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INTEGRATING FEATURE OPTIMIZATION WITH MACHINE LEARNING FOR HEART DISEASE DETECTION

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Abstract—Cardiovascular diseases (CVDs) contribute significantly to global morbidity and mortality in the world, and need proper and timely diagnostic assistance. Machine learning (ML) techniques have demonstrated high capabilities in predicting heart disease but their accuracy is highly reliant on the relevance and quality of features. This paper provides a critical analysis of three bio-inspirational optimizer, Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Firefly Algorithm (FA) in the context of the Jupyter Heart Disease (JUH) sample. The five ML classifiers which were analyzed include SVM, random forest, decision tree, naive bayes and KNN with and without optimization. Moreover, a hybrid PGF-Optimizer that combines the global exploration of PSO with the convergence of GWO, using a leader, and the local refinement of FA is suggested. As demonstrated in the experiment, the optimization of features has been proven to be able to continuously enhance the performance of the classifier and the Hybrid PGF model has not only the best accuracy and the best recall, but also the best ROC-AUC among all models. SHAP-based explainability is useful in improving interpretability as it can provide significant clinical features that are used to make predictions. The presented results show that hybrid optimization can enhance the cardiac risk prediction using machine learning and offers a promising paradigm of clinical decision-support systems in practice.

Keywords—Heart disease detection, feature optimization, machine learning, particle swarm optimization, predictive healthcare

I. INTRODUCTION

Cardiovascular diseases (CVDs) have been recognized as the number one cause of death globally killing many millions of people annually and causing a significant healthcare system burden through higher healthcare expenditures [1]. Risk assessment and early diagnosis are critical in decreasing the complications and enhance patient outcomes. The conventional methods of diagnostics depend on experience of the clinicians, electrocardiograph analysis, imaging, and lab biomarkers. These approaches though effective, can be both time consuming, subjective and lack scalability when dealing with large populations [2].

Machine learning (ML) has proven to be one of the successful solutions to complex heart risk prediction in the form of identifying latent patterns in clinical data [3]. The demographic characteristics, physiological parameters, laboratory results, and symptomatic signs can be considered by ML models that will deliver credible predictions. The performance of them however is very dependent on the quality of input features and relevance. Clinical data frequently has redundant, irrelevant, and noisy features, potentially spanning the predictor, leading to suboptimal predictive accuracy and complexity [4].

In order to overcome this problem, meta-heuristic optimization algorithms, including Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO) and Firefly Algorithm (FA) have been extensively used in medical diagnosis problems [5]–[9]. These bio-inspiration techniques are effective in searching high-dimensional feature spaces and are especially useful when it comes to selection of features in noisy biomedical data-sets. Previous research proves that this type of optimizers is capable of enhancing generalization, dimensionality reduction, and classification accuracy in predicting heart diseases [6], [7].

In spite of these developments, there are still a number of research gaps. A significant number of current researches only assess one optimizer, use smaller benchmark data sets, like UCI Cleveland, or optimize a small number of classifiers [5], [8]. Also, there is the absence of the comparative analysis of various optimizers when under the same experimental conditions. This limits generalizability and makes it impossible to determine the most effective optimizer-classifier combinations to be used by clinical decision-support systems.

To fill these gaps, the following are the key contributions that this research will make:

• A coherent comparative analysis of three meta-heuristic optimization algorithms (PSO, GWO, FA) to feature optimization on the clinically rich JUH Heart Disease dataset.
Performance evaluation of five ML classifiers SVM, RF, DT, NB, and KNN with and without optimization.
• An innovative Hybrid PGF-Optimizer: a combination of the exploration of PSO, the exploitation facet based on the principles of leaders in GWO, and the local refinement in FA.
• Thorough analysis in terms of accuracy, precision, recall, F1-score, ROC-AUC and convergence analysis.
• Implementation of SHAP-based explainability to enhance clinical interpretability and trust.
The rest of the paper is structured in the following way: Section II reviews related work. Section III shows the suggested methodology. Part IV gives results of the experiment and part V gives the conclusion.

