



Improved Diabetic Classification Using Chaotic Grey Wolf Random Forest Optimiser for Hyperparameter Tuning

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ABSTRACT

The application of machine learning in medical diagnostics has significantly advanced the early detection and classification of diabetes. However, classifiers often suffer from challenges related to high-dimensional data, overfitting, and ineffective hyperparameter tuning, which compromise their predictive performance and generalisation capability. To address these limitations, this study proposes an improved diabetic classification framework using a chaotic Grey Wolf Optimisation (cGWO) algorithm for hyperparameter tuning of a Random Forest (RF) classifier. The cGWO enhances the standard GWO by improving its exploration and exploitation abilities, thus reducing the risk of local optima and premature convergence. Using the BRFSS dataset, the study evaluated the proposed cGWO-RF model and compared its performance against an RF and a standard RF-GWO model. The cGWO-RF outperformed the RF-GWO method, achieving a 0.03% increase in accuracy, 0.51% in sensitivity, 0.31% in precision, 0.51% in F1-score, 0.2% in AUC, and 1.46% in average precision-recall because of the balance in exploration and exploitation introduced by the cGWO. These results show the efficacy of the cGWO in optimising RF hyperparameters, leading to more accurate, efficient, and generalisable models for diabetes classification. The study contributes an optimisation strategy that enhances predictive modelling in healthcare and supports more reliable decision-making for early diabetes diagnosis.

KEYWORDS: Diabetes classification; Grey Wolf Optimisation; Machine Learning in Healthcare, Random forest; Hyperparameter Tuning

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1. INTRODUCTION

In today's data-driven world, machine learning and artificial intelligence have become integral components of decision-making processes across various fields (Choudhury & Devi Rajeswari, 2021). Among the widely used machine learning techniques is the random forest estimator, known for its robustness, accuracy, and ability to handle large datasets with multiple variables. Random forest is a popular ensemble learning estimator that constructs multiple decision trees during training and outputs the class, the mode of the classes, or the mean prediction of the individual trees (Aliyu *et al.*, 2024; Hennebelle *et al.*, 2024). Despite its widespread application, random forest performance must be improved by fine-tuning its hyperparameters, the number of trees, the depth of the trees, and the features considered at each split. Optimising these parameters is imperative for effectively classifying diabetes patients, improving the estimator's predictive performance and efficiency.

Meta-heuristic optimisation algorithms have emerged as powerful tools for optimising machine learning models (Raji *et al.*, 2022). These biomimicry algorithms offer flexible strategies to explore a large search space effectively and find optimum solutions. The Grey Wolf Optimisation (GWO) is one such optimisation algorithm. The algorithm was inspired by the social hierarchy and hunting behaviour of grey wolves (Mirjalili *et al.*, 2014). GWO has proven successful in many optimisation tasks because of its simplicity, ease of implementation, and ability to balance exploration and exploitation during the search process. However, like many meta-heuristic algorithms, GWO may

face challenges, such as getting stuck in local optima or premature convergence, particularly when applied to complex, high-dimensional optimisation problems.

In El-Kenawy *et al.*, (2020), the authors introduced a modified binary Grey Wolf Optimiser (MbGWO) improved with Stochastic Fractal Search (SFS) to address limitations in the standard GWO, such as low precision and slow convergence in feature selection problems. The MbGWO enhances exploration and exploitation through an exponential iteration scheme, integrating crossover and mutation operations to increase population diversity. The addition of SFS's Gaussian-based diffusion process further refines the best solutions. Originally designed for continuous domains, the algorithm was adapted to a binary form of feature selection and tested on 19 University of California, Irvine (UCI) datasets using K-Nearest Neighbours for evaluation. The MbGWO-SFS outperformed several leading binary optimisers (PSO, SBO, WOA, GA), with statistical significance confirmed by the Wilcoxon rank-sum test, showing improved accuracy, convergence speed, and robustness in selecting optimal feature subsets. In Hassan *et al.*, (2022) the authors introduced an intrusion detection model using an optimized binary Manta Ray Foraging Optimisation (MRFO) algorithm with a random forest classifier. The MRFO, enhanced with an adaptive sigmoid function, effectively selected relevant features while reducing redundancy. Tested on NSL-KDD and CIC-IDS2017 datasets, the model achieved 99.3% and 98.8% accuracy, respectively, outperforming existing methods in precision, recall, and computational efficiency, thus strengthening cybersecurity through intelligent feature selection.

