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A Hybrid PSO-GWO Optimized Neural Network with LIME-Based Explainability for Robust Breast Cancer Diagnosis

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Abstract: Breast cancer is one of the main causes of death among women in many countries of the world and this is the reason why better and interpretable diagnostic tools are required. We present a new hybrid optimization method that combines Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO) in this paper purposed to optimize neural network hyperparameters such as neural network hidden units and learning rate, among others. The hybrid PSO-GWO algorithm combines the global exploration and local exploitation ability and achieves better classification accuracy on Wisconsin Breast Cancer dataset. The optimized neural network had good accuracy (about 96%) and AUC 0.99 showing a good discrimination between benign and malignant cases. Moreover, to obtain feature-level explanations and aid clinical decision-making procedure, localizable explanations are obtained through LIME (Local Interpretable Model-Agnostic Explanations). Conducting comparative analysis with the traditional classifiers (Logistic Regression, SVM, Random Forest), it can be noted that the proposed model has competitive or better performance, as well as transparency. The process is completely replicable and scalable on Kaggle, which opens the way to the possibility of more people getting access to it, and subsequent integration into clinical practice

***IndexTerms* - Breast cancer detection, Hybrid optimization, Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Neural networks, LIME, Interpretability, Hyperparameter tuning, Kaggle, Medical AI**

1. INTRODUCTION

It is an established fact that breast cancer is one of the major causes of death among the women population, and hence the investigation of the appropriate and timely means of detecting it is essential. Heterogeneity and complexity of the breast cancer progress imply severe issues concerning the application of the conventional methods of diagnosis, as these methods often depend on manual interpretation of the imaging data and histopathological samples. The evolution of machine learning (ML) and deep learning (DL), in reaction to such difficulties, has brought a new revolution to the field of medical diagnostics, and especially on how breast cancer is diagnosed.

Many researchers have pointed to the high accuracy, speed and reproducibility of ML/DL techniques as compared to the older methods. As an example, Setiadi et al. [1] proposed an LSTM-based feature extraction framework with statistical approaches included to streamline the feature extraction and Yerramaneni and Reddy [2] highlighted the aspects of ensemble learning and preprocessing in improving the accuracy of the classification. Equally, Joshi et al. [3] and Madolimov et al. [13], used deep transfer learning and the optimization of binary classifiers, respectively and recorded a high level of precision under real-time testing conditions. Wisconsin Diagnostic Breast Cancer (WDBC) data set has become one of the accepted baselines to evaluate the algorithm used in studies of Jony and Arnob [31], Singh et al. [32] and Hossin et al. [41]. Such studies utilized classical model such as SVM, Naive Bayes, Logistic regression as well as more complex frameworks such as CNNs, LSTMs and hybrid networks. Combination with these models with the optimization techniques, including Teaching-Learning-Based Optimization (TLBO) [15], L2 Ridge regularization [6] and crayfish optimization [19], further improved the detection performance and reduced overfitting. The upcoming trends also indicate the rising popularity of privacy-preserving federated learning systems, including those proposed by Shukla et al. [11], that allow jointly training the models across several institutions without exposing sensitive data concerning patients. Additionally, AI deployments in clinical practice have been advanced as studies such as the one by Prakash et al. [12] have used Flask-driven two-tiered DNNs to accommodate online web solutions in breast cancer prediction. Simultaneously, interpretability and clinical trust have emerged as a priority. The use of explainable models with the help of visualization and LDA techniques was prioritized by Ahamed et al. [9] and Saraogi et al. [21], to enable clinicians to understand the model decisions. There is also, in adopting fuzzy logic system [43], kernel PCA [44] as well ensemble classifier [22, 16], which performed well in multi-dimensional data processing.