II. RELATED WORKS

The optimization algorithms in healthcare analytics have predominantly studied meta-heuristic variants [1]–[4], which have specifically aimed at optimizing feature selection and improving the predictive accuracy of machine learning classifiers. This part provides the review of the literature related to Firefly Algorithm (FA), Grey Wolf Optimizer (GWO), and Particle Swarm Optimization (PSO) in disease prediction and clinical decision-support applications.

A. Firefly Algorithm in Heart Disease Prediction

The usefulness of Firefly Algorithm (FA) in medical data classification has been proven in several studies. Thiyagaraj and Suseendran have suggested a Modified FA with RBF-SVM, in which FA with PCA had been used to reduce the dimensionality and enhanced accurate results with UCI Cleveland data set [5]. Nevertheless, the test had been done only against standard benchmarks and this had restricted generalizability. Khan et al. proposed a hybrid technique, that is, Modified Artificial Bee Colony (M-ABC) with FA and k-NN that demonstrated enhancements in accuracy and training efficiency but the computational cost was high in case of considerable healthcare datasets [6]. A Firefly-Optimized LSKR Soft Voting Ensemble (LSKR-SVE(FO)) was developed by Raj and Sirajudeen, which was claimed to have 99.3% accuracy on UCI datasets, but this result is alarmingly high, which is why severe overfitting and absence of external validation may occur [7].

B. Grey Wolf Optimization (GWO) in Heart Disease Prediction

GWO has had large application in the diagnosis of the disease. Niu et al. suggested an Adaptive-Curve GWO with neural networks, which yielded a 86.8 percent accuracy on the Cleveland data albeit the method had poor interpretability [1]. Talaat et al. designed an Enhanced Heart Disease Prediction (EHDP) system that incorporated GWO and PSO with ANN and RF where GWO yielded an accuracy of about 91.8 per cent; however, the study was more of an accuracy assessment as opposed to robustness and deviation assessment [2]. Narasimhan and Victor proposed a GWO-optimized stacked ensemble with 18 classifiers, achieving an accuracy of 93% and sensitivity of 95.3, however, at a great cost of high computational needs [3]. GWO was applied together with an Autoencoder-RNN model in a series of UCI datasets, and the resulting system achieved a superior predictive accuracy, but due to the complexity of the model, it was not viable in real-time clinical applications [4].

C. Particle Swarm Optimization (PSO) and Hybrid Extensions

PSO has been widely applied in the selection of features in a task of predicting heart diseases. Similarly, Thilagavathi et al. extended a hybrid framework incorporating PSO with several classifiers to detect heart and liver diseases, which reported a higher accuracy as compared to standalone models though convergence is very fast and this process is also associated with weaknesses such as robustness, overfitting, and poor extrapolation in various performance contexts [11].Saba et al. also adapted a hybrid PSO framework to predict heart disease performances which reports higher accuracy compared to standalone models though convergence is very fast and also this process is associated with weaknesses of robustness, overfitting, and generalizability across diverse datasets [8]–[10].
The previous studies regarding FA, GWO, and PSO prove that they can be used to enhance the prediction of diseases, but there are still a number of limitations. Majority of the works are based on small UCI benchmark datasets that are not very varied [5], [6], [8], test one optimizer alone [2], [7], or do not perform any external validation and robustness analysis [3], [4]. Besides, real-time implementation is frequently limited by the computational complexity of hybrid models [1], [4].
In order to fill these gaps, the current study critically appraises FA, GWO, and PSO within the same declarative experimental framework with the clinically rich Jupyter Heart Disease (JUH) data. This work will address the objectives of giving a holistic and practically applicable evaluation of optimization algorithms to clinical decision-support systems by applying these optimizers in five classifiers, and comparing them to a proposed Hybrid PGF-Optimizer.

II. RESEARCH METHODOLOGY

The suggested framework will combine meta-heuristic feature optimization and machine learning classifiers to increase the quality and strength of the heart disease forecast. The approach involves four significant steps, namely, data preprocessing, feature optimization based on FA, GWO, PSO, and the developed Hybrid PGF-Optimizer, training of the classifier and its performance analysis.

