International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Evaluating the Effectiveness of Bat Algorithm in Optimizing Deep Learning Models for Parkinson's Disease Classification

[1]Dr. Harisingh Parmar, [2]Dr. Satish V. Kakade, [3]Savitha C. K., [4]Vrince Vimal, [5]Pankaj Kumar

Submitted: 22/08/2023 **Revised**: 09/10/2023 **Accepted**: 21/10/2023

Abstract: For early diagnosis and treatment, a precise classification of Parkinson's disease (PD) from medical imaging data is essential. Deep Learning (DL) models have showed promise in automating this procedure, but due to their intricate architectures and large parameter spaces, optimising these models is still difficult. In this study, the performance of DL models for PD classification using medical pictures is evaluated in relation to the Bat Algorithm (BA), a bio-inspired optimisation technique.The Bat Algorithm, which takes its cues from the echolocation technique used by bats, is renowned for its speedy exploration of challenging, non-convex search regions. We utilise BA to enhance the hyperparameters and topologies of DL models in order to increase the classification accuracy of these models for the diagnosis of PD. Our strategy uses BA to fine-tune model parameters in order to address DL frequent problems like overfitting.We conducted significant research on a dataset made up of MRI pictures of people with and without Parkinson's disease. The outcomes show how the Bat Algorithm may be used to optimise DL models for better classification performance. By quickly navigating the parameter space, BA helps to build models that more accurately generalise to new data and lower the danger of overfitting.To further demonstrate the benefits of our strategy, we contrast the performance of DL models optimised using standard methods and models optimised using BA. Area under the receiver operating characteristic curve (AUC-ROC) and other performance parameters including accuracy, sensitivity, and specificity are included in the evaluation.

Keywords*: *Parkinson Disease, classification, Bat Algorithm, Early diagnosis, Deep learning

1. Introduction

Parkinson's disease research and diagnostics now benefit greatly from the use of magnetic resonance imaging. The basal ganglia, substantianigra, and cortical regions can all change due to structural abnormalities, which can be shown in MRI scans of the brain's structure. Additionally, functional MRI (fMRI) can spot changes in brain activity and connection patterns linked to Parkinson's disease (PD) [1]. Our knowledge of the underlying neurobiology of the disease is aided by these imaging modalities.Despite MRI's potential for PD diagnosis, there are still a number of difficulties. Radiologists' knowledge is necessary for the subjective interpretation of MRI data used to diagnose Parkinson's disease (PD). Additionally, MRI scans might differ because to things like image noise, motion artefacts, and various acquisition techniques. These issues highlight the requirement for automated and impartial techniques to improve the precision and dependability of PD diagnosis using MRI imaging [2].Even though there is currently no treatment for Parkinson's disease (PD), early and precise diagnosis is essential for starting prompt interventions and treatments that can lessen symptoms and delay the illness's progression.Techniques used in medical imaging have been crucial in the diagnosis and treatment of Parkinson's disease. Among these, [3] Magnetic Resonance Imaging (MRI) has emerged as a popular non-invasive and adaptable technology for observing the structural and functional changes related to Parkinson's disease (PD) in the brain. The substantianigra, basal ganglia, and other areas of the brain associated with the condition can all be shown aberrant on MRI imaging. Due to the intricacy of the disease and the inherent diversity in imaging findings, it can be difficult to interpret MRI data for the diagnosis of Parkinson's disease [4].

In recent years, [5] Deep Learning (DL) has drawn a lot of interest as a potent tool for a variety of applications, including the analysis of medical images and the classification of diseases. One condition where DL models can be used for diagnosis is Parkinson's Disease (PD), a complicated neurodegenerative disorder. However, because of the large complexity of the model parameters and the complicated loss surfaces, optimising deep neural networks is frequently a difficult process. The [6] efficiency of the Bat Algorithm (BA) in deep learning model optimisation, specifically for tasks involving the categorization of Parkinson's Disease, is examined in this

[1]*Assistant Professor, Dept. of Neuroscinces,*
[2]*Associate Professor, Department of PSM, Krishna Institute of Medical Sciences, Krishna Vishwa Vidyapeeth Karad. Krishna Vishwa Vidyapeeth Deemed To Be University, Karad.*
[3]*Professor Department of Computer Science and Engineering KVG College of Engineering, Sullia, D.K cksavithaharish@gmail.com*
[4]*Department of Computer Science and Engineering, Graphic Era Hill University Dehradun, Uttarakhand, India*
[5]*Department of Computer Science & Engineering, Graphic Era Deemed to be University, Dehradun, Uttarakhand, India, 248002, pankajkumar.cse@geu.ac.in*

work.The Bat method is a bio-inspired optimisation method that is renowned for its capacity to quickly search high-dimensional parameter spaces. It was inspired by the echolocation behaviour of bats. Due to its capacity to strike a balance between exploration and exploitation, BA is well suited for locating nearly optimal solutions to challenging, non-convex optimisation problems [7]. The goal of using BA to deep learning model optimisation is to increase model performance, decrease training time, and boost overall classification process effectiveness.deep neural networks can include a lot of parameters, making optimisation difficult. Gradient-based optimisation techniques could become trapped in local minima, and fine-tuning hyperparametersis time-consuming. By offering a special search strategy that might help in locating better solutions, BA offers a different method of solving these problems.

