Hybrid Model Optimization With Modified Metaheuristics for Parkinson's Disease Detection

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Abstract

Parkinson's disease, a progressive neurological disorder primarily affecting elderly males, stems from dysregulation within the extrapyramidal tracts, notably the substantia nigra, lentiform nucleus, caudate nucleus, and ruber nucleus. This condition manifests as heightened cholinergic activity in the brain, correlating with cognitive decline, gait disturbances, sleep disorders, psychiatric symptoms, and olfactory dysfunction. Early detection is crucial for enhancing patient prognosis. Although neurological damage cannot be reversed, treatment can mitigate progression. However, patients often delay seeking treatment until symptoms significantly impair daily functioning, underscoring the importance of early detection. This study investigates the fusion of long short-term memory and extreme gradient boosting classifiers to develop an early detection system utilizing non-invasive shoe-mounted sensor data for observing patient gait. A tailored optimizer is introduced to enhance classification accuracy, achieving a notable accuracy of 0.896370, surpassing other contemporary optimizers in identical conditions.

Keywords: Parkinson's disease, Medical Data, Diagnosis, Optimization, Sinh cosh optimizer

© The Author(s) 2024
N. Bacanin and H. Shaker (eds.), *Proceedings of the 2nd International Conference on Innovation in Information Technology and Business (ICIITB 2024)*,
Advances in Computer Science Research 113,
https://doi.org/10.2991/978-94-6463-482-2_8

1 Introduction

Parkinsons disease is a progressive illness of the nervous system, most often affecting older male individuals. Its roots lay in the disorder of extrapyramidal tracts, more specifically bodies in the brain known as substantia nigra, lentiform nucleus, caudate nucleus, and ruber nucleus [1]. A reduced concentration of dopamine, as well as a lower concentration of serotonin and norepinephrine are noted in these areas in patients with the disease [2]. This, in turn, results in higher cholinergic activity of the brain, which is further connected to the decline in cognitive ability of the patients, issues with gait and freezing of gait (FOG), sleeping disorders, psychiatric symptoms of the disease as well as olfactory difficulties [3]. In addition to these abnormalities in the brain structure, Lewy bodies and senile plaques are also often found in the patients brains [4], both connected to dementia, which Parkinson's may or may not lead to.

Patients with Parkinson's are recognizable for the following manifested symptoms: rigor (extrapyramidal type hipertonia) with muscles overly stiff and tight, a lack of willing and spontaneous emotional expressions in face and body movement, tremor of extremities showing when a person is resting [5]. The individuals movement is slowed (bradykinesis) and extremly basic (hipokisesis), while their speech sounds monotonous, slurred, slow (bradylalia, bradyphasia, bradyphrasia). Their walking is slow and happens in small steps, while it can sometimes completely freeze, with the patient unable to will their legs to move, a symptom know as Gait freezing. Beyond the age and gender factors, genetic predispositions are another crucial risk factor for the disease, as well as exposure to certain kinds of toxins [6].

While a cure for this illness is yet to be found, certain measures can be taken to allow for better everyday life and longer life expectancy of the people affected. These measures include medication that helps balance out the dopamine and acetylcholine levels in the body, which in turn helps reduce the symptoms of the disease. Other measures regard the lifestyle changes that can be made to accommodate patients and slow down the progression of the illness. In order for these measures to have an optimal effect, the disease should be detected as early as possible.

As the disease most often affects older people, and the symptoms begin very slowly, the disease is hard to detect and diagnose in early stages. The symptoms not only begin slowly and are easily confused with the natural process of aging, meaning the patients do not seek medical aid until a later stage, but are also overlapping with other neurodegenerative disorders. Tests and biomarkers can not provide definitive diagnosis on their own, while the waiting lists for scans remain long and difficult to access, resulting in a need for holistic diagnosis process and extremely skilled professionals. Considering the high demands for accurate classification, the clinical diagnostic process leaves much to be desired. Mistakes happen even when the illness has fully manifested, let alone in the earlier stages [6].

Advances in the field of technology have resulted in wearable devices that can help measure and track the motor symptoms. Such devices are helpful not only for monitoring patients well-being, but also serve the purpose of data gathering, aiding in research of the disease. However, the data collected this way is immense, and sorting through it and analysing it by hand would be very time-consuming and tedious. Instead, machine learning (ML) can be used to make the process more manageable. ML models show greatest results when presented with large databases, presenting their capability to gleam patterns in the information a human brain may miss due to cognitive biases. By employing artificial intelligence algorithms for data processing, medical professionals gain another perspective and tool in understanding the given medical condition [7]. Still, in order to properly train these algorithms, the knowledge and expertise of said professionals is necessary to diagnose and define the diseases the algorithm is helping research.

