Hybrid Harris Hawks Optimization For Detecting Parkinson's Disease Using Deep Learning

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***Abstract*—Parkinson's disease is very crucial, and early diagnosis is necessary so that effective treatment methods can be used for the treatment of the disease. Traditional methods take a lot of time to give results. Hence, we need to develop efficient methods that help in the detection of Parkinson's disease so that Patients can take necessary steps for treatment. This method is developed using a Deep Learning technique, which is combination of two nature-inspired algorithms, those are Particle Swarm Optimization and Harris Hawks Optimization Algorithm, which achieved the accuracy of 98.12%. This is a method used to classify whether the patient has Parkinson's Disease or not.**

***Index Terms*—Parkinson's Disease, Deep Learning, Particle Swarm Optimization, Harris Hawks Optimization, Medical Diagnosis**

I. Introduction

Parkinson's disease is a nerve disorder that affects speech and motor control. This affects the daily life of patients. Early detection and accurate assessment are useful, which helps in effective treatment. There have been so many methods that assist in detection. There has been a recent development in Artificial Neural Networks (ANN), which help in quality detection using biomedical data. The performance is based on the availability of better features. Feature selection is efficient and helps in improving model accuracy.

For addressing this issue, optimization algorithms have gained importance. Hence Particle Swarm Optimization Algorithm is a widely used population-based algorithm inspired by the social behavior of bird flocks, which efficiently explores the search space using collective intelligence. On the other hand, Harris Hawks is a recent nature-inspired algorithm that shows the excellent exploration and exploitation ability like Harris Hawks.

In this work, a hybrid optimization approach, which was combined with two algorithms, those are PSO and HHO, is proposed to improve feature selection. It enhances the classification performance. Also, a deep learning Model is used to enable accurate and better classification. By using nature-inspired algorithms as well as deep learning technology this method improves the performance of detecting Parkinson's Disease.

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II. Literature Survey

In [1] approach Whale ant optimization was used for feature selection in Parkinson's disease detection.This achieved an accuracy of 90.29%. Combines exploration and exploitation, which are better than single algorithms, but it uses a small dataset of only 195 values. The [2] study shows that Parrot Optimization was used to diagnosis Parkinson's Disease and they got an accuracy of 99%. It worked well with voice data, and also it was effective in feature selection. Since this model was not a deep learning model, it could not capture complex data patterns compared to the neural network approach. From [3] research, they have used the squirrel search algorithm, which could select important features. It used an ensemble method that combined models and could yield better predictions. The limitation was that it used only one optimization algorithm, hence it was less effective in feature selection. In [4] study Parkinsons disease was detected using a handwritten sample, and it combined Deep Learning with Harris Hawks optimization, which improved model performance. But it used a single Optimization algorithm that could not balance exploration and exploitation. The [5] work included Harris Hawks Optimization with simulated annealing which improved feature selection. It performed well in exploration and exploitation. Since there was no deep learning, there was no pattern recognition. In the [6] study, they used the Grasshopper algorithm for selecting Parkinson's disease, and it helped in removing irrelevant and redundant features. Uses a single Optimization algorithm, like exploration and exploitation. The [7] study is about a hybrid approach using Quantum Mayfly Optimization with a feature subset and a hybrid deep learning model. This works well with different types of Parkinson's disease. It uses CNN and LSTM with quantum Optimization, which gives high complexity. In [8], a disease diagnosis is proposed with feature selection and parameter tuning. It uses a single metaheuristic algorithm with a limited exploration and exploitation balance. The [9] study, it proposes an optimised feature selection which uses transfer learning. The limitation is that it uses only a single optimised approach. In [10], research shows that various ML models like K Nearest Neighbors,Decision Tree and SVM were used for Parkinson's Disease Classification. It helps in using well-known ML techniques. Since Deep learning models are not used not effective in training the data. In the [11] study, it uses deep learning with an better version of Harris Hawks Optimization Algorithm for detecting Alzheimer's disease. It also captures complex patterns in medical data but uses a single Optimization technique. In the [12] study, Hybrid Harris Hawks Optimization based model was used for diagnosing coronary artery disease. It uses Hybrid HHO for effective feature selection but doesn't include a deep learning model for complex pattern learning. From the [13] approach, they have used K Fold cross validation Technique using PSO. It helps in selecting the best performing ML model, but has Lower accuracy, like 86.95%.In the [14] study, it combines Oppositional Aquila Optimiser and Artificial Ecosystem Optimization to detect Parkinson's with an accuracy of 98.29%. It uses complex architecture, like a two-stage system with DBN. Last from the [15] study, it proposes a multimodal AI-based framework for detecting Parkinson's disease using voice imaging and clinical data. Deep Learning was used and handles diverse datatypes, but no Optimization algorithm was used.

