forest (RF), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM), which are checked with and without the HHO feature selection method. The idea remains to present an ideal framework that helps overcome the certain limitations imposed by the conventional machine learning models in order to detect PD with higher accuracy and enhancement in efficiency. This study's contributions are as follows:

- The Harris Hawk Optimization (HHO) was introduced for feature selection in the Parkinson's disease dataset, showing notable improvements in the accuracy and reliability of several classifiers. This approach effectively reduces data dimensionality while retaining the most relevant features, resulting in enhanced performance for PD detection.
- In this regard, the full comparison of SVM, RF, KNN, and DT classifiers in unoptimized and optimized conditions using an HHO-based feature selection technique was carried out. It can be seen from the results obtained after using the HHO feature selection that this method improves the performance, and then RF has given accuracy of 98.33%, and also SVM has shown high value improvements in performance metrics.
- This work presents a thorough comparison with recent works by others dealing with the Parkinson's disease dataset in order to prove the efficacy of the approach proposed here. In fact, these comparisons place this approach as a new benchmark for PD detection, with superior accuracy and reliability in early diagnosis using voice signal data.

## 2. Related Works

This section highlights recent research from the past four years on PD detection. Typically, the PD classification is conducted using voice signal analysis, utilizing artificial intelligence techniques, particularly deep and machine learning classifiers. For instance, there is the approach by Abdullah et al. [9], embedding the 3 main machine learning classifiers of RF, XGBoost, and DT, coupled with filtering-a preprocessing method for removing constant features and genetic selection for choosing relevant features from two different datasets with the rationale of enhancing diagnostics. This combo strategy brought in remarkable precision in PD diagnosis from data of vocal signals. Similarly, Mohammed et al. [10] investigated eleven classifiers and later applied the multi-agent feature selection approach in order to choose the best subset of features with the most accurate results. The hybrid model-HM-outperformed other classifiers and showed promise for a diagnostic accuracy of 96.6% for PD.

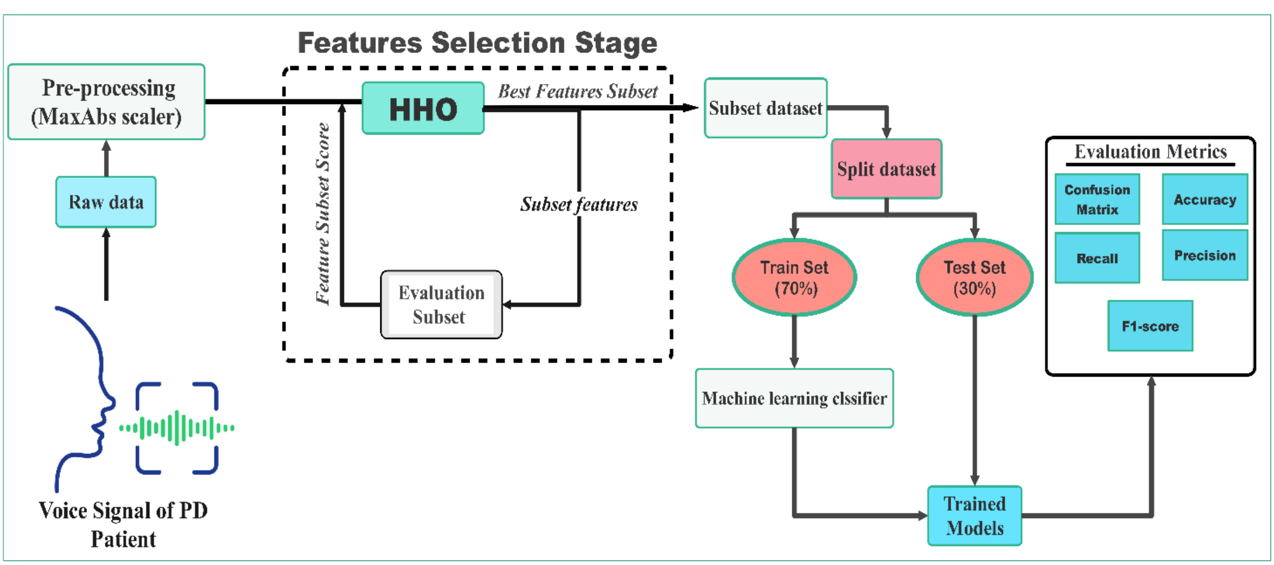
Another approach was presented by Rehman et al. [11], their method utilized a hybrid model with a combination of the GRU and LSTM network for early detection of PD. They integrated different oversampling techniques in their model, such as SMOTE, random under-sampling, and random over-sampling. Among all these techniques, SMOTE yielded the best results-an accuracy of 98% regarding the detection of PD. The research by Arti et al. [12] utilized three different machine learning classifiers, namely SVM, KNN, and Naive Bayes, together with Artificial Neural Networks, to diagnose Parkinson's disease through the examination of speech patterns. To improve the models further, they enriched the dataset using wrapper and filtering techniques. Amongst these, SVM and KNN contributed 87.17% of accuracy, beyond which was topped by the efficiency rate of ANN at 96.7%.