Another factor in getting a high-accuracy model is selecting the appropriate parameters to guide the learning process. For this work metaheuristic optimization will be used. The present research has a goal of exploring the potential of combining a modified version of the sinh cosh optimizer (SCHO) [8] with Long Short term memory (LSTM) [9] networks with their final layer classified by the extreme gradient Boosting (XGBoost) [10] algorithms in order to detect signs of Parkinson's disease from data collected from shoe mounted sensors. The main contributions of this work can be summarized as:

- A poprosal for a hybrid LSTM-XGBoost classified applied to PD detection
- The introduction of a modified metaheursitic optimizer based on the SCHO
- The introduction of a combined approach for PD detection based on shoe mounted sensor data collected in a non invasive manner for mpatioents

The remainder of this work obeys the following structure: Section 2 covers preceding works. Section 3 provides a detail description of the proposed methodology. In Section 4 describes the simualtion configuration followed by the attained results in Section 5. In Section 6 the work is concluded.

2 Literature overview

The time constraints that occur during patient visits in healthcare settings mean making a complex diagnosis such as this harder. A quicker and more efficient approach could be achieved by integrating artificial intelligence (AI) into the diagnosis process in order to create an automated and dependable method for detecting anomalies in the patients results as an aid to the doctors diagnosis.

In recent years, the pervasive availability of computational devices has ushered in a transformative era for the practicality and applicability of Artificial Intelligence (AI). The field of medicine, in particular, has reaped substantial benefits, witnessing a surge in works that apply sophisticated algorithms for diagnosis and detection to ultimately enhance patient outcomes [11, 12]. Beyond diagnostic applications [13], AI techniques have proven instrumental in filtering noise from complex data samples [14], obtaining information that might otherwise be challenging to acquire.

Parkinson's diagnostics have also been tackled with AI, showing vast potential [15–18]. Thus, the novelty of this work is not necessarily in the idea of AI implementation, but in the presentation of a practical model tailored to the problem, as high accuracy in the field of medicine can make a world of difference.

In order to reach the highest accuracy of a model for the given task, the hyperparameters must be selected carefully. While this can be done by hand, and traditionally has been, with the growing complexity of the issues addressed grows the complexity of the task of hyperparameter selection. One solution for this is the use of metaheuristic algorithms, which have the power to take into account varying continuous and discrete factors. A tailored approach to each issue is favoured in order to get the optimal accuracy from the model. Metastatic algorithms have showcased impressive capabilities when addressing challenges form several fields. Some notable examples include medicine [19–23], and credit card frauds identification [24, 25].

Moreover, swarm algorithms showcase interesting results when combined in to hybrid approaches. Some examples include optimization problems [26, 27], plant classification[28], predicting green energy production [29, 30], economic problems [31–36], enhancing the audit opinion [37], defect identification in software testing [38], feature selection [39–42], computer security, phishing and intrusion detection [43–50], environmental monitoring and pollutants tracking [51–53], as well as improving wireless sensor networks optimization [54–56] and general optimization of machine learning models [57–64].

2.1 Overview of Long-short term memory

A recurrent neural network (RNN) based algorithm called Long-short term memory (LSTM) was developed to overcome the inadequacies of standard RNNs by efficiently capturing long-term reliance in sequential input [65]. Compared to RNNs, LSTMs avoid the problem of vanishing and exploding gradients because of these updated; instead, it learns long-term dependencies by preserving a memory state that keeps data for extended periods of time [66]. Because of this characteristic, LSTM networks function especially well for assignments involving time-series data, speech recognition, natural language processing (NLP), and other sequential data issues.

LSTMs have four layers to their gating system, making them able to retain a higher quality of data than RNNs. This approach improves optimization, helps with creating a dynamic and personalized selection, and eliminates cell inputs to enable long-term memory keeping.

The cell state serves as storage, preserving important info. The forget gate is made up of a sigmoid function seen in (Eq.(1))) that determines which information is significant and should remain in the cell state.