III. Methodology

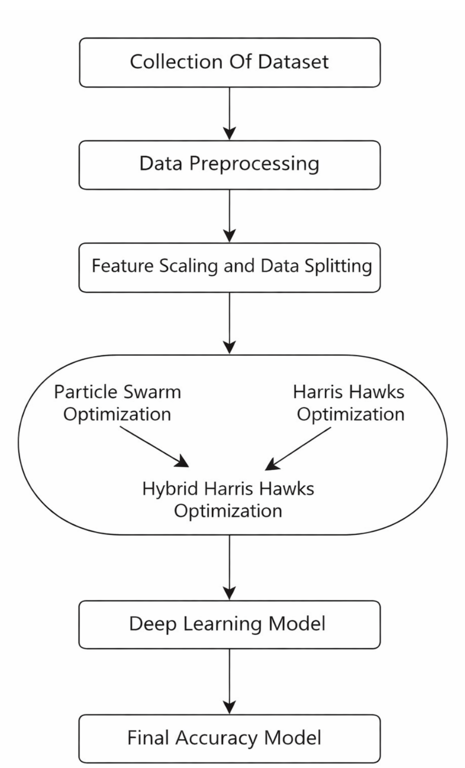

Fig. 1. Flow Diagram Of Methodology Used in Hybrid Harris Hawks Optimization

A. Collection Of Dataset

The Parkinson's Disease dataset has biomedical voice measurements collected from multiple objects over time. Each record contains features such as jitter, shimmer,NHR and various other features. The dataset was transformed into a classification problem by converting the continuous total_UPDRS score into a binary label.

B. Data Preprocessing

In Data preprocessing, first, we removed irrelevant identifier columns. Then we performed the conversion of all feature values into numeric. Handling of values was done by removing incomplete records. Then Normalization of features was done using a standard scaler. To stop the data leakage it is divided into training and testing data.

C. Feature Scaling and splitting Data

Feature was applied so that it can normalize the data.By doing this it can improve the performance and stability of the learning model.Standard Scaler was used to calculate the average of the data.Then scaling was trained where the data was split into training and testing.Almost 80% of the data was used for training and 20% for testing.A fixed random state was used which gave better results.Feature scaling was used to normalize the data.Before the train-test split scaling was conducted to prevent data leakage.

D. Particle Swarm Optimization

The Particle Swarm Optimization algorithm for selecting features, in which each particle represents a potential subset of features recorded as a binary vector, is implemented by this code. Particles are first created as 0s and 1s, and their velocities are then allocated at random. A fitness function is used to assess each particle's fitness, and its most well-known position is recorded. The global best particle is chosen from among all the particles. Particle velocities are adjusted in each iteration according to three factors: social, cognitive, and inertia. Particle locations are updated in binary form after velocities are transformed into probabilities using a sigmoid function. New positions are assessed for fitness, and if improvements are discovered, personal and global bests are updated appropriately. The algorithm continues iterating, printing the best accuracy at each step, and finally returns the best feature subset along with its best accuracy score.