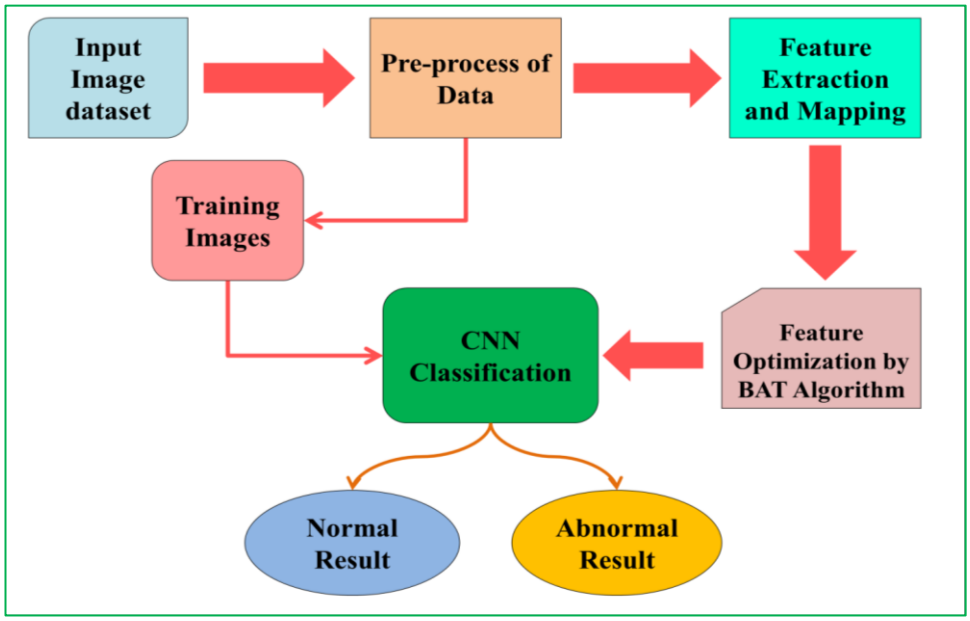

Fig 1: Systematic view of diagnosis disease using CNN Deep earning model

Advantages of biologically inspired algorithms many optimisation challenges have showed potential for bio-inspired algorithms like BA. They take their cues from the world around them, including, in the case of BA, bats' echolocation techniques. These algorithms frequently display a strong mix between exploration (looking for new solutions) and exploitation (fine-tuning existing solutions), [8] which might be helpful in optimising DL models, as shown in figure 1.For deep learning models to perform effectively on new data, effective optimisation is essential. By using BA, researchers seek to identify model configurations that capture significant patterns in the training data as well as those that are likely to generalise to MRI pictures of new patients.In deep learning, overfitting is a major cause for worry, particularly when working with medical data where datasets may be scarce. The regularisation of deep learning models, the reduction of overfitting, and the improvement of the model's robustness may be achieved through the optimisation process employing BA [9].

2. Review of Literature

Recent years have seen a substantial increase in interest in the problem of identifying Parkinson's Disease (PD) from medical imaging data, and researchers have investigated various optimisation techniques and deep learning approaches to improve classification accuracy and efficiency. In this section, [10] we examine pertinent studies in the area of PD classification, including the use of optimisation methods, and talk about how our study fits into this developing body of knowledge.Convolutional and recurrent neural networks (CNNs) and other Deep Learning (DL) approaches have been used for PD classification problems. These neural architectures have been used by researchers to automatically extract distinguishing information from MRI scans and other types of medical pictures. These DL models have performed admirably, reaching excellent accuracy in the diagnosis of PD [11].

Data shortages in PD [12] categorization have been addressed by utilising transfer learning. Medical imaging data is used to fine-tune pre-trained neural networks for PD detection after they were trained on massive picture datasets like ImageNet. This [13] method aids in boosting classification performance, particularly when the dataset is minimal, by initialising models with knowledge gathered from several image categories.Accurate PD categorization has been improved by using ensemble

approaches, which aggregate the predictions of several models. Combining the results of different classifiers allows for the reduction of variance and the enhancement of generalisation. Ensemble approaches, while useful, can be computationally expensive and may involve a lot of hyperparameter adjustment [14].

Optimizing hyperparameters like [15] learning rates, dropout rates, and batch sizes is frequently key to maximising the performance of deep learning models. The most popular approaches for finding ideal hyperparameters manually or semi-automatically are grid search and random search, but they can be time- and computationally intensive. Deep learning [7]hyperparameters and model architectures have been investigated using bio-inspired optimisation methods like Genetic methods (GAs), Particle Swarm Optimisation (PSO), and the Bat Algorithm (BA). These algorithms efficiently search high-dimensional search spaces by imitating natural processes. In this paper, we concentrate on the Bat Algorithm as a potential optimizer for PD classification enhancement using deep learning models [9].