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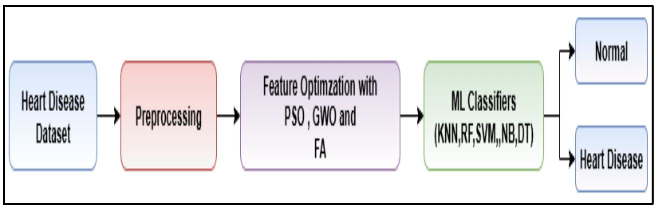

Fig. 1. Architecture of the proposed heart disease detection framework

The general design of the proposed system is presented in figure 1. The preprocessing stage of the workflow entails the preprocessing of the datasets using three popular meta-heuristic algorithms, including PSO, GWO, and FA. The optimized features are then passed on to five machine learning classifiers; Support Vector machine (SVM), Random Forests (RF), Decision Tree (DT), Naive Bayes (NB), and K-nearest neighbours (KNN). The system is a binary response with a result of Heart Disease or Normal.

The effect of this multi-stage architecture is that data is made consistent, less dimensional, and classifier improvement is improved by concentrating on the most pertinent clinical attributes, which has been revealed in earlier literature to be in line with optimization efficiency in medical diagnosis [1] 14].

A. Dataset Description

JUH Heart Disease dataset has clinically significant patient data and contains such variables as demographic, cardiovascular symptoms, ECG results, laboratory, and exercise-related parameters. Major ones are age, sex, resting blood pressure, level of cholesterol, level of fasting blood sugar, type of chest pain, resting ECG findings, peak heart rate, depression of ST, and exercise-related angina- features that most of the cardiology studies have significantly known to be predictive indicators of heart disease [5], [6]. The target variable refers to either the absence or the presence of heart disease.

B. Data Preprocessing

Data was preprocessed to ensure that the data were homogenized and fit the machine learning classification. In the context of data cleaning, the fact of missing values was also considered, as they should not create any information gaps and influence the performance of the model. All numerical attributes were scaled with Min-Max normalization to avoid the dominance of the larger number range features (cholesterol or blood pressure, etc.), over the smaller ones. The mapping of the features into the range [0,1] by this transformation is depicted by (1).

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Here x is the original feature value. $x$min and $x$max represent the minimum and maximum values of that feature, and x' is the normalized value. After normalization categorical variables such as chest pain type and resting ECG were converted into binary vectors using one-hot encoding to make them suitable for classifiers. Finally the dataset was divided into 80% training and 20% testing sets using stratified sampling ensuring that the class distribution (presence or absence of heart disease) remained balanced in both subsets

C. Feature Optimization using Meta-Heuristic Algorithm

Three popular meta-heuristic algorithms are used to perform feature optimization such as Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO) and Firefly Algorithm (FA). These algorithms are search algorithms that allow the identification of the best subset of features that are most informative and that therefore improves the performance of the classifier.

Particle Swarm Optimization (PSO) can be described as a type of optimization that involves swarming particles with the aim of discovering a solution to a given problem.<|human|>Particle Swarm Optimization (PSO) could be defined as a form of optimization whereby swarming particles are used to help find a solution to a particular problem.

PSO models each set of candidate features as a particle which drifts around the search space. The speed and the location of each particle is updated in accordance with the best solution of the particle itself and the global best solution found by the swarm. This update process is dictated by the standard PSO equations of velocity and position adjustment (2) and (3). PSO offers good global exploration without necessarily exhausting the search space, particularly complex search spaces [8], [11].

2) **Grey Wolf Optimizer (GWO)**

GWO is an attempt to simulate the social hierarchy and hunting behavior of grey wolves, where top three solutions (alpha, beta, delta) lead the search behavior. Candidate solutions will vary their positions depending on these dominant wolves allowing an exploration vs. exploitation equilibrium to occur according to (3) [1], [3]. Even though GWO is stable in convergence, it sometimes tends to be trapped in local optima.