E. Harris Hawks Optimization

Each hawk represents the binary features during the feature selection method. One hawk is assigned to a starting solution, and the population is started at random. A fitness function is used to obtain the fitness value of each hawk and the bunny, which is the global best, the accurate solution. Hawks use escaping energy (E), which regulates exploration and exploitation, to update their positions across iterations. Hawks investigate by going in the direction of random solutions if $|E| \geq 1$. They use tactics like soft besiege, strong besiege, or quick dives based on random circumstances if $|E| < 1$. Better options are chosen once new candidate solutions were created and then compared. The best hawk was checked until the ultimate best solution is obtained, positions are transformed into binary form, and fitness is updated.

Algorithm 1: Particle Swarm Optimization Algorithm

Initialising the particles' positions and velocities
Evaluating the fitness of each particle
Initialise the personal best (pbest) and global best (gbest)
for $t = 1$ to max_iter **do**
  for $i = 1$ to population size **do**
    Generate two random numbers r_1, r_2
    Update velocity:
      $v_i = w \cdot v_i + c_1 r_1 (pbest_i - x_i) +$
        $c_2 r_2 (gbest - x_i)$
    Apply sigmoid transfer:
      $prob = \frac{1}{1+e^{-v_i}}$
    Update position:
      $x_i = 1$ if rand $<$ prob else 0
    Evaluate the fitness of updated particle
    if fitness(i) is greater than pbest_score(i) **then**
      pbest(i) is equal to particle(i)
      pbest_score(i) is equal to fitness(i)
    end if
  end for
  Update the value of global best (gbest)
end for
Return gbest and its fitness value

Fig. 2. Algorithm of PSO

Algorithm 2: Harris Hawks Optimization Algorithm

Initialising hawks' positions randomly
Insert initial solution into population
Evaluate the fitness of all hawks
Set best hawk as rabbit position (X_{rabbit})
for $t = 1$ to max_iter **do**
  for $i = 1$ to population size **do**
    $X_i \leftarrow$ current hawk position
    $E_0 = 2 \times rand() - 1$
    $J = 2 \times (1 - rand())$
    $E = 2E_0(1 - t/T)$
    Generate the random number r
    if $|E| \geq 1$ **then**
      Select random hawk X_{rand}
      $X_{new} = X_{rand} - rand \cdot |X_{rand} - 2rand \cdot X_i|$
    else
      if $r \geq 0.5$ and $|E| \geq 0.5$ **then**
        $X_{new} = X_{rabbit} - E \cdot |X_{rabbit} - X_i|$
      else if $r \geq 0.5$ and $|E| < 0.5$ **then**
        $X_{new} = X_{rabbit} - E \cdot |J \cdot X_{rabbit} - X_i|$
      else
        Compute Y and Z and convert them to binary
        Select best between Y and Z
    Convert X_{new} to binary
    Evaluate fitness of X_{new}
    if fitness improves **then**
      Update hawk position
    end if
  end for
  Update rabbit position (best hawk)
end for
Return rabbit position and its fitness value

Fig. 3. Algorithm of HHO

Algorithm 3: Hybrid HHO-PSO Algorithm

1. Initialize pop_size, dim, max_iter
2. Run PSO with max_iter/2 iterations
3. Obtain the best solution X_{pso}
4. Run HHO with max_iter/2 iterations
5. Use X_{pso} as initial solution
6. Obtain final solution X_{best} and fitness f_{best}
7. Return X_{best} and f_{best}

Fig. 4. Algorithm of HHO-PSO

F. Hybrid Harris Hawks Optimization

The Hybrid PSO and HHO Optimization algorithm combines Particle Swarm Optimization and Harris Hawks Optimization, which enhances the solution quality. First, it runs PSO for 25 iterations of the 50 iterations and HHO for 25 iterations. Unlike for only PSO and HHO the algorithm ran for 50 iterations for different algorithms. Here it reduced to half so that it is balance and gives the best solution. There it refines it over the remaining iterations are to achieve a more accurate feature detection. This hybrid approach uses PSO exploration and HHO has strong exploitation capabilities, which are used to get the accuracy of the deep learning model.

