A Hybrid Metaheuristics for Prediction of Thyroid Disease

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***Abstract* – In this study, a hybrid method between two metaheuristics, Practical Swarm Optimization, and Gray Wolf Optimization, was applied to evaluate thyroid disease based on the analysis results. An optimization function was built to build a subgroup from the next choice, which should maximize the predictive performance of a disease prediction model. The results achieved are impressive and open to other metaheuristic tests.**

***Keywords* – optimization, PSOGWO, Metaheuristics, thyroid disease, future selection.**

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1. Introduction

Diagnosing thyroid disease is often a challenge for doctors, as it requires extensive processes to reach accurate conclusions. This includes a combination of several analyses performed along with various results [3]. A comprehensive physical examination and many blood tests are part of the standard process. Therefore, a model that can identify thyroid illness early on has to be developed. The term "thyroid diseases" refers to a group of disorders that impact the thyroid gland [15], a small but essential organ in the neck. Hormones that control vital body processes including metabolism, heart rate, and disease-related temperature regulation are produced by the thyroid gland.

Therefore, there is a need to develop a model with a high standard for diagnosing this disease in its early stages. This is mainly responsible for the generality of hormones that regulate body functions such as heartbeat, regulation of body temperature, and regulation of metabolism. This disease is classified in two stages if the TSH values decrease; this is called hypothyroidism, and the opposite when its value increases is called hyperthyroidism. The signs of the disease vary depending on the group to which they belong, distinguishing them from one another. Our research makes the following important contributions to this disease.

- A new meta-learning model is proposed, which is based on two metaheuristic methods, Practical Swarm Optimization and Gray Wolf Optimization, which are combined to create a hybrid method.
- The performance of the applied methods shows an improvement in the accuracy of the links compared with the results achieved so far. An objective function was also built to maximize predictive performance.

In a review of the author's literature, which includes different stories applied to chronic diseases, they agree that hybrid methods have an advantage over simple methods.

The author of [1] proposed a new hybrid method for treating Parkinson's disease. This integration improved the learning phase of the Premier Volleyball League binary method and reduced its execution costs. Experimental findings suggest that hybrid metaheuristics exhibit improved performance compared with alternative metaheuristics.

In [2], the authors proposed a new HPSGWO algorithm for the registration of CT images of the lungs of a patient infected with COVID-19. The tests performed show that the proposed approach achieves registration with high precision and robustness compared with other methods.

The binary GWO-CSO algorithm was used in this study to further improve the selection ability function [3]. This hybrid optimization approach successfully solved the challenges of high-dimensional feature space in diabetes disease data and enhanced the generalization capabilities of the system.

The paper [4] proposes a hybrid version of flamingo binary search with a genetic algorithm (HBFS-GA) to overcome the FS problem using a wrapper model. This model also includes transfer functions to convert the continuous search into discrete. 18 groups of data were used, and this hybrid method achieved good results for both the existing dataset and the lung cancer disease, with an accuracy of 99.51% and a calculation time of about 00.031 seconds, which was shorter than that of other methods used in the study.

By combining Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), the study [17] suggests a novel method for classifying thyroid diseases. PSO and ACO hybridization improves association efficiency rule mining for feature selection by strengthening exploration and exploitation abilities. The suggested approach seeks to pinpoint significant correlations between thyroid disease characteristics to enable precise categorization. The findings demonstrate the potential of the hybrid PSO and ACO association rule mining strategy to enhance thyroid disease detection systems by outperforming conventional techniques.

The goal of this study [18] is to provide a sophisticated meta-learning method for the prompt identification of thyroid syndrome. A novel collection of K-Neighbors (KN) and Random Forest (RF) models served as the foundation for the authors' new meta-learning approach. They then used the combined experience of the pooled models to construct a meta-learning Logistic Regression (LR) model. Thyroid syndrome is successfully diagnosed for the first time using the newly suggested KRL approach (KN-RF-LR). By lowering the thyroid mortality rate, the study improved human life by revolutionizing the early identification of thyroid illness.

2. Methodology Section

Practical Swarm Optimization is an optimization algorithm limited to the population, which is inspired by the social behavior of the gathering of birds [5]. The model focuses by initializing the population, which is actually the results of thyroid tests of different patients and then repeating the action until improvement following two rules:

1. Finding the best position (pBest) which represents the best position found.
2. Global best (gBest) which shows the best position that each particle of the cluster has found [5].