The study in [13], which was conducted by Senturk et al., used SVM, ANN, and CART as major classifiers for early detection in Parkinson's disease. They used Recursive Feature Elimination to improve the accuracy in their dataset, and it selected 13 features. The maximum accuracy of about 93.84% was given by the SVM. Out of the three, ANN gave the least performance of 91.54%, whereas CART took 90.76%. The study by [14] proposed methodologies for the PD classification using patients' voice signals, incorporating the following 4 classifiers: RF, Logistic Regression (LR), KNN, and SVM. Pre-processing is done on the dataset in this method, followed by splitting into training and test sets. Among these, the RF model performed the best and was able to predict PD with a classification accuracy of 91.83%. Yadav et al. [15] proposed another study on the classification of normal and diseased subjects by applying six supervised classifiers, namely Gradient Boosting, Bagging, KNN, AdaBoosting, DT, and RF. Their dataset had 23 features; they then performed chi-square feature selection, giving them 10 out of 23 as the most relevant. DT combined with chi-square feature selection had given the highest accuracy of 94.87% beating all the rest of classifiers in this study.

Nalini et al. [16] have proposed three deep learning algorithms, namely, the Multilayer Perceptron, Recurrent Neural Network, and Long Short-Term Memory. These algorithms were used to identify voice characteristics associated with PD. Various pre-processing techniques were used to increase the accuracy of which the LSTM had better precision compared to the MLP and RNN using the same dataset. In this regard, another paper proposes the PDD-ET, Kalyan et al. [17], comprises RF, Boosting, LSTM, SVR, Stacked LSTM, and GRU to perform early detection on PD. In this respect, the dataset is pre-processed by normalization using the z-score method and split up in order to get the optimum performance during the detection process in PD, with the general accuracy of the model being 95.325%. In the work presented in [18], a design for early PD detection is proposed using the machine learning classifiers-RF, SVM, AdaBoost, KNN, and LR-with voice signal data. Their approach began by normalizing all the dataset values within a range of 0 to 1 for better accuracy in the classifier. The RF classifier outperformed the rest, doing so with high accuracy of 95%, unlike in other classifiers.

## 3. Methodology

The methodology of the proposed framework includes a series of critical steps designed to ensure effective evaluation and optimization of deep and machine learning classifiers for Parkinson disease classification. Initially, the Parkinson disease dataset undergoes preprocessing to remove any inconsistencies, followed by MaxAbs scaling to standardize the data. Feature selection is then performed using Harris Hawk Optimization (HHO), which identifies the optimal subset of features to improve accuracy and reduce computational costs. After feature selection, the dataset is split into training (70%) and testing (30%) subsets to prepare for model training and validation. Various classifiers, including KNN, SVM, RF, and DT, are trained on the training data, as shown in Fig. 1. Performance of each trained classifier is then evaluated across a variety of metrics: F1-score, precision, confusion matrix,, recall, and accuracy, providing a comprehensive analysis of each classifier's effectiveness in classification




between healthy persion and PD patients.

**Fig. 1-** Proposed approach of PD detection.

### *3.1. Dataset description*

The dataset used for Parkinson's disease classification is sourced from Max Little of Oxford University and is available through the UCI Machine Learning Repository [19]. This dataset comprises 195 voice recordings, with 147 recordings from individuals diagnosed with Parkinson's disease and 48 from healthy individuals. It includes 23 distinct features extracted from sound signal, each tailored to capture vocal attributes associated with PD. Table 1 provides a breakdown of these 23 features, along with descriptions that explain their relevance to PD diagnosis. The dataset is of high quality, containing no duplicate or missing values. The primary goal of this data is to differentiate between PD patients and healthy individuals, a distinction marked by the "status" column, where a value of 1 indicates PD and 0 indicates a healthy individual. Due to the breadth of vocal measurements, it offers, this dataset has become a valuable resource for researchers aiming to develop automated methods for Parkinson disease classification.