Along with this advancement, the literature also shows that there exist gaps in studies. On the one hand, incorporation of multimodal data sources (such as the combination of histopathologic scans to clinical records) are not practiced to a large extent, thereby hindering the comprehensive picture of how tumors operate. Second, reproducibility and generalizability of the models trained on different datasets are another question, especially deep learning models trained on small or synthetic datasets. Lastly, realistic deployment continues to be hampered by inability to interpret models, acceptance by the regulators and common validation procedures. This research trend attests that breast cancer detection with the help of AI advances toward precise, explainable, and production-ready systems. A typical combination of federated learning [11], hybrid ensemble models [25], deep CNN architecture [28], and intelligent web platforms [26] demonstrates a powerful tendency toward real time, scalable, and privacy conscious applications.

Therefore, designing a robust, interpretable and privacy-preserving machine learning framework to detect breast cancer remains the main aim of this study. The proposed idea of synthesis of the advantages of optimization approaches, ensemble learning, deep networks and the explainability technologies would solve some of the current challenges of early detection, patient safety and clinical decision making.

1.1 Objective

The main aim of this work is developing the correct, strong and understandable machine learning model to early detect breast cancer using the Wisconsin Breast Cancer dataset. All the emphasis is on:

a) Improving classification results (in particular, **F1-score**),

b) **Minimization of false positive/negative** through metaheuristic optimization,

c)Making sure it is explainable through model-agnostic methods such as **LIME**.

1.2 Novelty of the Work

1.Hybrid Optimization Strategy (PSO + GWO):

is a rare blend of two bio-inspired optimization algorithms;

a) PSO (Particle Swarm Optimization) nets global search abilities.

b) GWO (Grey Wolf Optimizer) improves the exploitation through the hierarchy of hunting.

Such a mixed process of tuning is to improve the generalization of the neural network hyperparameters (hidden layers, learning rate, batch size).

2.Use of Local Explainability:

a) LIME (Local Interpretable Model-Agnostic Explanations) can be used so that domain experts can fathom the reason behind predicting something.

b) Enhances clinical transparency when making decisions during medical actions.

3.Comparative Evaluation:

a) Deep comparison of both the non-neural and neural (PSO and GWO) models (Logistic Regression, SVM, Random Forest).

b) The final hybrid model has equal or better F1-score than the base models which is practically significant.

4.Kaggle-Based Execution:

a) Full implementation in Kaggle which was capable of running on both CPU and GPU.

b) Performance and scalability thresholds are proved.