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{1}$$

f_t signifies the forget gate, x_t refers to the inputs at the t time, h_{t-1} denotes the formerly hidden state, W_f and U_f denote the input weight coefficients, and b_f is the bias vector. The input gate sigmoid function (i_t) is responsible for selecting the incoming information to be stored in the cell state, as per Eq. (2).

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{2}$$

Here, b_i defines the bias, while W_i and U_i denote the complementary weight factors. Using the *tanh* layer, a set of extra choices is generated in accordance with Eq. (3).

$$\tilde{C}_t = tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{3}$$

accounting for the bias b_c and the weight variables W_c, U_c. The previous cell state C_{t-1} is removed from storage to make room for the addition of new data to the updated cell state C_t by using an element-wise product $\odot$ with the forget gate f_t. Next, the potential values $\tilde{C}_t$ that arise from multiplying them with the input gate i_t are combined using Eq. (4).

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{4}$$

Before the new concealed state is created in the *tanh* layer using (Eq. (6)), the first sigmoid output o_t is sent on in a format that has been constructed by the following equation (Eq. (5)) based on the cell state.

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{5}$$

$$h_t = o_t \odot tanh(C_t) \tag{6}$$

W_o and U_o are the weight factors, b_o defines the bias parameter.

2.2 Overview of XGBoost

The XGBoost [10], a well-known member of the ensemble learning family, employs a decision tree-based learning technique to combine forecasts from multiple inferior learners. The trees make use of a gradient boosting framework to correct for stage-prior errors. XGBoost achieves great efficacy because of the parallel processing choices and regularization features. Combining regularization and gradient boosting techniques improves model creation capabilities in addition to optimization. The intricate relationship between the input and target patterns is the basis of the model's prediction. The XGBoost model's goal function is improved by incrementally training the model. Due of its extensive parameter usage, XGBoost is difficult to tune, therefore the trial-and-error method is insufficient. Certain scenarios require a very strong model due to their tremendous complexity. A good model needs to be quick, accurate, and able to generalize. Training iteratively yields the best results. Eq. 7 shows the objective function of XGBoosts.

$$\mathrm{obj}(\Theta) \ = \ L(\theta) \ + \ \Omega(\Theta), \tag{7}$$

$L(Theta)$ represents the loss function, $Omega(Theta)$ is utilized for the regularization term, and $Theta$ indicates all of the XGBoost hyperparameters. $Omega(Theta)$ also controls the complexity of the model, and the loss function is determined by the specific situation being studied.

$$\mathrm{L}(\Theta) = \sum_i (y_i - \hat{y_i})^2, \tag{8}$$

in the equation y_i marks the predicted value, and the forecast target in all iterations i is $\hat{y_i}$.

$$L(\Theta) = \sum_i [\, y_i \ln(1 + e^{-\hat{y}_i}) + (1 - y_i) \ln(1 + e^{\hat{y}_i})]. \tag{9}$$

The presented process is used for differentiation between real and expected values, while lowering the total loss function aids the classification capabilities of the model.

3 Methodology

3.1 Original SCHO optimizer

The recently proposed SCHO metaheuristics [8] are based on mathematical qualities, as they draw inspiration from the characteristics of basic hyperbolic functions, sinh and cosh. Two features that sinh and cosh display are used by the algorithm. A steering threshold is used to differentiate between the stages of exploration and exploitation based on the first attribute of cosh consistently having a value greater than one. Second, the exploration and exploitation processes are both enhanced by the sinh property of the closeness to 0 inside the interval $[-1, 1]$.

The initialization of the algorithm, based on population-centric approaches, is illustrated in Equation 10, demonstrating an initial population represented by considerable chaos.

$$A = \begin{bmatrix} a_{1,1} ... a_{1,j} ... a_{1,D} \\ a_{1,2} ... a_{2,j} ... a_{2,D} \\ a_{N,1} ... a_{N,j} ... a_{N,D} \end{bmatrix} \tag{10}$$

where P represents the population of solutions, and each agent's location $A_{i,j}$ is calculated with respect to Equation 11. The parameters D and N represent the dimensionality and the number of agents.

$$a = rnd(N, D) \times (ub, lb) + lb \tag{11}$$

here, rnd is a random number, and ub and lb define the upper and lower bounds of the search realm.

After the initialization stage, the method must strike a balance among exploration and exploitation, directing the individuals towards promising areas of the search space. Exploration is divided to a pair of stages, and the balance is controlled by Equation 12:

$$S = floor(\frac{T}{ct}) \tag{12}$$

above T denotes maximal quantity of iterations, while ct is a control value, established through empirical experiments to value 3.6.