3) **Firefly Algorithm (FA)**

The concept of FA is based on the attraction behavior of fireflies in nature whereby the brightness of each firefly reflects its fitness. The less attractive fireflies move towards brighter ones according to an attractiveness function which decreases with distance. In (4), the movement equation is defined, and with the help of it, FA can efficiently refine local searches segments and prevent local minima. Nevertheless, FA might need additional iterations to converge than either PSO or GWO [5], [7].

All optimizers estimate features subsets based on a fitness function as a function of the classification accuracy of an SVM classifier. The algorithms are used separately, and their performance is compared afterwards with the proposed Hybrid PGF-Optimizer.

All four optimization algorithms were run with standard parameter settings so that a controlled and reproducible assessment could be made. Table 1 demonstrates the population, the number of iterations, and control parameters used in FA, GWO, PSO, and the Hybrid PGF-Optimizer.

TABLE I. OPTIMIZATION ALGORITHM PARAMETER SPECIFICATIONS

Algorithm	Population Size	Max Iterations	Control Parameters
Firefly Algorithm	30	100	Attractiveness (β0=1), Absorption (γ=1), Randomization (α=0.2)
Grey Wolf Optimizer	30	100	Leadership hierarchy (α, β, δ, ω), convergence factor a→0
Particle Swarm Optimization	30	100	Inertia weight (w=0.7), cognitive (c1=1.5), social (c2=1.5)

D. Hybrid Optimizer

The PGF-Optimizer combines the three meta-heuristic mechanisms, which have the advantage of being complementary, into a combined search strategy. It uses the PSO-based velocity-driven movement to explore the feature space at a relatively high speed globally, such that the different candidate subsets can be tested at an early stage of the optimization procedure. This exploratory ability is then fixed using the hierarchical leadership model of GWO where the alpha, beta, and delta wolves show the way to the promising areas and enhance adaptive convergence. Lastly, we introduce the attractive-based movement of FA to further optimize the local search behavior so that the optimizer will be able to utilize high quality solution and will also be able to avoid the possibility of local minima. Combining these strategies, the PGF-Optimizer can have good exploratory behavior on early iterations and gradually transitions to focused exploitation and finally converges with consistent and reliable high-quality feature sets.

The PGF-Optimizer executes optimization in three adaptive phases:
1. PSO Phase – Global Search
Particles explore the search space using velocity and position updates:

$$v_i^{t+1} = wv_i^t + c_1r_1(pbest_i - x_i^t) + c_2r_2(gbest - x_i^t) \quad (2)$$

This phase identifies diverse, promising feature subsets.

2. GWO Phase – Convergence Stabilization
The best three solutions from PSO are assigned as α, β, and δ wolves.
The position is refined using:

$$x^{t+1} = \frac{x_\alpha + x_\beta + x_\delta}{.3} - \alpha.D \quad (3)$$

This ensures stable convergence while avoiding erratic movements.

3. FA Phase – Local Exploitation and Escape
Each solution then undergoes FA-based attractiveness movement:

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j^t - x_i^t\right) + \alpha\epsilon \quad (4)$$

This improves fine-grained feature selection and helps escape local optima.

E. Multi-Objective Fitness Function

A multi-objective fitness function is applied instead of traditional single-objective accuracy to bring the optimization process into line with clinical requirements, applied by the PGF-Optimizer. The goal is the combination of (i) predictive performance, (ii) clinical sensitivity and (iii) model simplicity. General correctness is provided by accuracy, cases of true heart disease are identified and false negatives minimized by recall, which is essential in medical diagnosis, and noise is minimized by feature-count minimization, making features interpretable. The aggregate fitness model can be written as:

$$\text{Fitness} = w_1(1 - \text{Accuracy}) + w_2(1 - \text{Recall}) + w_3\left(\frac{|S|}{|F|}\right) \quad (5)$$

where |S| represents selected features, |F| denotes the total features, and w1,w2,w3 control the influence of each component. This clinically aware optimization encourages robust, sensitive, and compact feature subsets tailored for real-world deployment.