**Table 1 - Detail of PD dataset.**

| Characteristic | Description |
|---|---|
| Associated tasks | Classification |
| Attributes characteristic | Real |
| Dataset characteristic | Multivariate |
| Types of classification | 1 for PD patient and 0 for healthy |
| Missing values | N/A |
| No. of instances | 197 |

### *3.2. Preprocessing Dataset*

Effective dataset preprocessing, in general, helps a lot in improving the performance of deep and machine learning classifiers. Similarly, in the Parkinson disease classification, proper preprocessing methods will improve quality, reduce noisiness, and normalize the scale of features. Further, this improves accuracy by helping the model learn the pattern and avoid dominance, convergence, and overfitting problems [20]. This way, the preprocessing normalizes the data; hence, it generalizes well on newer data, enhancing robustness and predictive accuracy. One of the most useful scaling methods used in the study is MaxAbs Scaling. The MaxAbs scaling method scales a feature within the range of -1 to 1 using the maximum absolute value. It works effectively in models sensitive to variation in the range of data since large values cannot be able to overawe smaller values, creating any biases. The formula for MaxAbs scaling is given by:

$$\boldsymbol{X_{scaled}} = \frac{X}{|X_{max}|} \tag{1}$$

Where $\boldsymbol{X}$ represents the original feature value, $\boldsymbol{X_{max}}$ and is the maximum absolute value of the feature. By applying this transformation, the dataset becomes more suitable for training various models, allowing for faster convergence and, ultimately, better accuracy in the Parkinson's disease classification.

### *3.3. HHO Feature Selection*

Feature selection is an crucial step stage of deep and machine learning that considers giving more significant enhancement to any model by focusing on only those features of importance in the dataset. Feature selection selects only the key features that improve the accuracy of the model and reduce computation costs [21]. It is therefore a very important step toward reducing noise and avoiding redundancy, thus allowing the model to learn the pattern so much more effectively and efficiently. Indeed, feature selection does make the processes of training faster and more suitable to get more accurate predictions of the problem, especially such a complex activity as detecting Parkinson's disease.

In this work, the feature selection method selected was the Harris Hawk Optimization (HHO) algorithm. The HHO algorithm dynamically explores and exploits the space of features, inspired by the hunting nature of Harris hawks, in order to get the optimal features. The algorithm emulates hawks' adaptive attacks to their prey; hence, this algorithm can be used to perform a broad search at the beginning time for different features combinations and converge to the most promising ones [22]. Therefore, training the model with HHO allows it to learn from the most relevant data attributes, thus enhancing the prediction accuracy without losing computational efficiency. The HHO algorithm operates in two key phases: exploration and exploitation. In the exploration phase, the algorithm searches widely across the feature space to avoid being trapped in local optima. This process is guided by an adaptive equation:

$$\boldsymbol{X_{t+1}} = X_{rand} - r_1 \times |r_2 \times X_{rand} - X_t| \quad (2)$$

Where $\boldsymbol{X_{t+1}}$ represents the position of the hawk in the next iteration, $\boldsymbol{X_{rand}}$ is a randomly selected solution, $r_1$ and $r_2$ are random numbers between 0 and 1, and $X_t$ is the current solution. This equation allows the model to explore new and diverse feature combinations. Once promising features are identified, HHO moves to the exploitation phase, refining the search by focusing on these high-value features. In this phase, the following equation is used:

$$\boldsymbol{X_{t+1}} = X_{best} - r_3 \times |X_{best} - X_t| \quad (3)$$

Where $\boldsymbol{X_{best}}$ is the best solution found so far, and $\boldsymbol{r_3}$ is another random number in the range from zero to one. This will make the model converge towards a better solution set by converging into the most promising solutions. This adaptiveness resembles the potentials of the HHO towards high-quality feature selection, high accuracy in models, and reduced computation costs. Concentrating on the most informative features, the models trained with the HHO are able to provide more efficient and effective results for disease detection.

### *3.4. Evolution Metrics*

Some essential evaluation metrics have been used in determining the performances of the models in the detection of Parkinson's disease; these will offer useful insight into the capability of the models to classification between non-PD and PD patients. The metrics that give a further understanding of the model's effectiveness in clinical setup include the following: F1-score, precision, confusion matrix, recall, and accuracy.

- **Confusion Matrix:** A confusion matrix is a table that represents the outcomes of model predictions across four types: correctly predicted positives (TP), correctly predicted negatives (TN), incorrectly predicted positives (FP), and incorrectly predicted negatives (FN). As it is the case with Parkinson's disease detection, TP represents cases where a PD patient was correctly identified, TN represents cases where a non-PD patient was classified as such, FP represents cases where a healthy patient was misclassified as having PD, and FN represents cases where a PD patient was misclassified as non-PD. The confusion matrix, therefore, gives a clear view of the correct classifications and the incorrect classifications, hence showing the accuracy of the model and areas to possibly improve. Figure 2 illustrates the structure of the confusion matrix.