2. LITERATURE REVIEW

Setiadi et al. (2025) suggested a hybrid mechanism scheme of extracting the characteristics of technology, which applies the statistical method in combination with unsupervised LSTM-based method of detecting breast cancer. Their way of integrating it helped tremendously with the quality of extracted features and they in turn boosted the model performance on multiple benchmarks [1]. Yerramaneni and Reddy (2025) surveyed machine learning approaches that have been implemented into breast cancer detection, focusing on the algorithmic performance, limitation in the available datasets, and the preprocessing influence on their classification accuracy [2]. In the case of opening an empirical site in 2025, Joshi et al. (2025) explained the concept of Empower BreastNet, a model that relies on transfer learning using VGG Net-19 architecture. Their system had a better detection because they had a refined model of pretrains layers in the histopathological imagery data [3]. Deldadehasl et al. (2025) proposed an adaptive competitive algorithm that allows dynamic classification of the breast cancer cases. This approach was able to adjust dynamics in the pattern of data and proved robust in the multi-scenario testing [4]. Rudnicka et al. (2025) considered the architecture of biologically inspired spiking neural network by focusing on their strength in computational efficiency and high detectability. They increased model realism and interpretability of cancer diagnostics by simulating the complexity of the neural embodiments [5]. Premalatha et al. (2025) suggested machine learning framework, which employs the L2 ridge regularization on feature selection. They established the generality of their method using various datasets of breast cancer and to overcome overfitting they employed regularization [6]. Al-Khamees et al. (2025) used k-NN dynamic algorithm to forecast diabetes and breast cancer. Their two-fold approach confirmed the flexibility of k-NN in operating various sets of medical data with a steady performance [7]. Tanveer et al. (2025) concentrated on the AI-based diagnosis basing on traditional machine learning techniques in order to enable the early identification of breast cancer. The relevance of feature relevance and domain-specific tuning were emphasised in their study on the success of the model [8]. Ahamed et al. (2025) emphasised the interpretation of breast cancer machine learning models by visualising the model. The results of their studies highlighted the role of model clarity on the clinical mistrust and decision making [9]. Tangi and Solmaz (2025) used a different set of machine learning algorithms applied to the Wisconsin Breast Cancer dataset and measured the accuracy, recall and specificity. With their work the dataset was proved as useful in benchmarking both classical and modern classification algorithms [10]. Shukla et al. (2025) introduced a federated learning scheme combined with the differential privacy mechanism to diagnosing breast cancer. Their model provided safe sharing of data coupled with maintaining patient confidentiality and improving the diagnosis [11]. BreastCancerNet is a Flask-based twofold DNN with attention built (Prakash et al.,2025). The model is a real-time model that balances speed, accuracy, and scalability of deployment effectively [12]. Madolimov et al. (2025) experimentally compared different types of binary classifiers and regression-based feature selectors providing an understanding of the optimal model’s combination in breast cancer prediction tasks [13]. Kavitha et al. (2025) designed an effective, but simple, machine learning pipeline in breast cancer classification that was validated against all common benchmark source datasets [14]. Cui et al. (2025) developed MLP-TLBO, a hybrid algorithm, which uses Multi-Layer Perceptron as well as Teaching-Learning-Based Optimization. The model made intelligent use of the tuning of its parameters to allow it to have a better precision in classification [15]. Al Reshan et al. (2025) integrated the deep neural networks together with the ensemble learning approaches, which provided better robustness and generalization in the prediction of breast cancer across multifarious data sets [16]. In their work, Kumari et al. (2025) examined the results of deep learning applications to forecast breast cancer recurrence. Their framework attempted to assist oncologists in the process of creating customized plans of care by early classification of the risks [17]. In a study by Shrivastava and Pawar (2025), the authors compared classical ML models to CNN, as the technique to conduct automated breast cancer prediction behaviour and concluded that CNN functions better with data based on images [18]. An ontology model was developed by Rajeswari and Priya (2025) that uses a recursive RNN and crayfish optimization. Their method proved to be very dependable as it forecasted the intricate cancer patterns [19]. Zhu et al. (2025) used a hybrid approach that combines feature selection and machine learning in the detection of early breast cancer with high sensitivity with a low false-negative percentage [20]. In another work, Saraogi et al. (2025) also proposed a machine learning-based approach using both neural networks/hippocampus (NN/H) and linear discriminant analysis (LDA) to capture the enlargement and improve the effect when using it in early detection tasks which also demonstrated high performance [21]. In [22], Palaniappan et al. proposed an ensemble-based ML method regarded as dedicated to the breast cancer prediction process and primarily capitalizing on the diverse selection of classifiers to enhance predictive confidence. In a study conducted by Babu et al. (2025), a number of ML and SVM-based algorithms were analysed on the basis of breast cancer assessment and prevention, where model