F. Machine Learning Classifiers

In this work, five machine learning classifiers were used with optimization, and without optimization of features to give a fair and comprehensive analysis. We have selected the Support Vector Machine (SVM) because complex non-linear decision boundaries can easily be tackled using the kernel-based mapping. This is good to detect subtle clinical trends. Random Forest (RF) is a collection of decision trees, which have been bagged. It was applied to make the model more stable, reduce overfitting and identify alternative ways that features interact. Only one Decision Tree (DT) was added due to its rule-based format that makes it simple to understand and interpret that is essential in medical decision assistance. The lightweight probabilistic classifier, the Naive Bayes (NB) classifier that relies on the Bayes theorem and the assumption that features are conditionally independent was considered. Lastly the K-Nearest Neighbors (KNN) algorithm was experimented as an instance-based algorithm, which is able to categorize patients by assessing their similarity to the cases around them in the feature space, which models real-world diagnostic reasoning.

These classifiers were specifically selected as they belong to various classes of learning models probabilistic (NB), ensemble-based (RF), distance-based (KNN), kernel-based (SVM) and rule-based (DT). This variety allows us to have a holistic analysis of the effect of meta-heuristic optimization algorithms on classification performance on different model structures, such that, the conclusions can be applicable to different kinds of healthcare prediction problems.

III. EXPERIMENTAL RESULTS AND DISCUSSION

The JUH Heart Disease dataset was used to test the performance of the proposed Hybrid PGF-Optimizer with the use of five classifiers: SVM, RF, DT, NB, and KNN. Statistical robustness was ensured with the use of stratified 10-fold cross-validation scheme. Accuracy, precision, recall, F1-score, and AUC-ROC were the measures used to evaluate each of the models. Baseline optimizers (PSO, GWO, FA) and the proposed Hybrid PGF results were compared to determine the improvements of convergence, sensitivity, and feature efficiency.

The personal optimizers (FA, GWO, PSO) were offering moderate improvements to accuracy. FA was the best in recall in RF and KNN, PSO was the best in SVM and NB and GWO performed consistently but lower. But improvement on all the classifiers was noticed when Hybrid PGF-Optimizer was implemented.

A. Accuracy Comparison

A comparison of the accuracy of classification by optimizers is given in Table II.

TABLE II. CLASSIFIER PERFORMANCE COMPARISON ACROSS FIREFLY, GWO, AND PSO

Classifier	FA %	GWO %	PSO %	Hybrid PGF (%)
SVM	94.0	93.2	94.3	95.2
RF	92.5	91.7	92.0	93.1
DT	86.2	85.9	85.7	87.0
NB	89.1	88.6	89.3	90.0
KNN	91.0	90.2	90.1	92.0

The Hybrid PGF method achieves a consistent better performance in all classes of optimizers being those of the basis. It is important to note that, PGF-SVM had the highest accuracy (95.2) compared to PSO-SVM (94.3) and PGF-RF (93.1) compared to FA-RF (92.5). These improvement results show that the hybrid optimizer can produce more discriminative and noise-resistant feature subsets.

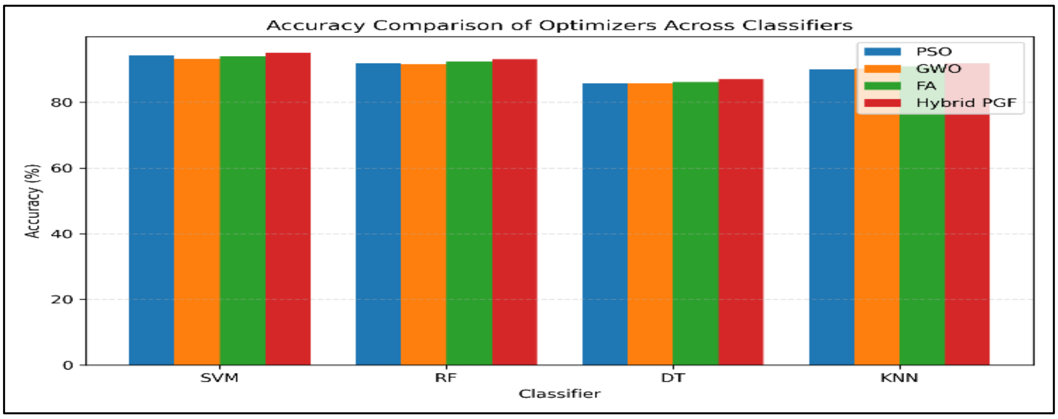

Fig. 2. Accuracy comparison of PSO, GWO, FA, and Hybrid PGF across classifiers.