Each particle repeats the action several times and positions itself at the best finding it has made, otherwise known as the optimal point. To return to previously successful areas in the search space, the search is processed as a result of modeling for this social behavior. Specifically, each particle's location (x) and velocity (v) will be altered based on the following phrases:

$$v_{ij}t + 1 = wv_{ij}(t) + c_1 r_1 (pB_{ij}(t) - x_{ij}(t)(+ c_2 r_2 (gB_{ij}(t) - x_{ij}(t)) \; ; \quad (1)$$

$$x_{ij}(t) + 1 = x_{ij}(t) + v_{ij}(t + 1) \quad (2)$$

where $v_{ij}(t + 1)$ is the velocity of particle i at iteration j, and $x_{ij}(t + 1)$ is the position of particle i at iteration j [5]. The optimal particle location in the swarm or maximal generations, which cannot be further enhanced after a sufficiently high number of generations, marks the end of the PSO process. Consequently, the PSO algorithm's demonstrated its resilience and effectiveness in resolving challenging optimization issues.

Gray Wolf Optimization is another optimization method which is based on hunting gray wolves in nature [7]. Here we have some defined categories:

1. Alpha category the best choice;
2. Beta category, second best choice;
3. Delta category, third best choice;
4. Omega category, other remaining choices.

These positions are used to repeat and achieve better results for finding an optimal solution. Additionally, these steps significantly contribute to the convergence of the best solution [7].

It is represented mathematically by Eqs. 1 and 2. As a result, the hunt will be encircled by the gray wolves' new location [16]:

$$\vec{D} = |\vec{C} * X_p(t)\vec{X}(t)| \quad (3)$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t)\vec{A} * \vec{D} \quad (4)$$

where $\vec{A}$ and $\vec{C}$ are coefficient vectors, t is the current iteration, $\vec{X}$ is the grey wolf's position vector, and $\vec{X}$ $(\vec{}$p is the prey's position vector. Eqs. 5,6 and 7 are used to calculate $\vec{A}$, $\vec{C}$, and $\vec{a}$, respectively [16]:

$$\vec{A}=2\vec{a}*r_1-\vec{a} \quad (5)$$

$$\vec{C}=2\vec{r}_2 \quad (6)$$

$$\vec{a}=(1-\frac{t}{T}) \quad (7)$$

where $\vec{a}$ is linearly decreased from 2 to 0 throughout iteration. It is used to get closer to the solution range. r_1 and r_2 are the random vectors in the range of [0,1] [16].

But how were these two methods found for the optimal solution in our model?

Workflow: Features were selected using PSO. This will serve to find a better subset of features for the classification task, and then train and test this model by dividing the dataset into 20% for training and 80% for testing. After selecting the features, the GWO was used to adjust the hyperparameters of the model. It then determines the arrival and accuracy of the built model using several metrics in a row, such as accuracy, precision, or the training graphs of the model on the broken and its accuracy.

An optimization method has to strike a balance between usage and exploratory abilities [9]. The core idea is that the accuracy of models developed so far, utilizing the GWO algorithm's exploration capabilities, serves as the driving force behind the hybrid approach [8].

Combining these abilities is meant to help us get to the global minimum more quickly. Test function measurements offer notable benefits over PSO and GWO.

For real-world issues, the hybrid approach also outperforms conventional approaches by a large margin [10]. The primary objective of these research is to steer clear of local optimum and global methods to optimization, while the PSO method has also been hybridized with other optimization strategies [11], [12]. These methods have demonstrated significant differences when evaluated on test functions [13]. Below is the updated technique's mathematical model.

$$D\alpha = |\vec{F}_1\vec{X}_\alpha - w * \vec{X}|, \quad (8)$$

$$D_\beta = |\vec{F}_2.\vec{X}_\beta - w * \vec{X}|, \quad (9)$$

$$D_\delta = |\vec{F}_3\vec{X}_\delta - w * \vec{X}| \quad (10)$$

$$V_i^{k+1} = w * (V_i^k + f_1 r_1(X_1 - X_i^k) + f_2\, r_2(X_2 - X_i^k) + f_3\, r_3(X_3 - X_i^k)) \quad (11)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (12)$$

"t" in the preceding equations refers to the current iteration value, whereas "$\vec{X}$" denotes the position vector with respect to the grey wolf. Wolves are represented by the letters A, β, and δ in the hierarchy [14]. The pseudo-code that demonstrates the steps involved in the hybrid method's functioning is described below showed in Table 1:

Table 1. Algorithmic representation of technique [6]

1.	Start
2.	Configure the relevant PSO and GWO settings, such as iteration and population size value.
3.	Calculate or simulate the cost function.
4.	Establish initial populations (randomly) and compute the corresponding fitness alpha, beta, and delta.
5.	Apply each wolf's position update.
6.	Proceed to the PSO procedures.
7.	Keep in mind the revised placements
8.	Update the a, a, and c values. Determine weach wolf's fitness value.
9.	Adjust the wolf-related alpha, beta, and delta position values.
10.	Return to step 5 if the last iteration is not achieved.
11.	The algorithm's termination

Below in Figure 1, we illustrate the steps followed in the principle of applying the hybrid alogorhythm.