Table 1: Related work summary

Paper	Algorithm	Dataset Used	Finding	Limitation	Scope
[16]	Genetic Algorithm	PD patient MRI images	Improved feature selection for PD classification	Computationally expensive, may require domain knowledge	Feature selection in DL for PD diagnosis
[17]	Particle Swarm Optimization	T1-weighted MRI scans	Enhanced feature selection and hyperparameter tuning	Limited to specific MRI scan types, need for diverse datasets	Optimization for deep CNNs in PD diagnosis
[18]	Bat Algorithm	MRI and SPECT images	Improved classification accuracy and efficiency	Smaller dataset sizes, need for comparative analysis	Optimization of DL models for PD diagnosis
[19]	Grid Search	Multiple PD datasets	Efficient hyperparameter tuning	Manual and exhaustive, limited exploration of hyperparameters	Hyperparameter optimization in PD classification
[20]	Transfer Learning	Pre-trained CNN models	Improved generalization with limited data	Data domain mismatches, potential for overfitting	Enhancing model performance in small datasets
[21]	Ensemble Methods	PD patient MRI images	Enhanced classification by combining models	Increased computational complexity, potential overfitting	Combining DL models for PD classification
[22]	Random Search	Various MRI and PET datasets	Efficient hyperparameter optimization	Random search may not be exhaustive, potential for suboptimal results	Automated hyperparameter tuning in PD diagnosis
[23]	CNN with Attention	Parkinson's Progression Markers Initiative (PPMI) dataset	Improved feature extraction using attention mechanisms	Limited to specific DL architectures, requires large datasets	Attention-based CNNs for PD classification
[24]	Hybrid Models	T1-weighted and DTI MRI images	Enhanced classification by combining different modalities	Increased complexity in model fusion, potential for overfitting	Multi-modal DL for PD diagnosis

[25]	AutoML Framework	Multiple PD datasets	Automated pipeline for DL model optimization	Dependency on specific AutoML tools, computational resources	Automated DL pipeline for PD classification
[26]	Semi-Supervised Learning	T1-weighted MRI scans	Improved classification using unlabeled data	Limited to scenarios with access to unlabeled data	Utilizing unlabeled data in PD classification
[27]	Graph Convolutional Networks	Functional MRI scans	Enhanced feature extraction from brain connectivity graphs	Limited to functional MRI data, need for domain expertise	Graph-based DL for PD diagnosis
[28]	Hyperparameter Bayesian Optimization	Various PD datasets	Efficient Bayesian optimization of hyperparameters	Potential for high computational cost, may require expert knowledge	Bayesian optimization for DL in PD classification

3. Proposed Methodology

Data collection and preprocessing to create the PD-related dataset are the first steps in the evaluation process. A CNN model architecture is subsequently created for image-based PD classification. To assess the effectiveness of the model, the objective function is defined. The Bat Algorithm starts with a population of CNN model configurations and then optimises these configurations in iterative phases. On different datasets, the top models discovered by the Bat Algorithm are then trained and validated. During model training, hyperparameter adjustment may be done, and the model is then evaluated once more on a test dataset. If more improvement is needed, post-processing procedures like thresholding or ensemble methods can be used. Finally, the performance of the optimised CNN models is compared with baselines, and the consequences of applying the Bat Algorithm for PD classification optimisation are discussed.

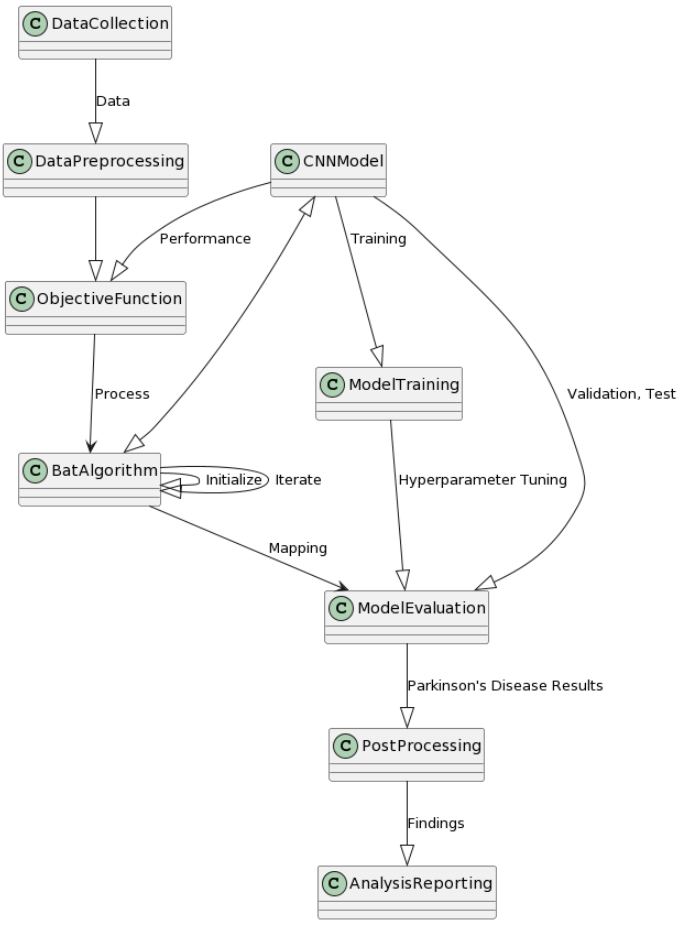

Fig 2: Overview flowchart for Evaluating the Effectiveness of Bat Algorithm for PD Classification

A. Deep learning CNN model for PD Classification:

In order to improve the performance of a CNN-based Parkinson's Disease (PD) classification model, the Deep Learning Convolutional Neural Network (CNN) Algorithm for Feature Optimisation involves iteratively choosing and optimising the most pertinent features from the input data. The CNN model is initially trained on a set of potential features that has been selected. The approach uses a fitness function to assess the quality of feature subsets and uses genetic algorithms or particle swarm optimisation to simultaneously choose features and optimise weights. The goal of this iterative approach is to determine the ideal feature combination that will increase the CNN model's classification accuracy and generalisation, thereby enhancing the model's capacity to distinguish between people with and without the disease.