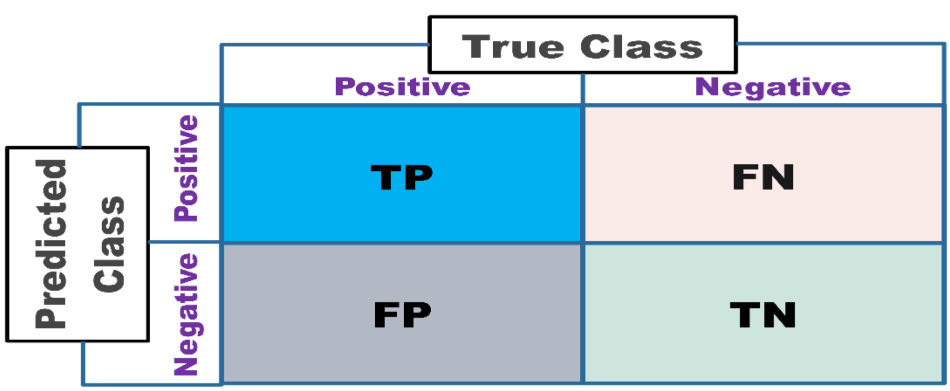



**Fig 2-** Structure of confusion matrix [23].

- **Precision:** Precision calculates the ratio of correctly identified positive cases to the total number of positive predictions. In this context, it represents the percentage of individuals predicted to have PD who are actually PD patients. Precision is calculated as:

$$\boldsymbol{Precision} = \frac{TP}{TP + FP} \quad (4)$$

- **Recall:** Recall, also known as sensitivity, gauges the model's effectiveness in correctly detecting true cases of Parkinson's disease. It represents the percentage of true PD patients who are correctly classified as having the disease, calculated as:

$$\boldsymbol{Recall} = \frac{TP}{TP + FN} \tag{5}$$

- **F1-Score:** The F1-score offers a balanced metric that combines precision and recall, reflecting the model's ability to limit both false negatives and false positives. It is calculated using the formula:

$$\boldsymbol{F1 - Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

- **Accuracy:** Accuracy indicates the percentage of correct classifications, including both true negatives and true positives, relative to the total number of instances. It is calculated by the formula:

$$\boldsymbol{Accuracy} = \frac{TP + TN}{TP + TF + FN + TN} \tag{7}$$

## 4. Results and Discussion

This section presents the results of the performances of the various classifiers, which are KNN, SVM, RF, and DT, while each was subjected to accuracy, recall, and precision while considering the F1-score and the confusion matrix. Later on, assessments will be carried out with and without feature selections, where feature selection is done using the Harris Hawks Optimization algorithm. This will help in drawing a proper comparison with regard to the performances of each classifier by the effects from feature selection on accuracy and reliability.

### *4.1. Performance of the machine learning classifier without HHO*

In this section, we assess the classifiers using five evaluation metrics without applying any feature selection (HHO), as outlined in Table 2.

**Table 2 - Machine learning classifiers performance without any feature selection technique.**

| Models | Recall | F1_Score | Precision | Accuracy |
|---|---|---|---|---|
| KNN | 81.25 | 83.87 | 86.67 | 91.53 |
| SVM | 82.35 | 87.5 | 93.33 | 93.22 |
| RF | 92.86 | 89.66 | 86.67 | 94.92 |
| DT | 75 | 77.42 | 80 | 88.14 |

The results in Table 2 highlight the baseline performance of each classifier without feature selection. Among the models, RF achieves the highest accuracy at 94.92%, demonstrating strong capability in distinguishing between PD patients and healthy individuals in the dataset. RF also records the highest recall at 92.86%, indicating its effectiveness in identifying true positive PD cases, a critical factor in medical diagnostics. SVM follows with an accuracy of 93.22% and achieves the highest precision at 93.33%, emphasizing its strength in minimizing false positives and reducing misclassification of healthy individuals as PD patients.

KNN performs reliably with an accuracy of 91.53% and balanced metrics, showing a recall of 81.25% and precision of 86.67%, which definitely makes it a good option, although a bit less effective than RF and SVM. In contrast, DT shows the worst performance in terms of accuracy, with a value of 88.14%, and relatively low recall and precision scores, which are 75% and 80%, respectively, which may indicate that DT is prone to both false negatives and false positives; hence, it would be less reliable for PD detection without further refinement. These results indicate that RF and SVM stand out as the most accurate classifiers in this initial assessment, with RF excelling in recall and SVM showing strong precision. This provides a baseline for further comparison to evaluate how feature selection might enhance each model's performance.

Figure 3 provides a detailed view of the classifiers' performance without HHO feature selection. RF demonstrates the best accuracy, with only one false negative and two false positives, confirming its strong ability to detect PD cases accurately. SVM also performs well, with low misclassification rates, excelling in minimizing false positives. KNN shows moderate performance, with slightly higher error rates than RF and SVM, while DT records the most misclassifications, indicating limitations in distinguishing PD patients from healthy individuals. These results highlight RF and SVM as the most reliable classifiers in this setup, suggesting potential benefits from applying feature selection to enhance model accuracy further.