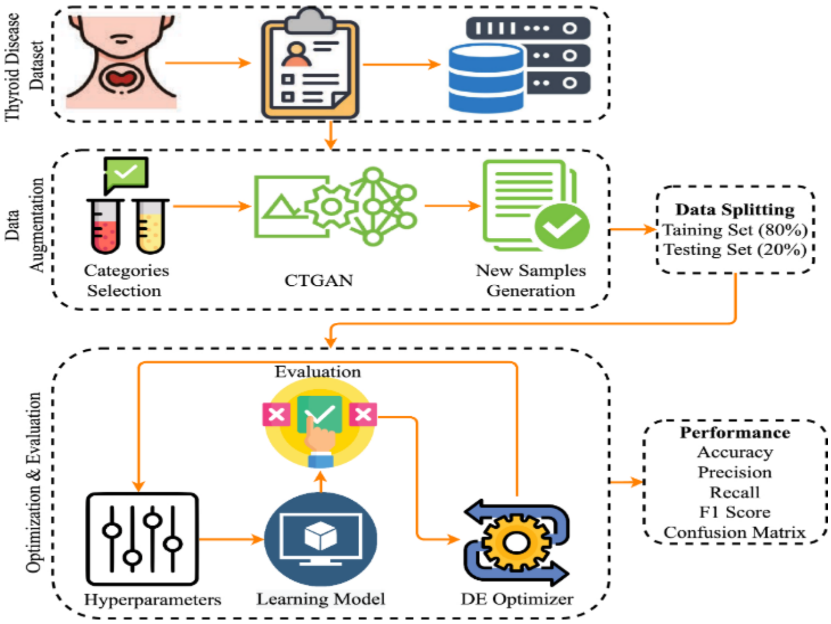

Figure 1. Steps of methodology

3. Results

The first step was the construction of the objective function, and then we observed how the obtained results were fulfilled. Model:

$$\text{Maximize } f(x) = \text{Fitness Metric } (y, \hat{y})$$
$$\text{Subject to } \sum_{i-1}^{n} x_i \leq k$$
$$x_i \in \{0,1\} \ \forall i \in [1;N]$$

where k is the maximum number of future allowed and $\hat{y}$ represents the predicted outcomes based on the selected features and represents the true outcomes.

The results obtained by the algorithm for the best results and the best parameters are as follows in Table 2:

Table 2. Results for the best parameters and the best solution of the hybrid metaheuristic algorithm

Algorithm	Best parameters results	Best Solution
PSOGWO	0.070	11

Graphically illustrated, the best results parameters are represented by the convergence curve, as shown in the Figure 2:

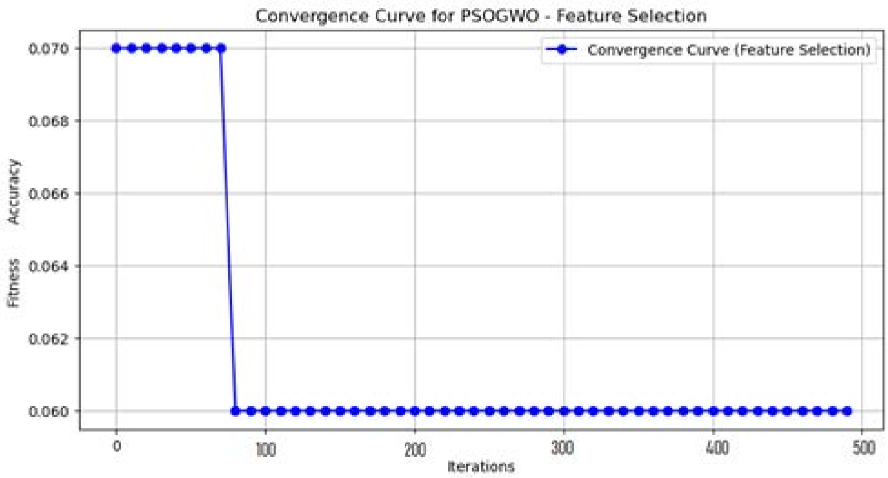

Figure 2. Convergences curve for hybrid algorithm

A small gbest value in MHA is crucial for demonstrating solution quality, guiding effectively moving, and ensuring the algorithm converges efficiently.

This helps in finding the best solutions while optimizing resource utilization.

The hybrid metaheuristics model had an accuracy rate of 97%, which is significantly higher.

Those results are showed in Figure 3.