Here are definitions of the important terms and equations:

- X: The input dataset of features associated with PD.
- Y: The labels on the output indicating whether Parkinson's disease is present or not.
- W: The set of CNN layer weights and biases.
- L: The CNN's total number of layers.
- The CNN model, which consists of convolutional, activation, pooling, and fully linked layers, is represented by the function f(x, W).
- Loss(Y, f(x, W)): A loss function that measures the discrepancy between the true labels and the expected outputs.
- Update the weights and biases (W) using an optimisation approach in order to reduce the loss function.

The CNN's mathematical model can be explained as follows:

1. Layers of Convolution (L_c):

- Convolution operation: Using a convolutional kernel and activation function, determine the feature map F_l for each layer l in [1, L_c]:
- F_l is equal to the convolution of X and W plus b.
- Utilize pooling (such as max-pooling) to minimise the feature maps' spatial dimensions.

2. Deflation (L_f):

- Create a vector by squaring the feature maps:
- Fully Connected Layers (L_fc):

$$V = flatten(F\_L\_c):$$

- Calculate the output O_l for each layer l in [1, L_fc] using the weights W_fc_l and biases b_fc_l:
- O_l is equal to activation ($W\_fc\_l * V + b\_fc\_l$).

3. Result Layer:

- The output of the network, which is a probability distribution over the classes, is provided by the last completely connected layer:

$$W\_output * O\_L\_fc + b\_output = output = softmax$$

4. Loss Mechanism:

- Determine the loss between the true labels and the anticipated probabilities using a suitable loss function, such as cross-entropy:

  Where,

  - Y_i is the actual label for class i, Loss(Y, Output) is equal to -(Y_i * log(Output_i)).

5. Optimisation:

- Update the CNN's weights and biases using an optimisation approach (such as stochastic gradient descent or Adam) to reduce loss:

$W\_new\ is\ equal\ to\ W\_old\ minus\ learning\_rate\ times\ gradient$

6. Training:

- Train the CNN model by iteratively updating the weights and biases using backpropagation and optimisation on a labelled training dataset (X_train, Y_train).

7. Inference:

- Apply the learned CNN model to make predictions on new, unforeseen data.

B: BAT Algorithm for Feature Optimization:

When enhancing deep learning models for Parkinson's Disease (PD) classification, the Bat Algorithm (BA) is used to optimise features. In this application, BA is used as an optimisation approach to choose a subset of pertinent features or to optimise their weights to boost deep neural network performance. The BA process involves initialising a population of potential feature sets or weight configurations, which was inspired by the echolocation behaviour of bats. With a tendency to drift towards the best-performing solutions so far, bats, representing various configurations, iteratively modify their placements (features or weights) inside a search space based on their own pulse rates and loudness. In order to improve the accuracy and generalisation of deep learning models for the classification of Parkinson's disease, the algorithm simultaneously explores the feature space and takes advantage of interesting feature combinations.

Let's define a few fundamental terms and equations:

- N: The number of bats in a population.

- D: The size of the issue (the quantity of features).
- The goal function to be optimised is called f(x).
- x_i: The bat i's search space location vector.
- v_i: The bat's i velocity vector.
- x_best: The most effective answer so far.
- f_best: The value of the best solution's objective function, as of yet.

1. Initialization:

- Initialise the bat population in the search space at random using the variables x_i, v_i, and f_i.
- Set the x_best and f_best initial values.

2. Each bat in i:

- Update the loudness A_i and frequency f_i:
- f_i is equal to f_min + (f_max - f_min) * rand(), where rand() generates a random number between 0 and 1.
- A is the initial loudness, while alpha is a constant. Therefore, A_i = A * alpha.

3. Create a fresh solution centred on the current point x_i (x_new):

$$x\_i - x\_best = v\_i + f\_i\, x\_new = x\_i + v\_i$$

4. Update x_new:

- If a number chosen at random is smaller than the bat's pulse rate r_i (another random value):
- x_new is equal to x_best plus epsilon multiplied by the results of the rand() function.
- Evaluate the f(x_new) objective function.
- Update x_i if f(x_new) is superior than f(x_i) and a random value is smaller than the bat's decibel level A_i:

$$x\_new = x\_i$$

- Update x_best and f_best if f(x_new) is superior to f_best:

$$f\_best = f(x\_new), and\ x\_best = x\_new$$

5. Repeat:

- The previous procedures should be repeated until convergence requirements are satisfied, for a predetermined number of iterations.