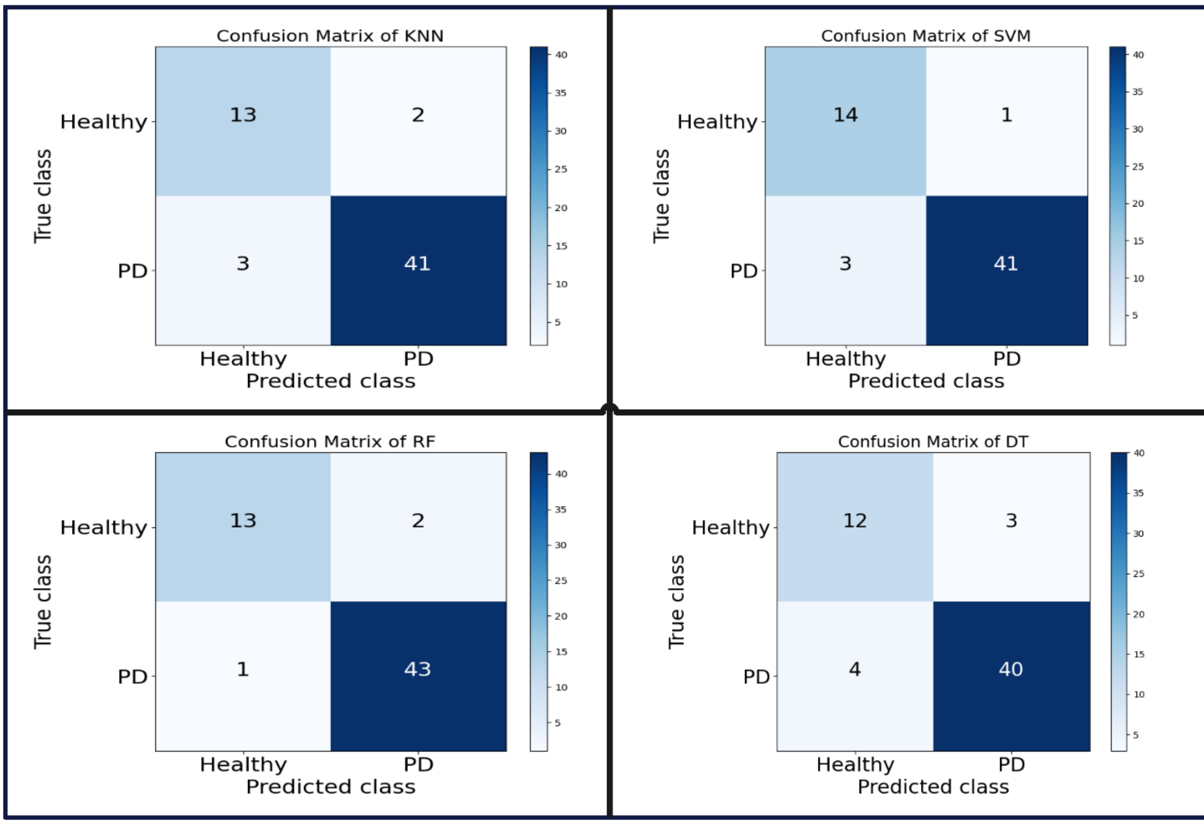



**Fig 3-** Confusion matrix of the machine learning classifiers without HHO.

### *4.2. Performance of the machine learning classifier with HHO*

In this section, we evaluate the classifiers based on the five metrics, with HHO feature selection algorithm, as outlined in Table 3.

**Table 3- Machine learning classifiers performance with HHO feature selection.**

| Models | Recall | F1_Score | Precision | Accuracy |
|---|---|---|---|---|
| KNN | 82.35 | 87.5 | 93.33 | 93.22 |
| SVM | 93.33 | 93.33 | 93.33 | 96.61 |
| RF | 100 | 96.55 | 93.33 | 98.33 |
| DT | 92.86 | 89.66 | 86.67 | 94.92 |

Table 3 shows the performance metrics of the classifiers after applying HHO feature selection, with clear improvements across all models. RF demonstrates exceptional results, achieving a perfect recall of 100%, accurately identifying all PD cases without false negatives. Additionally, RF achieves a high accuracy of 98.3% and an F1-score of 96.55%, reflecting a strong balance between recall and precision, positioning it as the top-performing model with minimal misclassifications.

SVM also shows significant improvement, reaching 96.61% accuracy with balanced metrics across recall, precision, and F1-score at 93.33%, indicating robust reliability in distinguishing PD from healthy cases. KNN and DT exhibit moderate gains, with KNN achieving 93.22% accuracy and DT at 94.92%. DT's recall improves to 92.86%, reducing false negatives, while KNN attains a high precision of 93.33%, effectively minimizing false positives. Although RF and SVM show the highest performance, HHO feature selection positively impacts all classifiers, enhancing their accuracy and reliability in this study on PD detection.