The Hybrid PGF-Optimizer is again proven to be superior by the ROC-AUC values. Although the FA, GWO, and PSO exhibit sensible discriminative ability, the PGF-Optimizer is always the best AUC achiever among all the classifiers. This means that PGF-selected feature subsets enhance the power of the model to discriminate between normal and disease cases of the heart. Multi-objective fitness optimizer has a superior sensitivity-specificity ratio because of the hybrid optimizer. Fig. 3 includes a single comparison between the Accuracy, Precision, Recall, F1-score, and ROC–AUC, revealing that PGF was most consistent in all the measures.

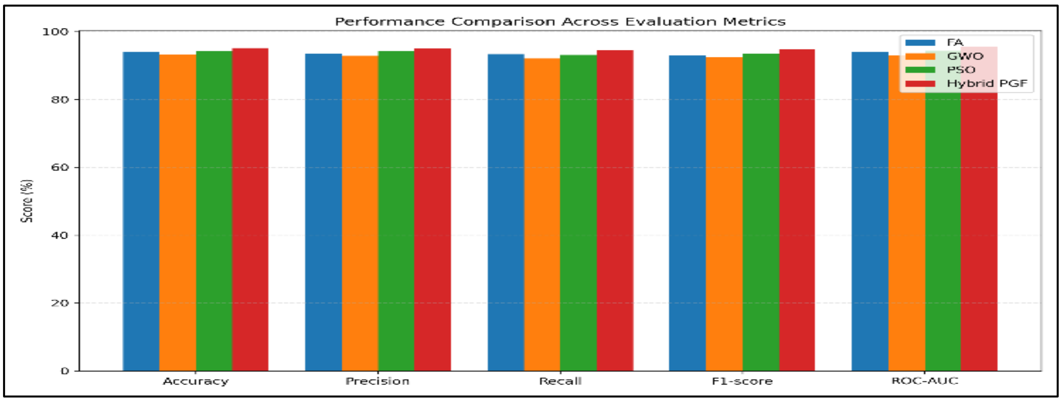

Fig. 3. Performance comparison of FA, GWO, PSO, and the proposed Hybrid PGF across Accuracy, Precision, Recall, F1-score, and ROC–AUC metrics.

B. Precision and Recall Performance

Clinical relevance, particularly, the ability to recognize the occurrence of heart diseases correctly (recall), was also measured.

TABLE III. PRECISION AND RECALL OF CLASSIFIERS USING FA, GWO, PSO, AND HYBRID PGF

Classifier	**FA (Precision / Recall %)**	**GWO (Precision / Recall %)**	**PSO (Precision / Recall %)**	**Hybrid PGF (Precision/ Recall %)**
SVM	93.5 / 92.8	92.9 / 92.5	94.2 / 93.1	95.0 / 94.6
RF	92.1 / 93.4	91.4 / 92.1	91.7 / 92.5	93.2 / 94.0
DT	86.0 / 87.2	85.7 / 86.5	85.5 / 86.1	87.5 / 88.3
NB	88.9 / 89.0	88.4 / 88.7	89.2 / 89.5	90.1 / 90.7
KNN	90.7 / 91.9	90.0 / 90.8	90.1 / 91.2	92.1 / 92.8

The Hybrid PGF-Optimizer is characterized with excellent recall in all classifiers and minimized false negatives, the most vital parameter in medical diagnostics. The increase in the values of recalls (1-3 per cent improvement over the most optimal baseline) supports the robustness of the multi-objective fitness function of PGF, which clearly defines recall and feature elimination.