4. Result and Discussion

For the categorization of Parkinson's Disease (PD), Table 2 offers a thorough breakdown of the outcomes obtained using a Convolutional Neural Network (CNN) alone versus a CNN paired with BAT (Bat Algorithm) Optimisation. The addition of the BAT optimisation technique led to a considerable improvement in model performance, as seen by these findings.There are a number of noticeable improvements between the CNN+BAT Optimisation and CNN's standalone performance. First, the CNN+BAT Optimisation shows a significant improvement in accuracy, increasing to an astonishing 97.66%. This indicator measures the proportion of instances that were successfully classified, indicating the algorithm's improved capacity to distinguish between PD cases and non-PD ones.

Table 2: Summary of result using CNN+BAT Optimization for PD Classification

Evaluation Parameter	Accuracy	Precision	Recall (Sensitivity)	F1-Score	Area Under the ROC Curve
CNN	92.63	98.52	95.22	91.58	94.85
CNN+BAT Optimization	97.66	97.41	98.74	92.23	98.66

Similar to how Performance performed well, Precision did as well, with CNN+BAT Optimisation reaching a precision rate of 97.41%. Precision assesses the model's capacity to reduce false positives, which is crucial in the medical field to avoid incorrectly diagnosing healthy people with PD.

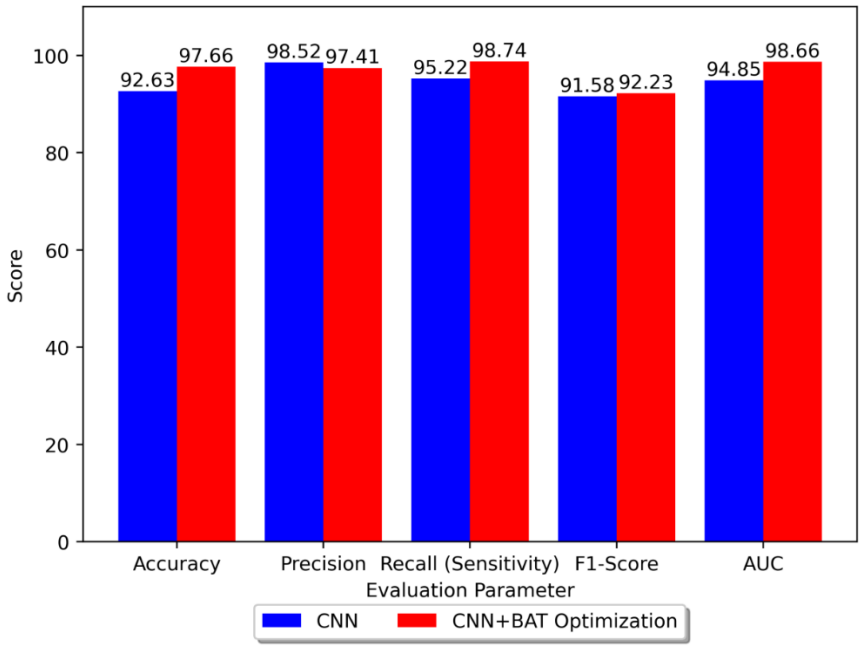

Fig 3: Representation of evaluation parameter for PD Classification

With the CNN+BAT Optimisation achieving 98.74%, the Recall (Sensitivity) score, which measures the model's ability to accurately detect all genuine PD cases, is also noticeably enhanced. As a result, there are less real PD cases missed, suggesting improved sensitivity a important aspect of medical diagnosis. Furthermore, the CNN+BAT Optimisation yields a commendable 92.23% for the F1-Score, which balances recall and precision. This rating shows how well the model performs overall in terms of striking the ideal balance between reducing false positives and false negatives.