G. Deep Learning Model

The Deep Learning Model used in this project is a feed-forward neural network built with a sequential structure to perform binary classification for Parkinson's Disease severity. It takes multiple input features, such as biomedical voice measurements and processes them through two hidden layers containing 64 and 32 neurons. These layers use RELU activation to learn complex patterns. The final layer contains a single neuron with sigmoid activation to produce an output value between zero and one, which represents the probability of high or low disease severity. The model is trained using the Adam optimiser to update weights and binary cross-entropy to measure the prediction of error.

H. Final Accuracy

This model achieved a final accuracy of 98.12 per cent after applying Particle Swarm Optimization for selecting features and training a neural network on the selected features. This high accuracy shows that the model is highly effective in distinguishing between high and low Parkinson's disease. severity. The use of optimised features reduces irrelevant information and achieves the better the learning capability of the model, resulting in better prediction performance on the dataset.

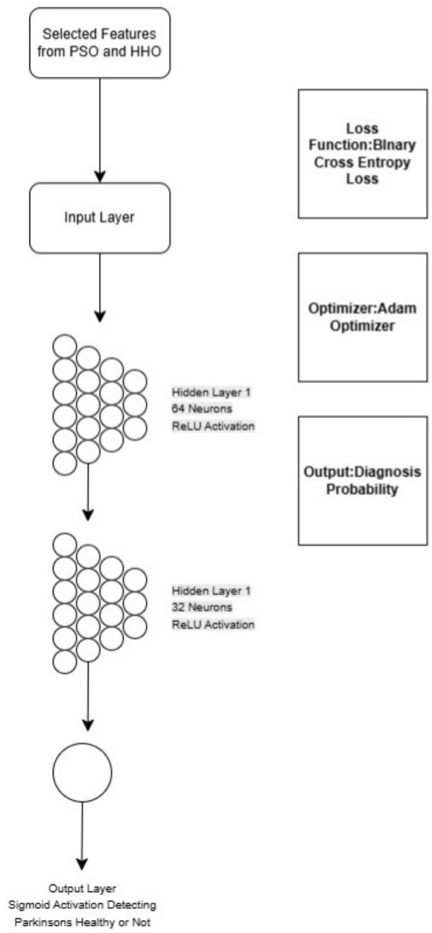

Fig. 5. Deep Learning Model with Visualisation of Different Layers

IV. Results and Discussion

The experimental findings show that the suggested strategy uses several optimization strategies for feature selection to attain good classification performance. The hybrid PSO and HHO strategy yielded the greatest accuracy of 98.12 per cent among the investigated approaches, demonstrating improved feature selection. capabilities. While GWO and HHO produced marginally worse but competitive outcomes, PSO by itself also performed with 98.04 per cent accuracy. The hybrid HHO and GWO model performed quite poorly, indicating that not all hybrid combinations yield better outcomes. The results show that by eliminating unnecessary information, good feature selection greatly improves model accuracy. For this dataset, the PSO The HHO hybrid worked best overall, improving generalization and predictive performance in tasks involving. categorizing of Paarkinsons Disease. The selected feature indices had 12 features. Since the target variable was total_UPDRS, the use of motor_UPDRS may cause target leakage and will contribute to better accuracy and results.In future it may include removing those corelated features.

The graph compares the classification accuracy attained by

TABLE I. Selected Features Obtained Using Hybrid PSO-HHO

Feature Indices	Features
0	age
1	sex
2	Test_time
3	Motor_UPDRS
5	Jitter(Abs)
8	Jitter:PPQ5
9	Jitter:DDP
10	Shimmer
11	Shimmer(db)
17	HNR
18	RPDE
19	DFA

TABLE II. Performance Comparison of Optimization Algorithms

Optimization Algorithm	Accuracy (%)
HHO	97.87%
GWO	97.96%
PSO	98.04%
HHO+GWO	97.44%
PSO+HHO	98.12%

employing various Optimization strategies for the model's feature selection. HHO, GWO, PSO, HHO combined with GWO and PSO, combined with HHO, are among the methods represented by each bar. With an accuracy of 98.12 per cent, the hybrid PSO and HHO strategy outperforms all other approaches in terms of choosing better features. With somewhat lesser accuracy, GWO and HHO follow PSO alone, which exhibits strong performance. The combined HHO and GWO approach performs the worst. Overall, the graph shows that when PSO When HHOs are combined, model accuracy is higher than when they are used separately.