During exploration stage, individuals update their positions as according to Eq 13:

$$A_{(i,j)}^{t+1} = \begin{cases} A_{best}^{(j)} + r_1 \times W_1 \times A_{(i,j)}^t & r_2 > 0.5 \\ A_{best}^{(j)} - r_1 \times W_1 \times A_{(i,j)}^t & r_2 < 0.5 \end{cases} \tag{13}$$

where, t annotates the current round, $A^{t+1}(i,j)$ corresponds to the j-th dimension of the i-th solution, while $A^{(j)}best$ describes the best solution inside j-th dimension. Arbitrary numbers inside limits $[0,1]$ are selected and assigned to r_1 and r_2. The parameter W_1 denotes a weighted coefficient of a particular solution obtained in the following way:

$$W_1 = r_3 \times b_1 \times (coshr_4 + \mu \times sinhr_4 - 1) \tag{14}$$

where b_1 will be decreased over the iterations, and r_3 and r_4 are random numbers from range $[0,1]$. Moreover, a sensitivity parameter marked as μ is also utilized.

Exploration stage makes use of the second strategy involving the usage of Eq 15

$$A^{t+1}_{(i,j)} = \begin{cases} A^{(j)}_{best} + |\epsilon \times W_2 \times A^{(j)}_{best} - A^{(t)}_{i,j}| & r_5 > 0.5 \\ A^{(j)}_{best} - |\epsilon \times W_2 \times A^{(j)}_{best} - A^{(t)}_{i,j}| & r_5 < 0.5 \end{cases} \tag{15}$$

here, ϵ is preset to value 0.003 with respect to [8]. The weight parameter W_2 may be obtained through:

$$W_2 = r_6 \times b_2 \tag{16}$$

here r_6 denotes an arbitrary value taken from $[0,1]$, and b_2 is a slowly reducing value.

Exploitation plays a crucial role during the optimization, as individuals converge towards promising spaces inside the search region, closing to the optimum. Once more, this metaheuristics utilizes a pair of strategies. Equation 17 is employed in the initial stage.

$$A^{t+1}_{(i,j)} = \begin{cases} A^{(j)}_{best} + r_7 \times W_3 \times A^{t}_{(i,j)} & r_8 > 0.5 \\ A^{(j)}_{best} - r_7 \times W_3 \times A^{t}_{(i,j)} & r_8 < 0.5 \end{cases} \tag{17}$$

where the parameters r_7 and r_8 are chosen inside $[0,1]$, and W_3 is defined in the following manner:

$$W_3 = r_9 \times b_1 \times (coshr_{10} + \mu \times sinhr_{10}) \tag{18}$$

here r_9 and r_{10} represent random values from range $[0,1]$.

The second procedure depends of the Eq 19:

$$A^{t+1}_{(i,j)} = A^{t}_{(i,j)} + r_{11} \times \frac{singr_{12}}{coshr_12} |W_2 \times A^{t}_{best} - A^{t}_{i,j}| \tag{19}$$

here r_{11} and r_{12} are again randomly taken from the interval $[0,1]$.

3.2 Modified SCHO

Despite the admirable performance of the original SCHO algorithm, as a recently introduced optimizer, performance improvements might be further improved though hybridization. The potential of modifications is yet to be explored in literature. This work incorporates two mechanisms to boost performance. Initially, population diversity is boosted by incorporating quasi reflexive learning (QRL) [67] in to the original algorithms initialization procedure. Initial 50% of agents are generated using standard SCHO procedures. The latter half of agents are placed in the solution space as per Eq 20.

$$A_z^{qr} = rand\left(\frac{lb_z + ub_z}{2}, a_z\right) \tag{20}$$

where lb and ub denote lower and upper bounds of the search space and rad denotes a random value within the given interval.