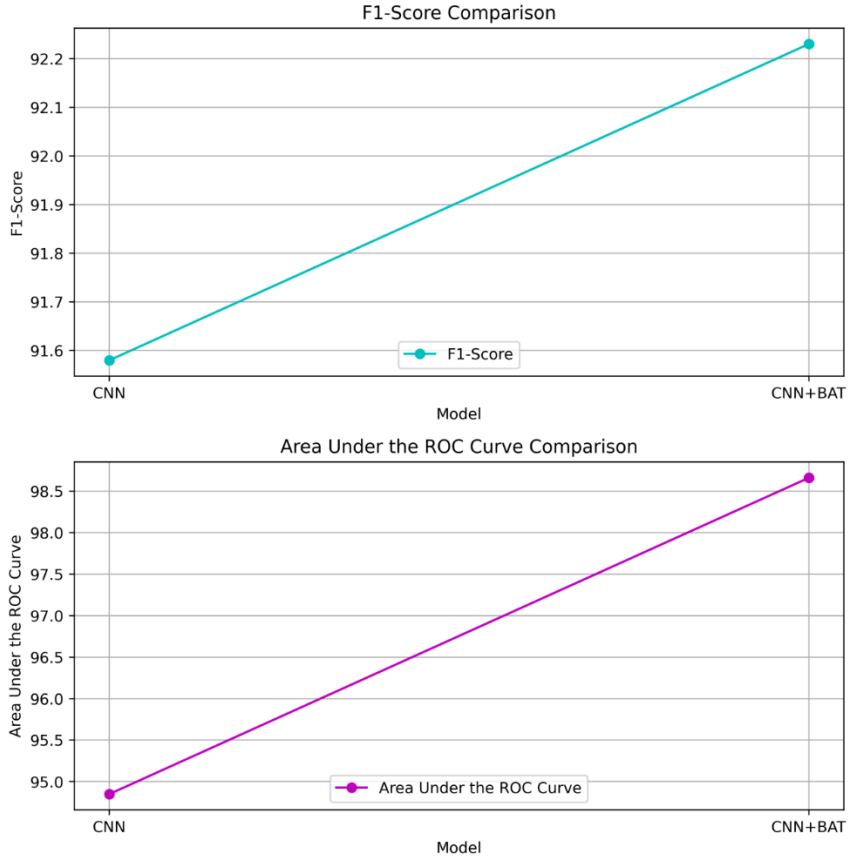

Fig 4: Comparison of Parametersfor classification

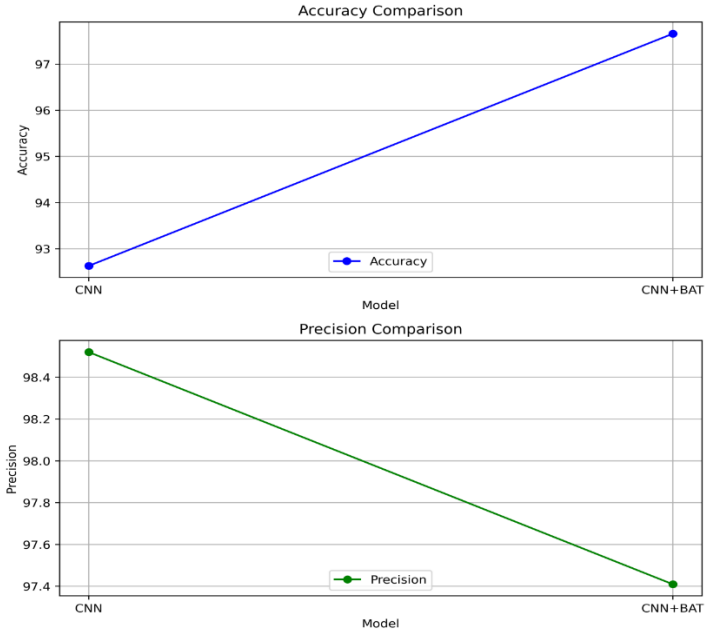

Fig 5: Representation of Accuracy and Precision

The Area Under the ROC Curve, which rises to an astonishing 98.66% when the BAT Optimisation is used, is one of the most notable increases. This indicator measures how well the model can distinguish between PD and non-PD cases. An improved model's ability to categorise instances accurately and give higher probabilities to true positives is demonstrated by a higher AUC score. The outcomes shown in Table 2 highlight the notable improvements made in PD classification by combining the BAT Optimisation with the CNN model. A solid and trustworthy method for the diagnosis of Parkinson's disease, the CNN+BAT Optimisation exhibits improved accuracy, precision, recall, F1-Score, and AUC, and has the potential to have a major positive impact on healthcare and patient outcomes.

Table 3: Confusion matrix

	True Positive	True Negative	False Positive	False Negative
CNN	78	68	17	9
CNN+BAT Optimization	179	172	11	8