Figure 4 presents the confusion matrices for each classifier with HHO feature selection applied. These matrices offer an in-depth look at model performance, displaying counts for TP, TN, FP, and FN. With HHO, RF achieves a perfect score, with no false negatives and only one false positive, highlighting its improved precision and recall. SVM also shows enhanced performance with only one misclassification in both false positives and false negatives, aligning with its high accuracy and precision. KNN and DT display some improvement as well, with KNN reducing false positives to one and DT showing a low error rate, indicating the positive impact of HHO on classifier effectiveness. This visualization confirms the increased accuracy and reliability of the classifiers after feature selection with HHO.

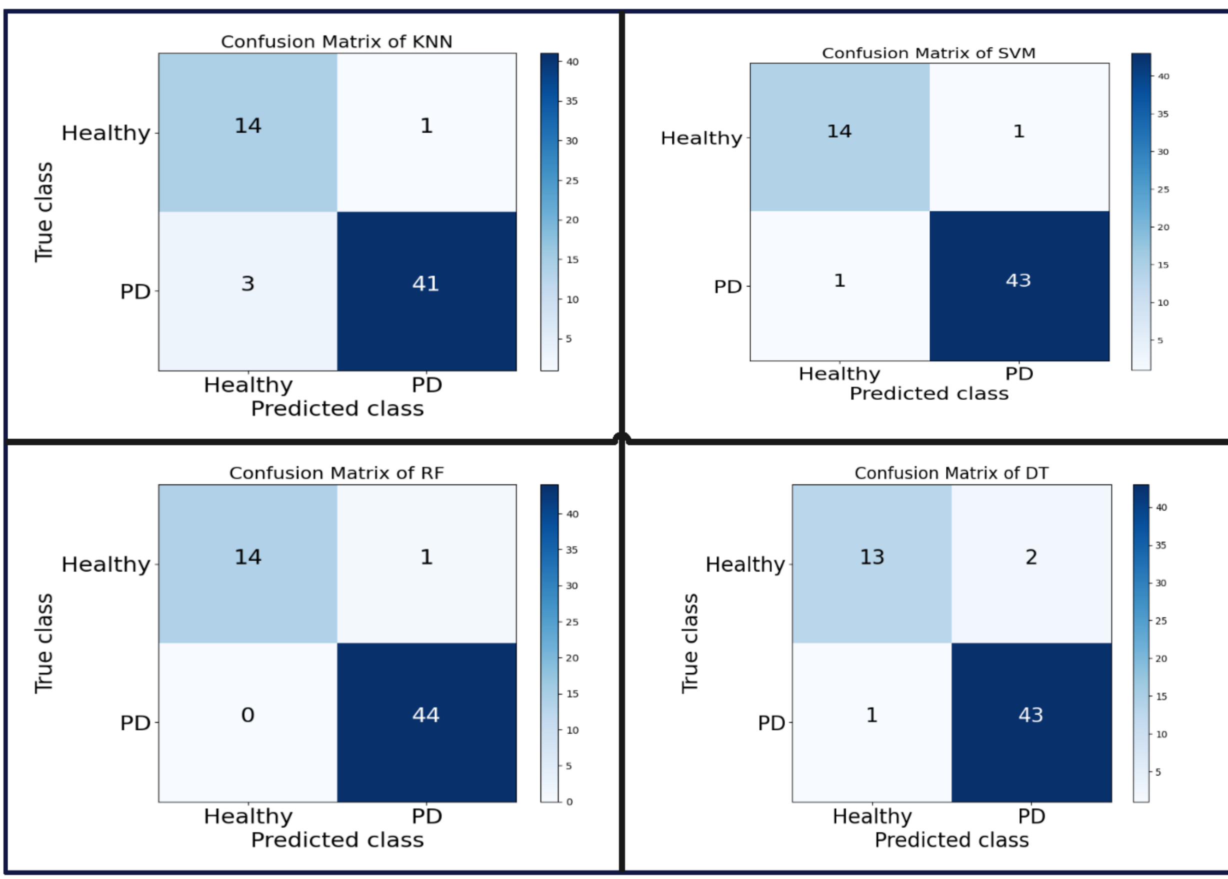



**Fig 4-** Confusion matrix of the machine learning classifiers with HHO.

### *4.3. Comparison with recent studies*

This section provides a comparison between the performance of proposed solution and recent studies that have employed the Parkinson's disease dataset. The focus of the comparison is on the accuracy obtained by different classifiers and feature selection approaches, as summarized in Table 4.