As exploration is initially boosted by the introduced approach, exploitation improvements are needed in later iterations. An adaptive parameter ψ is used to to alternate between the default search mechanism of the SCHO algorithm and a mechanism borrowed form the firefly algorithm (FA) [68]. The mechanisms is mathematically formulates as per **??**

$$X_i(t+1) \ = \ X_i(t) \ + \ \beta \ e^{-\gamma \ r_{ij}^2} \ (X_j(t) \ - \ X_i(t)) \ + \ \alpha \ \epsilon_i(t), \tag{21}$$

where β_0 represents the attractiveness at $r = 0$. However, Eq. (21) is commonly swapped for Eq. (22) to improve computational performance.

$$\beta(r) = \frac{\beta_0}{(1 + \gamma \times r^2)} \tag{22}$$

in this equation, $X_i(t)$ denotes the current position of agent i at iteration t, and r_{ij} represents the position of agent j at the same iteration t. The parameter β indicates the separation between agents indexed as i and j, serving as a measure of their mutual attraction. Termed the agent attraction coefficient, β governs their interaction. Additionally, γ signifies the light absorption coefficient, α regulates the level of randomness, and $\epsilon_i(t)$ represents a stochastic vector

The apatite parameter is used to switch between the search mechanisms. A random value is generated in range $[0, 1]$. Should this value exceed psi the FA is used. Otherwise SCHO search is applied. The initial value of ψ is set to 0.96 and in each iteration is it decremented by 0.4 as such exploration is encouraged in early, and exploitation in later stages of the optimization. The modified algorithm is dubbed the Modified SCHO and the pseudocode is presented in Alg 1.

Algorithm 1 MSCHO pseudocode.

```
Define ψ = 0.94
Initialize 50% of solutions
Apply QRL to the population
while do
    Assess populataion using indicator and objective fucntions
    Generate random value R from [0, 1]
    if R > ψ then
        Guide population updates using FA algorithm
    else
        Guide population updates using SCHO algorithm
    Update ψ = ψ − 0.4
Return best solution
```

4 Experimental Configuration

To validate the introduced approach several optimizers are tested alongside the introduced modified algorithm in a comparative analysis under identical conditions.

Table 1 Objective function overall outcomes for PD detection.

Method	Best	Worst	Mean	Median	Std	Var
XG-MSCHO	**0.792746**	**0.785259**	**0.789483**	**0.789541**	0.002183	4.76E-06
XG-SCHO	0.788470	0.778079	0.784708	0.785262	0.002868	8.23E-06
XG-GA	0.786786	0.769365	0.780465	0.781286	0.004798	2.30E-05
XG-ABC	0.783429	0.766468	0.777411	0.778689	0.005048	2.55E-05
XG-BA	0.786941	0.772264	0.782908	0.783653	0.004291	1.84E-05
XG-SSA	0.786790	0.780219	0.783198	0.783120	0.002357	5.56E-06
XG-HHO	0.785410	0.779302	0.782395	0.782434	**0.001721**	**2.96E-06**
XG-WOA	0.787247	0.777768	0.782145	0.783119	0.002979	8.87E-06

Table 2 Indicator function overall outcomes for PD detection.

Method	Best	Worst	Mean	Median	Std	Var
XG-MSCHO	**0.103630**	**0.107375**	**0.105264**	**0.105235**	0.001092	1.19E-06
XG-SCHO	0.105770	0.110967	0.107653	0.107375	0.001434	2.06E-06
XG-GA	0.106611	0.115323	0.109773	0.109362	0.002399	5.76E-06
XG-ABC	0.108292	0.116775	0.111301	0.110661	0.002525	6.38E-06
XG-BA	0.106534	0.113871	0.108550	0.108177	0.002145	4.60E-06
XG-SSA	0.106611	0.109897	0.108407	0.108445	0.001179	1.39E-06
XG-HHO	0.107298	0.110355	0.108808	0.108787	**0.000861**	**7.41E-07**
XG-WOA	0.106381	0.111120	0.108932	0.108445	0.001490	2.22E-06

Algorithms included in the evaluation include the original SCHO algorithm as well as other popular optimizers such as the GA [69] ABC [70] BA [71] SSA [72] HHO [73] WOA [74]. Each algorithms is implemented under identical conditions with a population size of eight agents. The iteration limit is set to 10 iterations. Finally all algorithms are independently implemented for this research with the default parameter taken form the source works that introduced them. Experiments are conducted thought 30 independent runs.

The first layer of the optimization users the introduced optimizer to select LSTM parameters and attain an accuracy of 50% when handling classifications. The final layer of the LSTM consisting of 10 outputs is then used as the input of XGBoost to handle final classification. This reduces computational times and increases overall accuracy of the model. XGBoost parameters are optimized by metaheuristics and the final models vaulted using standard classification metrics as well as Cohen's kappa. Cohen's kappa is used as the indicator function while error rate (calculated as $(1-Accuracy)$). To test the introduced methodology, a publicly available PD dataset is used [75] last accessed 05.04.2024 [1]. The initial 70% is relegated to model training, while the latter 30% for testing.