Also, a deep learning diagnostic system for Diabetic Retinopathy (DR) and Diabetic Macular Edema (DME) using a hybrid CNN model called DLCNN-MGWO-VW was presented (Purna Chandra Reddy & Gurralla, 2022). It combines ResNet50, disease-specific attention modules, and a Modified Grey Wolf Optimisation with variable weights for feature selection. Evaluated on the IDRiD dataset, the system achieved accuracy rates of 96.0% (DR), 93.2% (DME), and 92.23% (joint detection), offering high diagnostic reliability and early intervention capability in ophthalmology. In Zhang *et al.*, (2023) hospital resource management was addressed by developing SRXGWO, a novel GWO variant integrating Sobol sequences, Cauchy random replacement, and directional mutation. This improved algorithm optimized SVR parameters for accurate patient-flow prediction. Compared to 12 algorithms, SRXGWO-SVR showed superior accuracy and lower errors, aiding hospital operations through better forecasting and resource planning. The investigators in Aswal *et al.*, (2024) tackled challenges in medical image classification using DLFOW-RF, which integrates Discrete Lévy Flight Grey Wolf Optimisation with Random Forest. It handles data imbalance, annotation variability, and noisy data in medical images, especially for diabetic retinopathy grading. Achieving 90–95% accuracy, this method shows notable performance on limited and imbalanced datasets, reducing diagnostic subjectivity and reliance on extensive annotations. A Dynamic Waterwheel Plant Algorithm (DWWPA) and its binary form (bDWWPA) to enhance KNN performance for diabetes diagnosis was proposed in El-kenawy *et al.*, (2024). The model achieved a 98.9% accuracy through effective feature selection, confirmed via ANOVA and Wilcoxon tests. The model outperformed other approaches in consistency and precision, contributing to more accurate chronic disease classification.

The researchers in Khan *et al.*, (2024) introduced a hybrid model for diabetic eye disease classification using Genetic Grey Wolf Optimisation (G-GWO) combined with a Fully Convolutional Encoder-Decoder Network (FCEDN) and Kernel Extreme Learning Machine (KELM). This ensemble achieved 98.5–98.8% classification accuracy on datasets like IDRiD and ODIR, improving segmentation and disease stage detection. It reduces the need for manual diagnosis, enhancing automation in diabetic eye screening. Similarly, in Ulutas *et al.*, (2024), an ensemble learning framework for diabetes diagnosis was developed, leveraging boosting, bagging, voting, and stacking techniques. A PSO-GWO hybrid optimisation method was used to fine-tune model hyperparameters. The stacked model, especially with random forest, achieved 98.10% accuracy, showing improvement over existing methods and reinforcing the potential of ensemble-optimized models in medical diagnostics.

Despite the success of ensemble methods like a random forest classifier in machine learning, optimising these models for high-dimensional, complex datasets remains a challenge. Traditional and metaheuristic optimisation techniques often cannot manage the vast search space and risk overfitting, particularly when applied to datasets like BRFS that include demographic, lifestyle, and medical features (Chowdhury *et al.*, 2024). Although the GWO has been used for tuning machine learning models, its standard form suffers from issues such as premature convergence and limited exploration, especially in high-dimensional scenarios. Existing research lacks a robust approach to enhance Random Forest performance under such conditions. This study addresses this gap by proposing a modified GWO specifically

designed to optimise random forest hyperparameters, aiming to improve generalisation, reduce computational cost, and increase predictive accuracy, particularly for complex datasets in healthcare applications.