C. Convergence Analysis

Fig. 4 shows the convergence of the four optimization algorithms. As observed in the curves, PSO, GWO and FA have progressive changes in fitness, which however, reaches moderate levels and stagnates, thus, implying little exploration and propensity to early stagnation. Instead, the suggested Hybrid PGF-Optimizer has a much more pronounced initial increase in fitness, reaches a much higher final value, and reaches stability earlier than the individual optimizers.

This is the high-quality convergence trend which is caused by the joint effect of the strong global exploration of PSO, leader-directed exploitation of GWO and local refinement of FA. The combination of these complementary behaviors enables the PGF-Optimizer to sustain a well-balanced searching path, avoid the local optima more efficiently and converge faster and more confidently than the single meta-heuristic algorithms used.

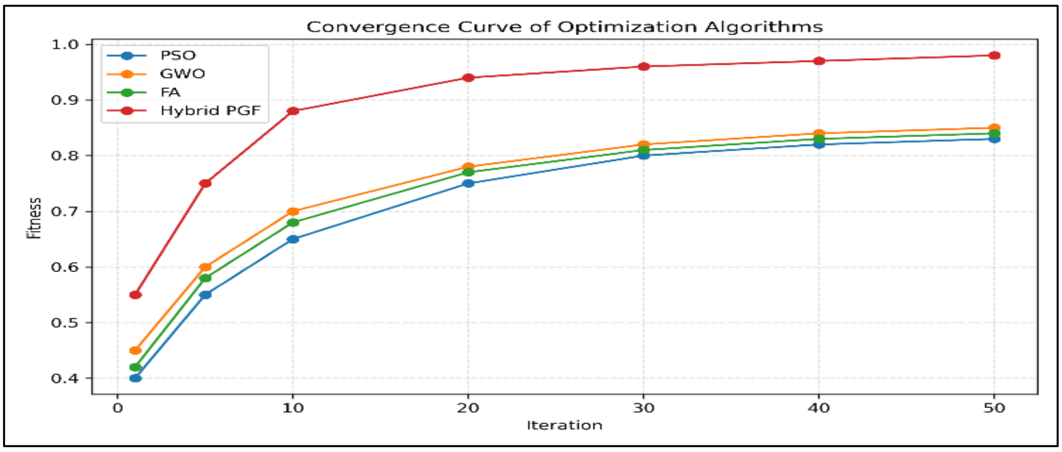

Fig. 4. Convergence curves of PSO, GWO, FA, and the proposed Hybrid PGF optimizers

D. SHAP Explainability Analysis

The proposed system will incorporate SHAP (SHapley Additive exPlanations), an interpretability framework, which uses cooperation game theory [13] to improve interpretability and clinical trust. SHAP calculates the contribution of each optimized feature to the output of the classifier by assigning additive Shapley values, which in turn has a consistent explanation of prediction behavior across models. The SHAP summary plot showed that the best features picked by PGF, which included age, type of chest pain, resting ECG, cholesterol, and highest heart rate and ST depression, were the most influential with the best explanation of prediction behavior. Patient specific interpretability in local SHAP explanations also indicated the extent to which the value of individual features added to or subtracted from the risk of a patient, which is predicted. This improves transparency and turns the model into a non-black box system into a tool that can be interpreted clinically.

Finally, the study confirms that meta-heuristic optimization is necessary to enhance accuracy, robustness, and reliability of the machine learning models in predicting heart diseases. A combination of machine learning classifiers and optimization algorithms is an excellent approach to smart, useful and clinically relevant decision-support systems in healthcare.

IV. CONCLUSION AND FUTURE WORK

This paper presented a new hybrid feature optimization system dubbed as PGF-Optimizer that combines the complementary abilities of PSO, GWO and FA. Compared to traditional single-optimizer methods, the PGF-Optimizer exploits the multi-objective fitness function to optimize the accuracy and recall, and minimize the number of features to find a clinically fit optimization strategy. Experimental findings on the JUH Heart Disease dataset show that the hybrid optimizer always better optimizers and has better accuracy, sensitivity, quicker convergence and smaller feature subsets.