**Table 4 - Comparison with recent studies on the PD dataset.**

| Ref | Feature Selection | Classifier | Accuracy (%) |
|---|---|---|---|
| [24] | Genetic algorithm | RF, NB and KNN | 95.58 |
| [25] | Fuzzy Cognitive Maps | RF | 91.83 |
| [26] | SMOTE | Random Forest - XGBoost | 98 |
| [27] | Cuckoo search | Gower distance | 98.3 |
| [28] | Bayesian Optimization | SVM | 92.3 |
| **Proposed** | **HHO** | **RF** | **98.33** |

Table 4 summarizes some of the feature selection methods that have recently been applied in this PD dataset such as: GA, SMOTE, Chi-square, and CS. The frequently used models are RF, NB, KNN, and SVM. RF appears to be mainly applied in this data owing to its effectiveness in the detection. This might be because in previously performed work, there was reportedly high accuracy in using the RF technique. For instance, some studies attained accuracies of 95.58% with GA, 98% with SMOTE and XGBoost, and 98.3% using CS with GD. Against these, our proposed method that combines the feature selection by HHO with RF reaches the highest value ever recorded: 98.33%, outperforming those mentioned above. This evidences that HHO has significantly enhanced the classifier's accuracy compared with other feature selection methods and reached a new benchmark in terms of the accuracy of PD detection using voice data. Obviously, the combination of HHO with RF turned out to give outstandingly exact feature selection, finally reflecting improvements in precision, recall, and F1-score values in the overall performance of the proposed model. It also shows the possibility of HHO toward further feature selection optimality, strengthening this approach as one of the most useful for the purpose of improving accuracy and reliability in performing the PD detection tasks.

## 5. Conclusion

This study demonstrated the effectiveness of the Harris Hawk Optimization (HHO) for feature selection in enhancing the classifiers performance on the UCI Parkinson's disease dataset. The preprocessing steps included data cleaning and applying MaxAbs normalization, followed by evaluating four classifiers: Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and Decision Tree (DT), both with and without HHO-based feature selection. The application of HHO brought an evident uplift in the performance of the classifiers; RF and SVM achieved the best at 98.3% and 96.61%, respectively, while KNN and DT also showed salient improvement due to the feature selection process. This approach, when compared to recent studies, outperforms the current methods and sets a new benchmark regarding the accuracy of PD detection using voice signal data. This work has shown the importance of efficient feature selection in improving the accuracy and dependability of machine learning models. The feature selection technique based on HHO was very useful for researchers and practitioners in developing accurate and efficient diagnostic tools. Future work may be focused on the application of this feature selection technique to other datasets and classifiers, exploring its potential in real-time PD detection systems.

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## References

[1] M. de De Rijk et al., “Prevalence of Parkinson’s disease in Europe: A collaborative study of population-based cohorts. Neurologic Diseases in the Elderly Research Group.,” Neurology, vol. 54, no. 11 Suppl 5, pp. S21-3, 2000.

[2] İ. Cantürk and F. Karabiber, “A machine learning system for the diagnosis of Parkinson’s disease from speech signals and its application to multiple speech signal types,” Arabian Journal for Science and Engineering, vol. 41, pp. 5049–5059, 2016.

[3] M. N. Kadhim, A. H. Mutlag, and D. A. Hammood, “Vehicle detection and classification from images/videos using deep learning architectures: A survey,” presented at the AIP Conference Proceedings, AIP Publishing, 2024.

[4] M. N. Kadhim, A. H. Mutlag, and D. A. Hammood, “Multi-models Based on Yolov8 for Identification of Vehicle Type and License Plate Recognition,” presented at the National Conference on New Trends in Information and Communications Technology Applications, Springer, 2023, pp. 118–135.

[5] D. Al-Shammary, M. N. Kadhim, A. M. Mahdi, A. Ibaida, and K. Ahmed, “Efficient ECG classification based on Chi-square distance for arrhythmia detection,” Journal of Electronic Science and Technology, vol. 22, no. 2, p. 100249, 2024.

[6] C. Ricciardi et al., “Classifying different stages of Parkinson’s disease through random forests,” presented at the XV Mediterranean Conference on Medical and Biological Engineering and Computing–MEDICON 2019: Proceedings of MEDICON 2019, September 26-28, 2019, Coimbra, Portugal, Springer, 2020, pp. 1155–1162.

[7] M. Shaban, “Automated screening of Parkinson’s disease using deep learning based electroencephalography,” presented at the 2021 10th international IEEE/EMBS conference on neural engineering (NER), IEEE, 2021, pp. 158–161.

[8] K. M. Alalayah, E. M. Senan, H. F. Atlam, I. A. Ahmed, and H. S. A. Shatnawi, “Automatic and early detection of Parkinson’s disease by analyzing acoustic signals using classification algorithms based on recursive feature elimination method,” Diagnostics, vol. 13, no. 11, p. 1924, 2023.