Therefore, an optimized random forest (RF) classification framework enhanced by a cGWO algorithm for the BRFSS dataset is proposed in this research. The proposed approach aims to improve the standard GWO's hyperparameter tuning capability by incorporating chaotic sequences, which enhance population diversity and dynamically balance exploration and exploitation. This modification mitigates the risk of premature convergence and local optima, leading to a more robust optimisation process (Nnamoko & Korkontzelos, 2020). When applied to the BRFSS dataset, the cGWO-tuned RF model showed improved performance compared to the GWO-tuned RF model. The results showed notable improvements, leading to the following contributions:

- a. A percentage improvement of 0.03% in accuracy, 0.51% in sensitivity, 0.31% in precision, 0.51% in F1-score, 0.2% in AUC, and 1.46% in average precision-recall, confirming the effectiveness of the proposed method for enhancing classification performance.
- b. The improvement in (a) stemmed from an enhanced standard random forest, which used chaotic sequences to balance exploration and exploitation.
- c. A significantly higher APR was achieved compared to (Aliyu *et al.*, 2024) giving it a practical advantage in real-world settings where reducing false positives is more important than slight improvements in overall accuracy.

Building on these contributions, this study emphasises the critical role of a cGWO-RF in enhancing classifier performance through effective hyperparameter optimisation. By leveraging data-driven insights, the approach aims to improve predictive accuracy and model robustness. The paper is structured as follows: Section 2 outlines the materials and methods, Section 3 presents the results and discussion, and Section 4 concludes the study with key findings and future directions.

2. MATERIALS AND METHODS

This section provides the detailed material and methods used to achieve the study objectives.

2.1 Materials for the study

The following outlines the materials used for the study.

- a. Computational Materials:
 - i. Software and Programming Languages: (Jupyter Notebook (Anaconda 3), MATLAB/Simulink 2022b) for simulations, and data analysis.
 - ii. Datasets: BRFSS.
 - iii. HP EliteBook 830 G5 Intel(R) Core (TM) i5- 8350U CPU @ 1.70GHz, 1.90 GHz.

2.1.1 The BRFSS Dataset.

The Behavioral Risk Factor Surveillance System (BRFSS) is an annual cross-sectional telephone survey conducted by the CDC to collect comprehensive data on health behaviors, demographics, chronic conditions, and social determinants from tens of thousands of US adults to help track trends and plan public health interventions (Chowdhury *et al.*, 2024).

2.1.2 The chaotic grey wolf optimisation algorithm

The Grey Wolf Optimisation (GWO) algorithm is a meta-heuristic inspired by the hunting behavior of grey wolves (Mirjalili *et al.*, 2014, 2016). While GWO is effective for global optimisation problems, it can experience premature convergence and limited search space exploration, especially when the random components lack sufficient diversity (Bello-Salau *et al.*, 2020; Sulaiman *et al.*, 2024). In a standard GWO, the position update of each search agent (wolf) is influenced by the three leading wolves: alpha, beta, and delta. The coefficient vectors $\vec{A}$ and $\vec{C}$ are calculated as in equations (1)-(2) (Bilal *et al.*, 2022; El-Kenawy *et al.*, 2020; Mirjalili *et al.*, 2014; Sun *et al.*, 2023)

$$\vec{A} = 2a * (r - a) \quad (1)$$

$$\vec{C} = 2 * r \quad (2)$$

Where $a \in [2,0]$ decreases linearly over the iterations and $r \in [0,1]$ is a uniformly distributed random number. To enhance the stochastic nature of GWO, the parameter r in equations (1)-(2) is replaced with a chaotic sequence generated using the logistic map in equation (3).

$$x_{n+1} = r \cdot x_n \cdot (1 - x_n) \quad (3)$$

where the current value in the chaotic sequence is x_n , the next sequence value is x_{n+1} , r is the control parameter with a range $3.57 \leq r \leq 4.0$ to ensure chaotic behaviour. The current value is constrained within $0 \leq x_n \leq 1$ to maintain the bounded values. Output of the logistic map to a desired range (lower bound L and upper bound U) is scaled using equation (4):

$$x' = L + (U - L) \cdot x_{n+1} \quad (4)$$

Where the transformed chaotic value is x' , the lower bound value is L and the upper bound value is U .

Thus, equations (1)-(2) are transformed to equations (5)-(6).

$$\vec{A} = 2a * (x' - a) \quad (5)$$

$$\vec{C} = 2 * x' \quad (6)$$

2.1.3 Splitting the dataset into testing and training data

The BRFSS dataset was divided into a 70% training set, used to train and validate different hyperparameter configurations. The remaining 30% was used for final evaluation after optimisation. Stratified sampling was used to maintain the proportion of diabetic and non-diabetic cases in both subsets.