5 Results

Objective function outcomes are provided in Table 1 followed by indicator function outcomes in Table 2. The introduced optimizer produced models that outperform competing optimizers demonstrating the best outcomes across the best, mean, median as well as worst case executions. However, the HHO demonstrates the highest rate of stability, despite not showcasing the best outcomes. Further insight in to algorithm behaviour can be discerned in Figure 1 and Figure 2.

When considering distribution plots of the attained outcomes for both the indicator and objective functions it can be observed that the solution attained by the introduced optimizer outperform competing algorithms. The introduced algorithm

[1] https://pubmed.ncbi.nlm.nih.gov/16176368/

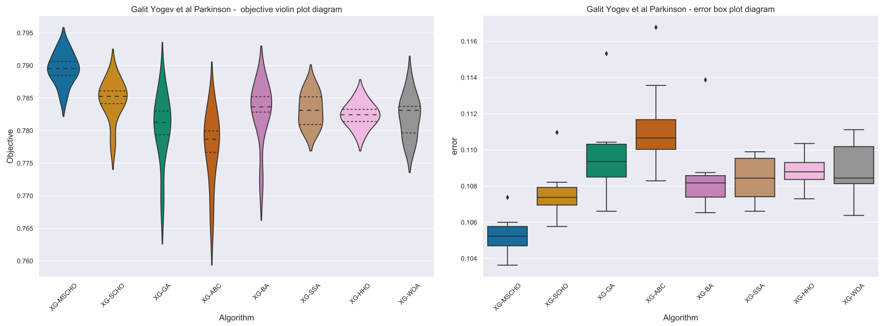

Fig. 1 Objective and indicator function distributions.

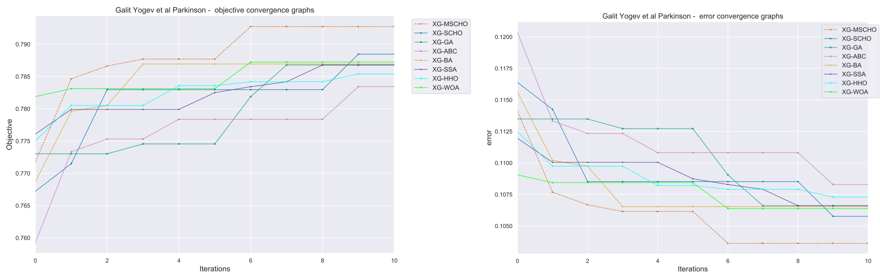

Fig. 2 Objective and indicator function convergence diagrams.

showcases grater stability then the original while also demonstrates overall better outcomes. The same can be observed in terms of indicator function. While the HHO showcases the best stability overall, mediocre outcomes can be observed compared to other optimizers.

Detailed metric comparisons are provided between the best constructed models in Table 3. A clear dominance can be observed for the introduced algorithm attaining the best outcomes across mos metrics, while matching performance in others. Further details on the best model can be observed in Figure 3 where the confusion matrix and PR curves for the best model are presented.

Finally, the parameter selections made for the best models are provided in Table 4.

6 Conclusion

Parkinsons disease is a progressive illness of the nervous system, most often affecting older male individuals. Its roots lay in the disorder of extrapyramidal tracts, more specifically bodies in the brain known as substantia nigra, lentiform nucleus, caudate nucleus, and ruber nucleus. The condiction results in higher cholinergic activity of the brain, which is further connected to the decline in cognitive ability of the patients, issues with gait, sleeping disorders, psychiatric symptoms of the disease as well as olfactory difficulties. Early detection is vital for improving patient outcomes. While

Table 3 Detailed metric comparisons of the best performing models generated by each optimizer.