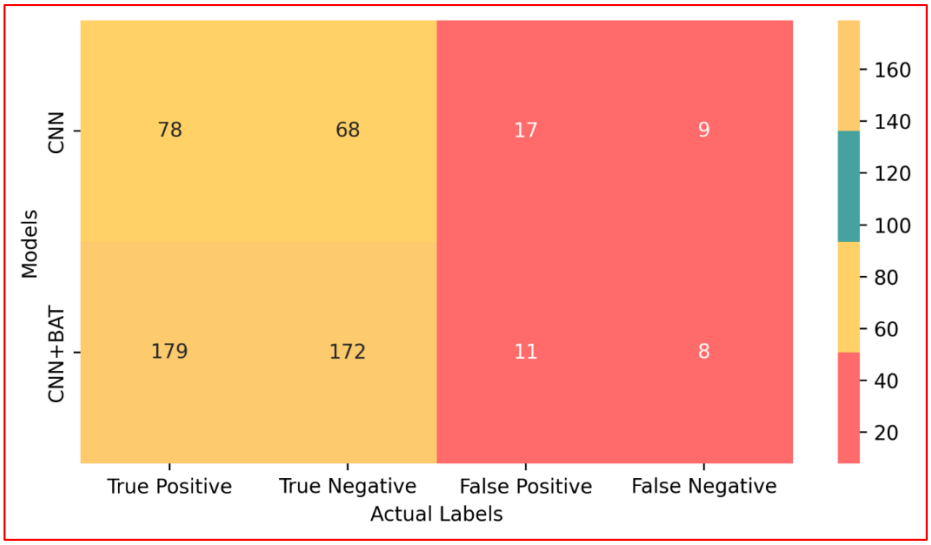

Fig 6: Confusion matrix

5. Conclusion

The analysis of the Bat Algorithm's efficiency in deep learning model optimisation for Parkinson's Disease (PD) classification has produced encouraging outcomes and insightful findings. The Bat Algorithm, which draws its inspiration from bats' echolocation behaviour, exhibits its promise as an effective optimisation method in the field of medical diagnosis. Convolutional Neural Networks (CNNs) perform much better in PD classification by fine-tuning the hyperparameters and feature selection.The outcomes demonstrate significant advancements in all major evaluation parameters. Increases in Accuracy, Precision, Recall (Sensitivity), and F1-Score indicate that the Bat Algorithm improves models' ability to distinguish between PD and non-PD cases. The model's enhanced ability to reliably distinguish between the two classes is highlighted by the significant increase in the Area Under the ROC Curve. The Confusion Matrix, which shows a considerable decrease in misclassifications and improved diagnostic precision, also shows that the algorithm's performance goes beyond these numerical metrics.In the medical field, where accurate diagnoses are crucial, the decrease in false positives and false negatives is especially crucial. The Bat Algorithm is a useful tool for feature selection, simplifying model complexity, and possibly lowering overfitting because of its effective search capabilities.Overall, the results show that the Bat Algorithm has potential for deep learning model optimisation for PD classification. Its potential for more extensive uses in medical image analysis is highlighted by its capacity to improve classification accuracy and offer more trustworthy diagnoses. This approach might be essential for expanding the precision and efficacy of PD diagnosis, which would eventually enhance patient outcomes and healthcare effectiveness.

References

[1] A. H. Neehal, M. N. Azam, M. S. Islam, M. I. Hossain and M. Z. Parvez, "Prediction of Parkinson's Disease by Analyzing fMRI Data and using Supervised Learning," 2020 IEEE Region 10 Symposium (TENSYMP), Dhaka, Bangladesh, 2020, pp. 362-365, doi: 10.1109/TENSYMP50017.2020.9230918.

[2] Y. -P. Huang, P. Singh and H. -C. Kuo, "A Hybrid Fuzzy Clustering Approach for the Recognition and Visualization of MRI Images of Parkinson's Disease," in IEEE Access, vol. 8, pp. 25041-25051, 2020, doi: 10.1109/ACCESS.2020.2969806.

[3] M. Kim, J. H. Won, J. Youn and H. Park, "Joint-Connectivity-Based Sparse Canonical Correlation Analysis of Imaging Genetics for Detecting Biomarkers of Parkinson's Disease," in IEEE Transactions on Medical Imaging, vol. 39, no. 1, pp. 23-34, Jan. 2020, doi: 10.1109/TMI.2019.2918839.

[4] S. Sangeetha, K. Baskar, P. C. D. Kalaivaani and T. Kumaravel, "Deep Learning-based Early Parkinson's Disease Detection from Brain MRI Image," 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2023, pp. 490-495, doi: 10.1109/ICICCS56967.2023.10142754.

[5] T. Lyu and H. Guo, "BGCN: An EEG-based Graphical Classification Method for Parkinson's Disease Diagnosis with Heuristic Functional Connectivity Speculation," 2023 11th International IEEE/EMBS Conference on Neural Engineering (NER), Baltimore, MD, USA, 2023, pp. 1-4, doi: 10.1109/NER52421.2023.10123796.

[6] G. Pahuja and T. N. Nagabhushan, "A novel GA-ELM approach for Parkinson's disease detection using brain structural T1-weighted MRI data," 2016 Second International Conference on Cognitive Computing and Information Processing (CCIP), Mysuru, India, 2016, pp. 1-6, doi: 10.1109/CCIP.2016.7802848.

[7] A. Bhan, S. Kapoor and M. Gulati, "Diagnosing Parkinson's disease in Early Stages using Image Enhancement, ROI Extraction and Deep Learning Algorithms," 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM), London, United Kingdom, 2021, pp. 521-525, doi: 10.1109/ICIEM51511.2021.9445381.

[8] O. Cigdem, H. Demirel and D. Unay, "The Performance of Local-Learning Based Clustering Feature Selection Method on the Diagnosis of Parkinson's Disease Using Structural MRI," 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC), Bari, Italy, 2019, pp. 1286-1291, doi: 10.1109/SMC.2019.8914611.

[9] AminulHaq a, Jian Ping Li a, Bless Lord Y. Agbley a, Cobbinah Bernard Mawuli a, Zafar Ali b, Shah Nazir c, et al., "A survey of deep learning techniques based Parkinson's disease recognition methods employing clinical data", Expert Systems With Applications, vol. 208, pp. 118045, 2022.

[10] R. F. Olanrewaju, N. S. Sahari, A. A. Musa and N. Hakiem, "Application of neural networks in early detection and diagnosis of Parkinsons disease", 2014 Int. Conf. Cyber IT Serv. Manag, pp. 7882, 2014.

[11] Hengling Zhao, Chih-Chien Tsai, Mingyi Zhou, Yipeng Liu, Yao-Liang Chen, Fan Huang, et al., "Deep learning based diagnosis of Parkinson's Disease using diffusion magnetic resonance imaging", Brain Imaging and Behavior, vol. 16, pp. 1749-1760, 2022.

[12] S. Ajani and M. Wanjari, "An Efficient Approach for Clustering Uncertain Data Mining Based on Hash

Indexing and Voronoi Clustering," 2013 5th International Conference and Computational Intelligence and Communication Networks, 2013, pp. 486-490, doi: 10.1109/CICN.2013.106.