3 RESULTS AND DISCUSSION

This section discusses the results of implementing the optimized chaotic random forest model. Comparing it with the standard GWO (Aliyu *et al.*, 2024), and evaluating its performance across various metrics.

3.1 Hyperparameter optimisation

This subsection presents the parameters of the random forest classifier. Table 1 shows the values of these parameters for random forest, standard GWO, and cGWO.

Hyperparameters	Class weight	Maximum depth	Minimum sample split	N_ estimators	Random Rate
Random Forest	Balanced	6	20	150	0
Random forest with GWO	Balanced	8	25	157	0
Random forest with cGWO	Balanced	10	27	200	0

Table 1 presents the hyperparameter configurations for the random forest, the GWO-optimized random forest, and the cGWO models. For all three classifiers, the class weight parameter was set to balanced, ensuring that the models were not biased toward either the diabetic or non-diabetic classes in the BFRSS dataset. Among the configurations, cGWO exhibited the highest maximum depth value of 10 and the largest number of estimators at 200.

The BFRSS dataset's predictive performance reflects the differences in hyperparameter configurations among the three classifiers. The cGWO model, with its high maximum depth and number of estimators, suggests that its increased complexity enabled it to capture better the underlying patterns associated with diabetic risk. However, this also comes at a higher computational cost. The GWO-optimized random forest, which employed a higher minimum sample split, achieved a more balanced value. The standard random forest model, while more conservative in its parameterization, served as a useful baseline, illustrating the performance gains achieved through evolutionary optimisation techniques.

These results highlight the importance of targeted hyperparameter tuning, particularly in the BRFSS datasets, where both precision and fairness are critical.

Figure 1 shows the flowchart of the proposed cGWO. This is combined with the random forest in Algorithm 1.