Method	Metric	Normal	PD	Accuracy	Macro avg.	Weighted avg.
XG-MSCHO	precision	**0.889911**	0.903006	**0.896370**	**0.896458**	**0.896474**
	recall	0.904091	**0.888686**	**0.896370**	**0.896388**	**0.896370**
	f1-score	**0.896945**	**0.895789**	**0.896370**	**0.896367**	**0.896365**
XG-SCHO	precision	0.885243	**0.903588**	0.894230	0.894416	0.894438
	recall	0.905316	0.883196	0.894230	0.894256	0.894230
	f1-score	0.895167	0.893276	0.894230	0.894222	0.894219
XG-GA	precision	0.887029	0.899923	0.893389	0.893476	0.893491
	recall	0.901027	0.885788	0.893389	0.893407	0.893389
	f1-score	0.893973	0.892800	0.893389	0.893386	0.893385
XG-ABC	precision	0.881002	0.902963	0.891708	0.891982	0.892008
	recall	0.905163	0.878317	0.891708	0.891740	0.891708
	f1-score	0.892919	0.890469	0.891708	0.891694	0.891691
XG-BA	precision	0.885071	0.902181	0.893466	0.893626	0.893646
	recall	0.903784	0.883196	0.893466	0.893490	0.893466
	f1-score	0.894330	0.892587	0.893466	0.893459	0.893457
XG-SSA	precision	0.883787	0.903422	0.893389	0.893605	0.893628
	recall	0.905316	0.881519	0.893389	0.893418	0.893389
	f1-score	0.894422	0.892336	0.893389	0.893379	0.893377
XG-HHO	precision	0.886525	0.899040	0.892702	0.892782	0.892797
	recall	0.900107	0.885331	0.892702	0.892719	0.892702
	f1-score	0.893264	0.892133	0.892702	0.892699	0.892697
XG-WOA	precision	0.884990	0.902587	0.893619	0.893789	0.893810
	recall	0.904244	0.883044	0.893619	0.893644	0.893619
	f1-score	0.894513	0.892708	0.893619	0.893611	0.893609
	support	6527	6558			

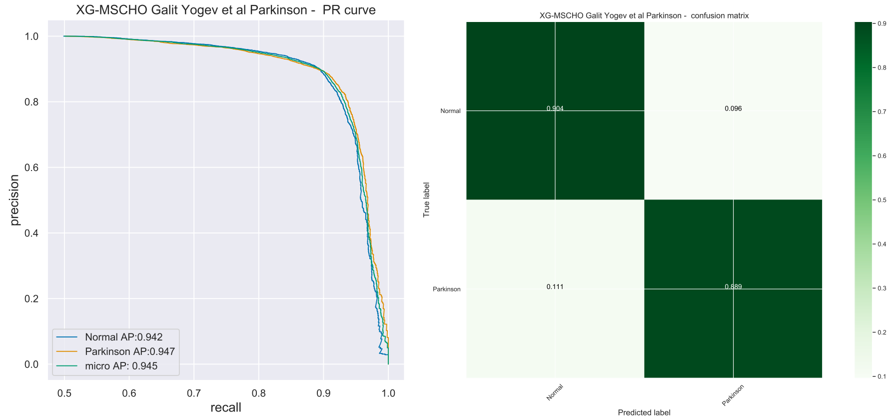

Fig. 3 Best MSCHO constructed model PR curve and confusion matrix.

there is no effective way for revering the neurological damage, treatment can slow down progression. However, patients often only seek treatment once symptoms significantly worsen and impair everyday function. Therefore early detection is vital. This work explores combining LSTM with XGBoost classifiers in order to form a early detection system form observing patient gait data form a non-invasive shoe mounted sensor. A modified optimizer is introduced to improve classification outcomes that attained an accuracy of 0.896370 outperforming other contemporary optimizers tested under identical conditions.

Future works will focus on addressing some of the limitations of this study. The limited availability of computational resources constrains the number of optimizes

Table 4 Parameter selections made by each optimizer for the respective best performing models.

Method	Learning Rate	Min Child W.	Subsample	Col by Tree	Max depth	Gamma
XG-MSCHO	0.541410	1.000000	0.706146	1.000000	10	0.344000
XG-SCHO	0.481746	2.342235	0.956147	0.958426	10	0.315849
XG-GA	0.767225	3.064870	0.867326	1.000000	10	0.033604
XG-ABC	0.428181	4.666781	0.739713	1.000000	10	0.498486
XG-BA	0.520161	6.153415	1.000000	0.886067	10	0.443784
XG-SSA	0.525032	7.702807	0.800874	1.000000	10	0.463654
XG-HHO	0.705189	2.202930	0.876996	1.000000	10	0.000000
XG-WOA	0.631316	1.000000	1.000000	1.000000	10	0.551453

that can be evaluated in a single work. Additionally, smaller population sizes and limited number of iterations is considered during the optimization. Additionally, further applications of the introduced model will be explored in other fields.

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