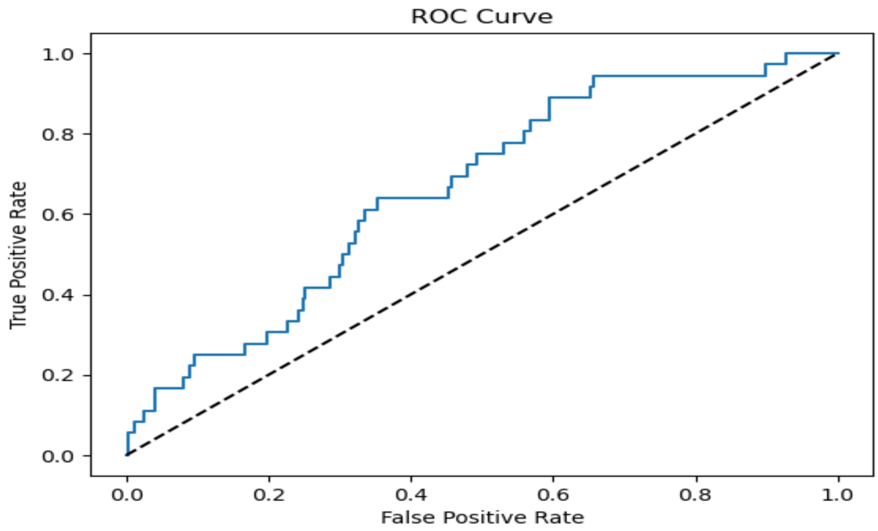

Figure 3. Roc Curve of PSOGWO

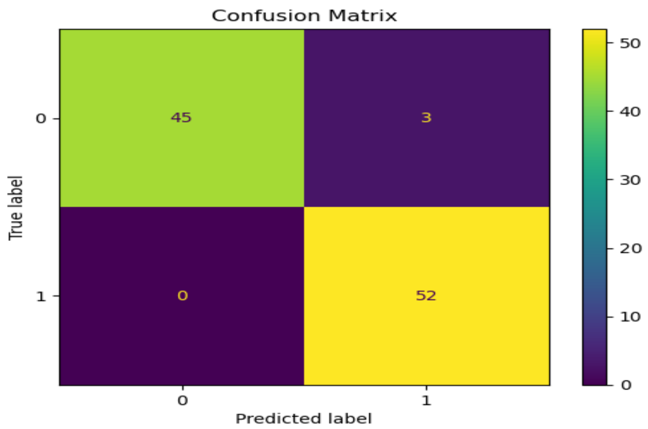

Figure 4. Confusion matrix of hybrid metaheuristics

A key metric for disease assessment is the "False Positive" rate showed in Figure 4, which refers to the correct selection. However, the machine learning model had a lower classification rate, making it more cost effective in the long term.

Another estimator that we used to evaluate the model above is the graph below in Figure 5:

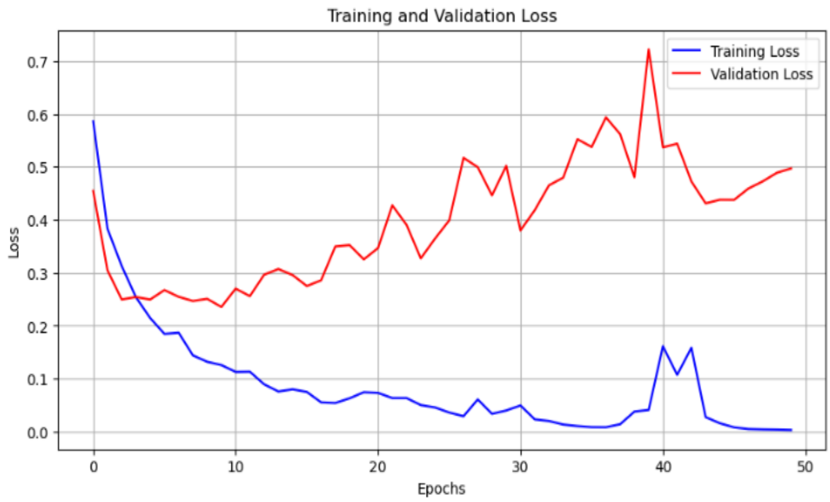

Figure 5. Graph of training and validation loss for PSOGWO

Good Initial Fit: Close lines at the start indicate a good initial fit.

Overfitting: Divergence points to overfitting, where the model excels on the training data but fails on the validation data.

4. Conclusion

The achieved results were satisfactory because the accuracy of the model was 97% and the achieved precision was 94%, which led to the conclusion that hybrid algorithms are suitable for application to medical data. However, this model still requires improvement, as shown in Figure 4. This result is due to the large gap between the two curves, indicating that the model is continuously adapting and unstable with respect to the training data. Thus, in future work, the goal will be not only to achieve high accuracy and precision, but also a better-trained and stable model where the data do not tend to fade.

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