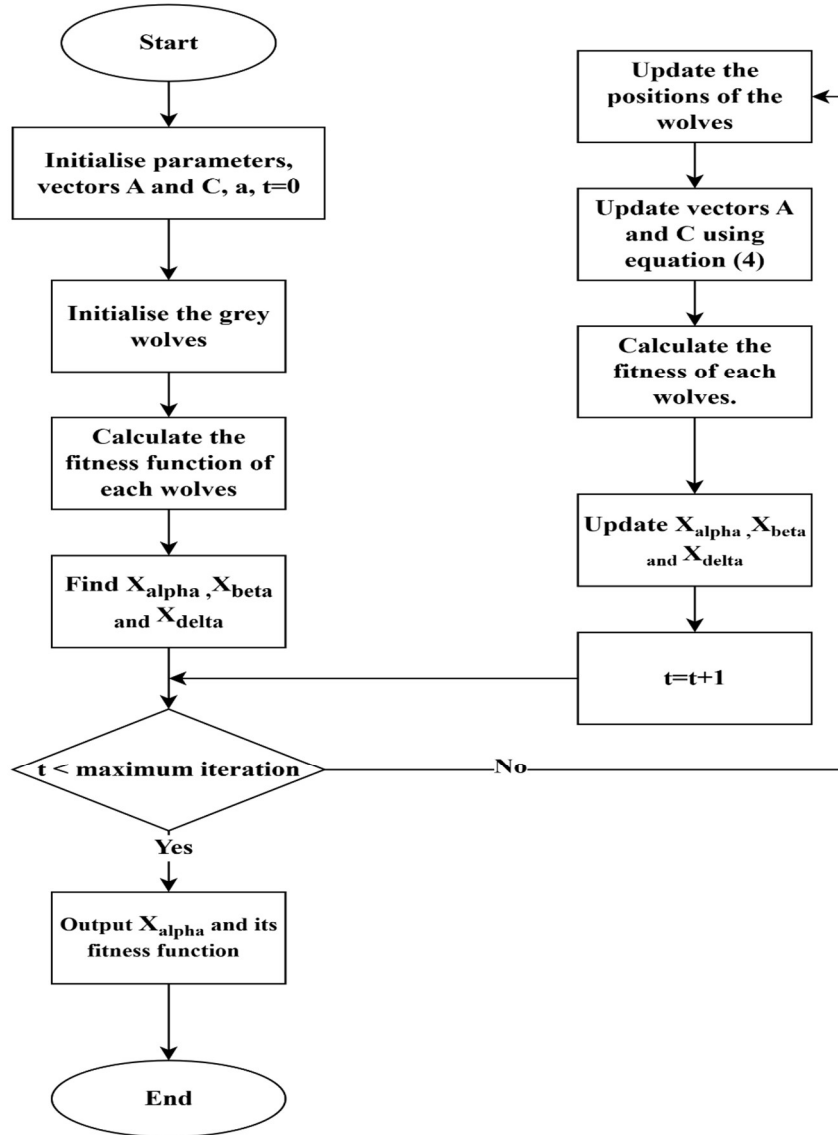


Figure 1: Proposed cGWO Flowchart

Algorithm 1 is the cGWO-based random forest classifier.