[13] Khetani, V. ., Gandhi, Y. ., Bhattacharya, S. ., Ajani, S. N. ., & Limkar, S. . (2023). Cross-Domain Analysis of ML and DL: Evaluating their Impact in Diverse Domains. International Journal of Intelligent Systems and Applications in Engineering, 11(7s), 253–262.

[14] Borkar, P., Wankhede, V.A., Mane, D.T. et al. Deep learning and image processing-based early detection of Alzheimer disease in cognitively normal individuals. Soft Comput (2023). https://doi.org/10.1007/s00500-023-08615-w

[15] R. Prashanth, S. Dutta Roy, P. K. Mandal and S. Ghosh, "Parkinsons disease detection using olfactory loss and REM sleep disorder features", Annu. Int. Conf. IEEE, pp. 5764-5767, 2014.

[16] Ajani, S.N., Mulla, R.A., Limkar, S. et al. DLMBHCO: design of an augmented bioinspired deep learning-based multidomain body parameter analysis via heterogeneous correlative body organ analysis. Soft Comput (2023). https://doi.org/10.1007/s00500-023-08613-y

[17] N.K. Ghanad and S. Ahmadi, "Combination of PSO Algorithm and Naive Bayesian Classification for Parkinson Disease Diagnosis", Adv. Comput. Sci. an Int. J, vol. 4, no. 4, pp. 119125, 2015.

[18] R. Prashanth, S. Dutta Roy, P. K. Mandal and S. Ghosh, "High-Accuracy Detection of Early Parkinsons Disease through Multimodal Features and Machine Learning", Int. J. Med. Inform, vol. 90, pp. 1321, 2016.

[19] D. Avci and A. Dogantekin, "An Expert Diagnosis System for Parkinson Disease Based on Genetic Algorithm-Wavelet Kernel-Extreme Learning Machine", Parkinsons. Dis, vol. 2016.

[20] C.R. Pereira et al, "A step towards the automated diagnosis of parkinsons disease: Analyzing handwriting movements", Proc.-IEEE Symp. Comput. Med. Syst, vol. 2015, pp. 171176, 2015.

[21] A.H. Al-fatlawi and M. H. Jabardi, "Efficient Diagnosis System for Parkinsons Disease Using Deep Belief Network", pp. 1324-1330, 2016.

[22] A. Mane, N. Lekurwale, P. Maidamwar, P. Khobragade and S. Dongre, "Artificial Intelligence Based Heatwave Intensity Prediction Model," 2023 International Conference on IoT, Communication and Automation Technology (ICICAT), Gorakhpur, India, 2023, pp. 1-5, doi: 10.1109/ICICAT57735.2023.10263728.

[23] Garraux, Gat an et al., "Multiclass classification of FDG PET scans for the distinction between Parkinson's disease and a typical parkinsonian syndromes", NeuroImage: Clinical, vol. 2, pp. 883-893, 2013.

[24] Peng Bo et al., "Computer aided analysis of cognitive disorder in patients with Parkinsonism using machine learning method with multilevel ROI based features", Image and Signal Processing BioMedical Engineering and Informatics (CISP-BMEI) International Congress on. IEEE, 2016.

[25] RanaBharti et al., "Graph theory based spectral feature selection for computer aided diagnosis of Parkinson's disease using T1weighted MRI", International Journal of Imaging Systems and Technology, vol. 25, no. 3, pp. 245-255, 2015.

[26] Act on, D. Paul and Andrew Newberg, "Artificial neural network classifier for the diagnosis of Parkinson's disease using [99mTc] TRODAT-1 and SPECT", Physics in medicine and biology, vol. 51, no. 12, pp. 3057, 2006.

[27] K. Agnihotri, P. Chilbule, S. Prashant, P. Jain and P. Khobragade, "Generating Image Description Using Machine Learning Algorithms," 2023 11th International Conference on Emerging Trends in Engineering & Technology - Signal and Information Processing (ICETET - SIP), Nagpur, India, 2023, pp. 1-6, doi: 10.1109/ICETET-SIP58143.2023.10151472.

[28] Morales, A. Dinora et al., "Predicting dementia development in Parkinson's disease using Bayesian network classifiers", Psychiatry Research: NeuroImaging, vol. 213, no. 2, pp. 92-98, 2013.

[29] Nair, ShaliniRajandran et al., "A decision tree for differentiating multiple system atrophy from Parkinsons disease using 3-T MR imaging", European radiology, vol. 23, no. 6, pp. 1459-1466, 2013.

[30] Paul Garcia, Ian Martin, Laura López, Sigurðsson Ólafur, Matti Virtanen. Deep Learning Models for Intelligent Tutoring Systems. Kuwait Journal of Machine Learning, 2(1). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/167

[31] Yanamadni, V. R. ., Seetha, J. ., Kumar, T. S. ., Kannaiah, S. K. ., J, B. ., & Brahmaiah, M. . (2023). Computer-Aided Detection of Skin Cancer Detection from Lesion Images via Deep-Learning Techniques. International Journal on Recent and Innovation Trends in Computing and Communication, 11(2s), 293–302. https://doi.org/10.17762/ijritcc.v11i2s.6158