This model demonstrated excellent performance. The confusion matrix the model achieves around 98% accuracy with two little misclassifications. The number of false negatives is low. The validation accuracy remains stable. Overall, the testing

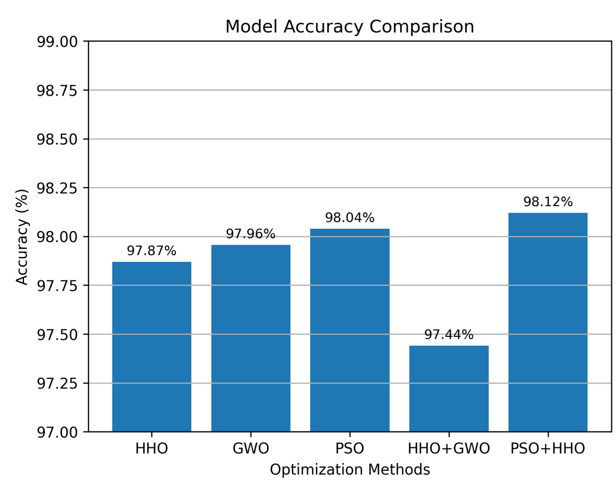

Fig. 6. Model Accuracy Comparison

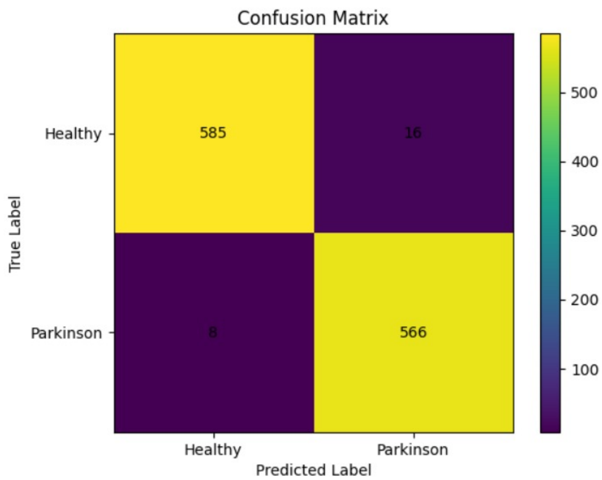

Fig. 7. Confusion Matrix of PSO-HHO Model

is required in real-world datasets. The Receiver Operating

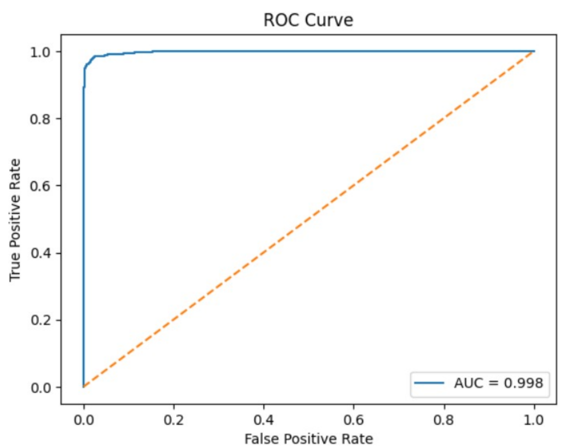

Fig. 8. ROC Curve of PSO-HHO Model

Curve(ROC) curve is used to check the performance of the classification model for detecting Parkinson's disease. This shows the relationship between the false positive and false negative rates. The different threshold values are displayed. A curve that is closer to the top left is considered. This indicates better performance. As it shows a high sensitivity rate and a low positive rate. The Area Under the Curve(AUC) will give one measure. The numbers that are close to 1 show the best model. The ROC curve shows that the model has a good capability of detecting Parkinson's disease as well as Healthy.