Algorithm 1: cGWO-based Random Forest

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1  Initialise population
2  Evaluate fitness
3  Identify the best three solutions  $\alpha, \beta, \delta$ 
4  For Epoch = 1 to maxEpoch do
5      Update control parameter a
6      Generate chaotic values
7      For each candidate solution, do
8          Update position using  $\alpha, \beta, \delta$ 
9      End for
10 Re-evaluate fitness
11 Update  $\alpha, \beta, \delta$ 
12 End for
13 Select best model for  $\alpha$ 
14 Evaluate model using performance metrics
15 Return optimal hyperparameters

```

3.2 Performance evaluation

The performance evaluations in this study are accuracy, sensitivity, specificity, precision, F1 score, AUC, and APR. They are analysed and discussed in this section. The mathematical formulas are expressed in Aliyu *et al.*, (2024).

3.2.1 Random forest evaluation.

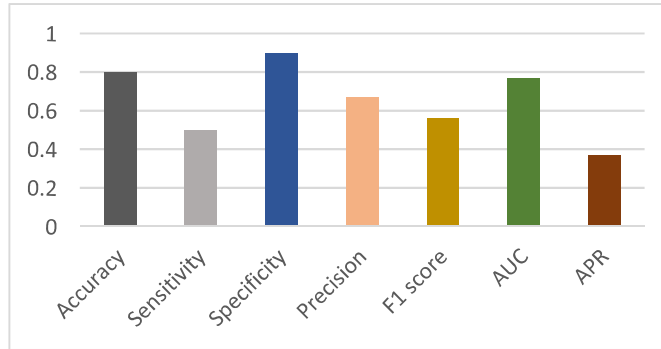


Figure 2: Random Forest Hyperparameters Metrics

Figure 2 shows the performance metrics of the random forest per unit. From Figure 2, the high Specificity of 0.9 reflects that the model is outstanding at correctly identifying non-diabetic individuals. This means a few false positives. The accuracy of 0.8 shows that the overall classification is good, reflecting convincing performance in the majority class. The AUC of 0.78 demonstrates that the model has good discriminatory power, enabling it to distinguish well between diabetic and non-diabetic classes.

Low sensitivity of 0.50 shows that the model misses many actual diabetic cases, which is concerning in a medical context. This suggests that under-detection of the positive class. A moderate precision of 0.67, which corresponds to around two-thirds of positive predictions, is acceptable but not optimal. Low APR of 0.35 shows limited reliability across different thresholds, especially for the minority class, likely diabetics. F1 score of 0.55 shows that the balance between precision and sensitivity is weak, reinforcing that the model underperforms in consistently identifying true positives.

3.2.2 GWO with random forest evaluation.

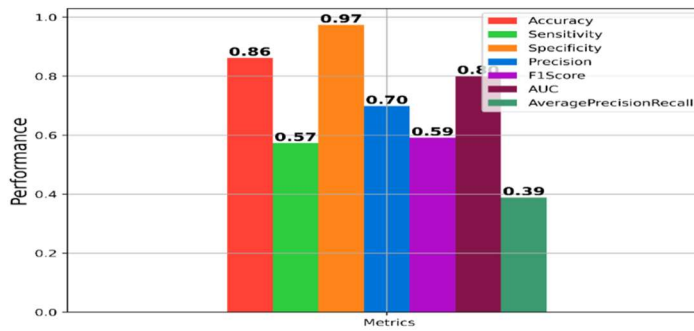


Figure 3: GWO Random Forest Hyperparameters Metrics

A specificity of 0.97 is recorded showing that the model is highly effective at identifying non-diabetic individuals (true negatives) as observed in Figure 3. The accuracy of 0.86 shows strong overall performance, suggesting the model classifies the majority class well (likely non-diabetics). The precision of 0.70 is respectable and reduces false alarms, and an AUC of 0.80 is fairly effective at distinguishing diabetic from non-diabetic cases across thresholds.

A sensitivity of 0.57 means the GWO classifier misses 43% of true diabetic cases, which is significant in healthcare. Class imbalance probably causes the model to favour the majority class. An F1 score of 0.59 suggests that both the detection rate and precision are not very strong. An APR of 0.39 shows limited reliability for detecting positive cases, especially at different thresholds. This further highlights the challenge of accurately identifying the minority class.

3.2.3 cGWO evaluation.

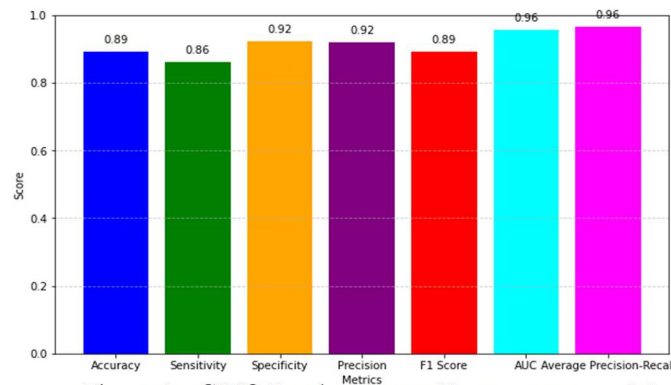


Figure 4: cGWO Random Forest Hyperparameters Metrics