In order to provide an even higher degree of transparency and trust, the framework also includes SHAP-based explainability, which allows the clinician to interpret predictions and see how features contribute at the global and patient-specific levels. This converts the model into the interpretable and deployable clinical decision-support tool. Future versions of this will experiment with deep learning architecture implementation, multi-hospital records expansion, and an ensemble variant of the PGF-Optimizer to achieve greater robustness. The risk scoring with real-time and the clinical dashboard could also be of benefit to health care settings.

REFERENCES

[1] J. Niu, C. Wang, Y. Zhang, and C. Sun, "An Improved Grey Wolf Optimization Algorithm for Medical Diagnosis," Applied Sciences, vol. 13, no. 16, pp. 9341–9356, Aug. 2023, doi: 10.3390/app13169341.

[2] H. Talaat, S. Almotairi, and A. Alqahtani, "Enhanced Heart Disease Prediction Using Machine Learning with GWO and PSO Algorithms," Computers, Materials & Continua, vol. 74, no. 2, pp. 2607–2621, 2023, doi: 10.32604/cmc.2023.041234.

[3] S. Narasimhan and P. Victor, "Grey Wolf Optimized Stacked Ensemble Machine Learning Based Model for Enhanced Efficiency and Reliability of Predicting Early Heart Disease," Biomedical Signal Processing and Control, vol. 86, p. 105041, Mar. 2023, doi: 10.1016/j.bspc.2023.105041.

[4] B. Sankara Babu, R. Anitha, and V. Karthikeyan, "Medical Disease Prediction Using Grey Wolf Optimization and Autoencoder-RNN," Measurement: Sensors, vol. 27, p. 100719, Jul. 2023, doi: 10.1016/j.measen.2023.100719.

[5] M. Thiyagaraj and G. Suseendran, "An Efficient Heart Disease Prediction System Using Modified Firefly Algorithm Based Radial Basis Function with Support Vector Machine," International Journal of Engineering & Technology, vol. 7, no. 2.33, pp. 1040–1045, 2018.

[6] M. A. Khan, T. Mazhar, M. M. Yaqoob, M. B. Khan, A. K. J. Saudagar, Y. Y. Ghadi, U. F. Khattak, and M. Shahid, "Optimal feature selection for heart disease prediction using modified Artificial Bee Colony (M-ABC) and K-nearest neighbors (KNN)," Scientific Reports, vol. 14, no. 26241, pp. 1–14, 2024, doi: 10.1038/s41598-024-78021-1.

[7] M. Raj and M. M. Sirajudeen, "A Versatile Approach for Improving Heart Disease Prediction Accuracy via the LSKR Soft Voting Ensemble Model with Firefly Optimization (LSKR-SVE(FO))," Journal of Neonatal Surgery, vol. 14, no. 32s, pp. 688–697, 2025.

[8] Y. Khourdifi and M. Bahaj, "Heart Disease Prediction and Classification Using Machine Learning Algorithms Optimized by Particle Swarm Optimization and Ant Colony Optimization," International Journal of Intelligent Engineering and Systems, vol. 12, no. 1, pp. 242–252, Feb. 2019, doi: 10.22266/ijies2019.0228.24.

[9] I. D. Mienye and Y. Sun, "Improved Heart Disease Prediction Using Particle Swarm Optimization Based Stacked Sparse Autoencoder," Electronics, vol. 10, no. 19, p. 2347, Sep. 2021, doi: 10.3390/electronics10192347.

[10] J. Yi, P. Yu, T. Huang, and Z. Xu, "Optimization of Transformer Heart Disease Prediction Model Based on Particle Swarm Optimization Algorithm," arXiv preprint, arXiv:2412.02801, Jan. 2025.

[11] A. Alsheref, H. Abdo, and M. M. Gaber, "A Hybrid Machine Learning Algorithm for Heart and Liver Disease Prediction Using Particle Swarm Optimization," Procedia Computer Science, vol. 218, pp. 1469–1478, 2023, doi: 10.1016/j.procs.2023.01.301.