This graph represents the model accuracy of training and validation data. The x-axis shows the number of iterations, and the y-axis shows the classification accuracy by the model. It shows that while the iterations increase, the accuracy gradually increases, showing that the Optimization algorithm. It effectively selects the good features. The curve shown here depicts high accuracy. The graph shows consistent performance. The graph Optimization process produces the models predicative capability.

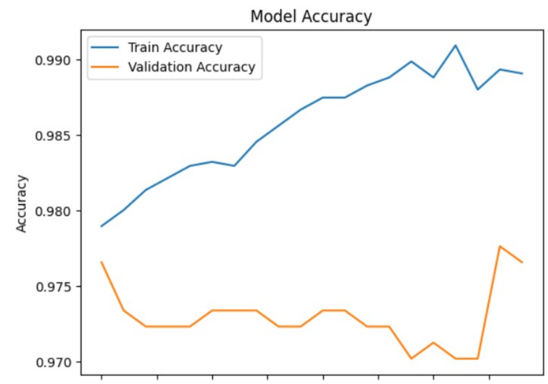

Fig. 9. Model Accuracy Graph

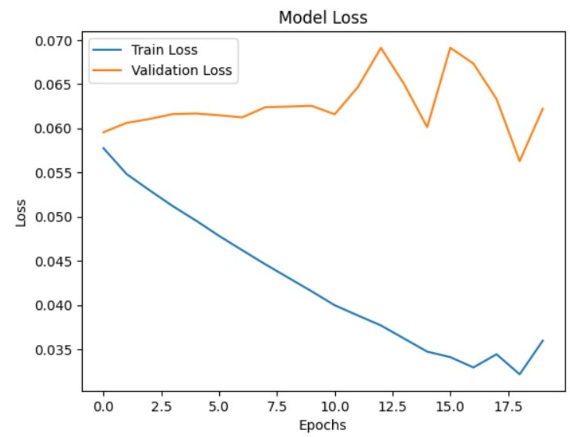

Fig. 10. Performance Trend of the Model During Optimization

The graph shown here represents the performance trend of the model during Optimization. It also shows how the accuracy changes over different iterations. The x-axis shows the number of iterations. The y-axis shows the accuracy achieved by the model that has been used. When the iterations increase, the curve generally increases. This shows that the algorithm is improving at selecting the features that enhance model performance.

V. Conclusion

The suggested solution combines optimization based feature selection methods with a deep learning model to provide an efficient way to classify Parkinson's illness. The hybrid PSO and HHO technique achieves the highest accuracy among all investigated methods, according to the experimental data, demonstrating its capacity to choose the best characteristics and enhance model performance. The hybrid approach offers superior generalization and lessens the influence of irrelevant data when compared to separate optimization. techniques. The ability to identify the patterns in the dataset is further improved by the usage of a neural network. The deep learning and Optimization work well together to increase classification accuracy in Parkinson's disease prediction tasks.

VI. Future Work

To improve robustness and generalization across various populations, future work can concentrate on improving the suggested model by combining larger and more diverse datasets. To further enhance the feature selection effectiveness and model performance, other hybrid optimization strategies should be investigated. To identify more intricate patterns in the data, sophisticated deep learning architectures like convolutional or recurrent networks can be studied. To further enhance the model, cross-validation techniques and Hyperparameter modification can be used. Here, feature scaling was applied before train-test and splitting the data, which might introduce slight data leakage and lead to producing good results, so in future it can be addressed by applying scaling and splitting separately, which will ensure better evaluation. Additionally, the system's practical usefulness and dependability for Parkinson's disease early detection and monitoring can be improved by including real-time data processing and testing it in clinical settings.

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