[9] A. M. Ali, F. Salim, and F. Saeed, “Parkinson’s disease detection using filter feature selection and a genetic algorithm with ensemble learning,” Diagnostics, vol. 13, no. 17, p. 2816, 2023.

[10] M. A. Mohammed, M. Elhoseny, K. H. Abdulkareem, S. A. Mostafa, and M. S. Maashi, “A multi-agent feature selection and hybrid classification model for Parkinson’s disease diagnosis,” ACM Transactions on Multimidia Computing Communications and Applications, vol. 17, no. 2s, pp. 1–22, 2021.

[11] A. Rehman, T. Saba, M. Mujahid, F. S. Alamri, and N. ElHakim, “Parkinson’s disease detection using hybrid LSTM-GRU deep learning model,” Electronics, vol. 12, no. 13, p. 2856, 2023.

[12] A. Rana, A. Dumka, R. Singh, M. Rashid, N. Ahmad, and M. K. Panda, “An efficient machine learning approach for diagnosing parkinson’s disease by utilizing voice features,” Electronics, vol. 11, no. 22, p. 3782, 2022.

[13] Z. K. Senturk, “Early diagnosis of Parkinson’s disease using machine learning algorithms,” Medical hypotheses, vol. 138, p. 109603, 2020.

[14] A. Govindu and S. Palwe, “Early detection of Parkinson’s disease using machine learning,” Procedia Computer Science, vol. 218, pp. 249–261, 2023.

[15] S. Yadav, M. K. Singh, and S. Pal, “Artificial intelligence model for parkinson disease detection using machine learning algorithms,” Biomedical Materials & Devices, vol. 1, no. 2, pp. 899–911, 2023.

[16] N. Chintalapudi, G. Battineni, M. A. Hossain, and F. Amenta, “Cascaded deep learning frameworks in contribution to the detection of parkinson’s disease,” Bioengineering, vol. 9, no. 3, p. 116, 2022.

[17] K. Chatterjee et al., “PDD-ET: Parkinson’s Disease Detection Using ML Ensemble Techniques and Customized Big Dataset,” Information, vol. 14, no. 9, p. 502, 2023.

[18] A. H. Al-nefaie, T. H. Aldhyani, and D. Koundal, “Developing system-based voice features for detecting Parkinson’s disease using machine learning algorithms,” Journal of Disability Research, vol. 3, no. 1, p. 20240001, 2024.

[19] M. Little, “Parkinsons,” UCI Machine Learning Repository, 2008.

[20] M. N. Dar, M. U. Akram, A. Usman, and S. A. Khan, “ECG biometric identification for general population using multiresolution analysis of DWT based features,” presented at the 2015 Second International Conference on Information Security and Cyber Forensics (InfoSec), IEEE, 2015, pp. 5–10.

[21] M. Y. Hassan, A. H. Najim, K. A. Al-Sharhanee, M. N. Kadhim, N. F. Soliman, and A. D. Algarni, “A Hybrid Cuckoo Search-K-means Model for Enhanced Intrusion Detection in Internet of Things,” 2024.

[22] Z. M. Elgamal, N. B. M. Yasin, M. Tubishat, M. Alswaitti, and S. Mirjalili, “An improved harris hawks optimization algorithm with simulated annealing for feature selection in the medical field,” IEEE access, vol. 8, pp. 186638–186652, 2020.

[23] M. Sadiq, M. N. Kadhim, D. Al-Shammary, and M. Milanova, “Novel EEG Classification based on Hellinger Distance for Seizure Epilepsy Detection,” IEEE Access, 2024.

[24] R. Lamba, T. Gulati, H. F. Alharbi, and A. Jain, “A hybrid system for Parkinson’s disease diagnosis using machine learning techniques,” International Journal of Speech Technology, pp. 1–11, 2022.

[25] K. Haritha, M. Judy, K. Papageorgiou, V. C. Georgiannis, and E. Papageorgiou, “Distributed Fuzzy Cognitive Maps for Feature Selection in Big Data Classification,” Algorithms, vol. 15, no. 10, p. 383, 2022.

[26] T. Mahesh, R. Bhardwaj, S. B. Khan, N. A. Alkhaldi, N. Victor, and A. Verma, “An artificial intelligence-based decision support system for early and accurate diagnosis of Parkinson’s Disease,” Decision Analytics Journal, vol. 10, p. 100381, 2024.

[27] M. N. Kadhim, D. Al-Shammary, and F. Sufi, “A novel voice classification based on Gower distance for Parkinson disease detection,” International Journal of Medical Informatics, vol. 191, p. 105583, 2024.

[28] A. M. Elshewey, M. Y. Shams, N. El-Rashidy, A. M. Elhady, S. M. Shohieb, and Z. Tarek, “Bayesian optimization with support vector machine model for parkinson disease classification,” Sensors, vol. 23, no. 4, p. 2085, 2023.