Figure 4 presents the performance metrics of the cGWO-optimized Random Forest classifier, demonstrating its superiority over the baseline Random Forest and GWO-Random Forest models. The model achieved a balanced sensitivity of 0.86 and specificity of 0.92, showing its effectiveness in correctly identifying both diabetic and non-diabetic individuals. This balance suggests low rates of false negatives, critical for early screening, and false positives, which help prevent overdiagnosis. The high precision score of 0.92 further reinforces the model's reliability in predicting diabetic cases, minimising unnecessary follow-up procedures and associated patient anxiety. The F1 score of 0.89 reflects a well-calibrated trade-off between precision and recall, making the model suitable for scenarios where both types of classification errors carry significant consequences. The Area Under the ROC Curve (AUC) value of 0.96 highlights the model's excellent discriminatory capacity across varying classification thresholds. Similarly, the high Average Precision Recall (APR) score of 0.96 shows strong and consistent predictive performance, which is valuable when handling class imbalance. Finally, an overall accuracy of 0.89 confirms the model's robustness and effectiveness across all prediction categories.

3.2.4 Comparison between GWO and cGWO.

Figure 5 shows that cGWO improves classification performance, especially sensitivity, with a 0.51% increase in correctly identifying positive cases. Although the accuracy improvement is minor at 0.03%, the results indicate that cGWO handles class imbalance more effectively while maintaining nearly the same specificity and false positive rate.

The results show that cGWO improves precision, F1 score, AUC, and APR, showing better classification performance. In particular, the 1.46% improvement in APR highlights its ability to detect minority class instances, making it highly suitable for applications such as medical diagnosis and rare event prediction. The cGWO shows improved generalization by consistently improving classification performance across various metrics. It shows particular strength in handling imbalanced datasets, with notable gains in sensitivity and average precision, indicating effectiveness in detecting minority-class instances.

However, a slight trade-off is observed, as the standard GWO performs marginally better in specificity, an important consideration in applications sensitive to false positives.

3.2.5 Comparison with Aliyu *et al.*, (2024)

The comparison in Figure 6 shows that the baseline method by Aliyu *et al.*, (2024). achieved slightly higher accuracy and F1-score (0.91) than the proposed method (0.89). However, the proposed method remains competitive, particularly in handling class-specific patterns and imbalanced data.

The two models show good class discrimination with nearly identical, high AUC scores (Aliyu *et al.*, (2024), achieving 0.98 and the proposed method 0.96), they diverge significantly in their precision-recall trade-offs. The proposed method delivers a superior APR score of 0.96 compared to Aliyu *et al.*, (2024)'s 0.90, proving that it is much more robust at sustaining higher precision and minimizing false positives in environments dealing with severe class imbalances.

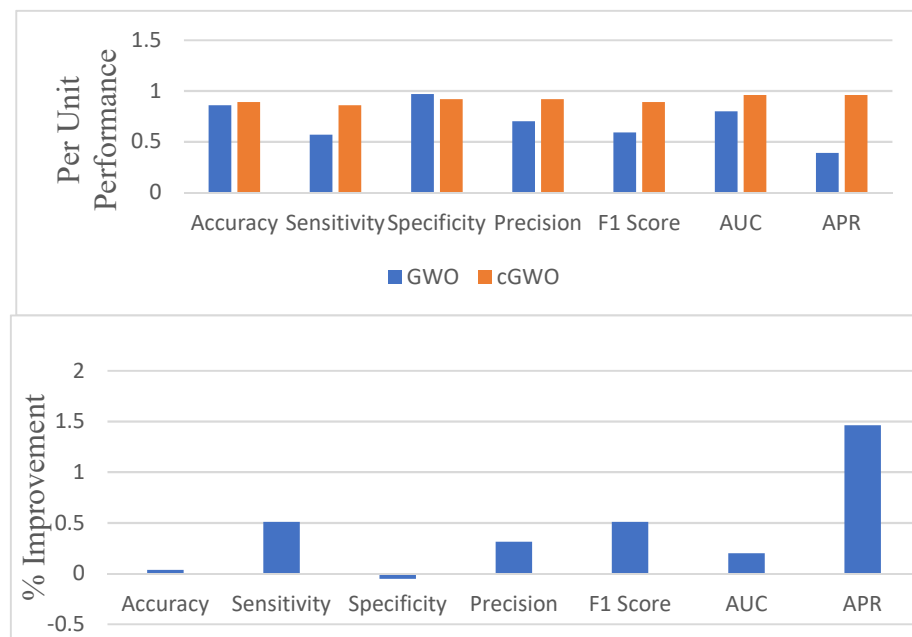


Figure 5: Comparison of Metrics between GWO and cGWO

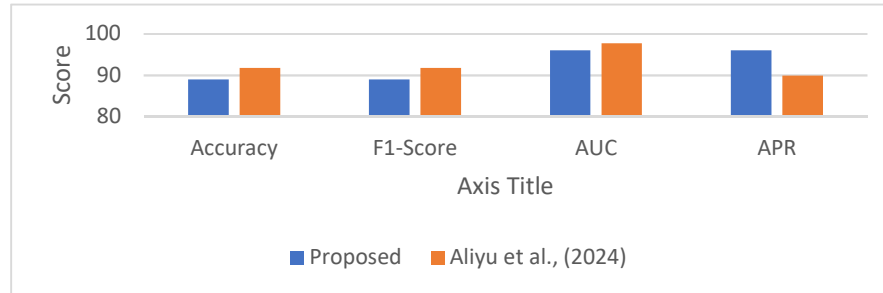


Figure 6: Comparison With Aliyu *et al.*, (2024)

1. CONCLUSION

This study presents a chaotic Grey Wolf Optimisation-enhanced Random Forest model for diabetes risk classification using the BRFS dataset. The proposed framework improves hyperparameter tuning, predictive performance, and model generalisation, achieving better accuracy, sensitivity, precision, F1-score, AUC, and average precision recall than standard GWO. The model provides an effective tool for early diabetes risk assessment, with future work focusing on deep learning integration, real-time monitoring, and application to other chronic diseases.

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