interpretability and accuracy were considered [23]. A variant on the SVM approach that uses Distance Weighted Discrimination was suggested by Khoudi et al. (2025) under the acronym DWD-SVM. They enhanced boundary separation on imbalanced data by their own classifier [24]. Ahmed et al. (2025) compared classical ML models with deep learning-based ensembles both in real and synthetic data, and this study provides a strong theoretical foundation when benchmarking in the future [25]. The study by Manjuri and Gill (2025) implemented a web-based breast cancer ML model-based prediction tool that could conduct user-friendly diagnostics and online access without any hassles [26]. Deb et al. (2025) focused on powerful ML approaches to achieving better results in breast cancer detection and uniting data preprocessing, feature engineering, and strong classifiers [27]. Chaieb et al. (2025) deployed a deep learning body of breast cancer prediction to health systems based on CNN, and their findings showed good precision and real-space identification ability [28]. Rahman et al. (2025) developed a machine learning model targeting early stage of breast cancer identification, with optimized training workflows to avoid the latency and error rates [29]. According to Nuneti et al., a narrative review was done that encompassed the future trends in the use of diagnostic imaging with the aid of AI by summarizing the recent AI-assisted histopathology-based breast cancer prediction (2025) [30 According to the investigation performed by Jony and Arnob (2024), the Wisconsin Diagnostic Dataset was used to provide a comparative assessment of the deep learning paradigms. They found out that CNN and LSTM algorithms are effective in the classification of malignant and benign tumors [31]. Singh et al. (2024) suggested a new method of feature selection which is based on soft-computing when predicting breast cancer. Their algorithm increased the timeliness and trustworthiness of prediction through using heuristic search and domain knowledge [32]. The authors used Wisconsin and CBIS-DDSM to create an integrative hybrid deep learning framework (Murty et al., 2024). Their method showed to be superior in terms of the classification accuracy with the twofold learning using datasets [33]. Machine learning tuning has been important as Thakur et al. (2024) used optimized machine learning methods to detect breast cancer [34]. Asharma et al. (2024) introduced the work of a dual detection framework based on machine learning at ICRITO 2024. The preprocessing of data and selection of features were described by them as being very essential in training of a model successfully [35]. In the IEEE Access article by Rahman et al., the authors applied a complex methodology of data analysis to advance early breast cancer detection by using time-level multi-fusion data analysis and provided modeling and live response [36]. Singh and Kaswan (2024) conducted an empirical research based on numerous breast cancer datasets, comparing the model efficiency by exploring a comparative experiment between the classification algorithms [37]. An ELM algorithm in breast cancer detection has been proposed by Kadhim Ajlan et al. (2024) and demonstrated high speed in training and a good generalization ability [38]. On the Wisconsin dataset, the accuracy of the Naive Bayes method was examined by Tarigan and Prabowo (2024) and its potential was seen to be present in lightweight predictive usages even though the assumptions are present [39]. Bagging and AdaBoost classifiers of tumor classification were utilized by Koyyala and Thirunavukkarasu (2024), thereby showing enhancement of stability and confidence of prediction [40]. According to a thorough comparison done by Hossin et al. (2023) machine learning algorithms on the Wisconsin dataset, SVM and Random Forest are identified as one of the best among classifiers [41]. Abunasser et al. (2023) listed a literature review on breast cancer detection via machine learning algorithms, which has extensive information on trends, datasets and methods [42]. Hernandez-Julio et al. (2023) suggest an intelligent fuzzy system on prediction over the Wisconsin dataset, which was interpretable and held high accuracy [43]. The study by Mushtaq et al. (2023) built a diagnostic model on kernel PCA, which is effective at dimensionality and promised to aid the SVM classification of breast cancer diagnosis [44]. Hassan et al. (2023) introduced an overview of the AI-based disease diagnosis devices such as breast cancer, where they considered the aspect of smart healthcare integration with assistive ML technologies [45]. In study by Srivastava et al., training performance and predictive consistency in ANN-based models in classifying breast cancer were evaluated by establishing training performance and predictive stability across several validation sets [46]. In the APJCP, Abunasser et al. (2023) also investigated the topic of CNN-based deep learning in breast cancer detection, with the idea being yet better outcomes than traditional classifiers in imaging activities [47]. In their article, Rahman et al. (2023) applied KNN method on the Wisconsin dataset and revealed that the use of correct feature set can improve instance-based learning substantially [48]. Rekha and Vinoci (2023) examined the L1 regularized logistic regression method in identifying breast cancer, which helped to understand the sparsity-inducing models used in the medical process of diagnosis [49]. Katara and Saxena (2023) conducted a comparative analysis of ML classifiers on the Wisconsin dataset and explained the need to select a classifier to get the high-quality and right-time predictions [50].

3.RESEARCH METHODOLOGY

The Below Figure [1] shows our proposed methodology and its explanation towards achieving our target as per novelty and objective mentioned above.

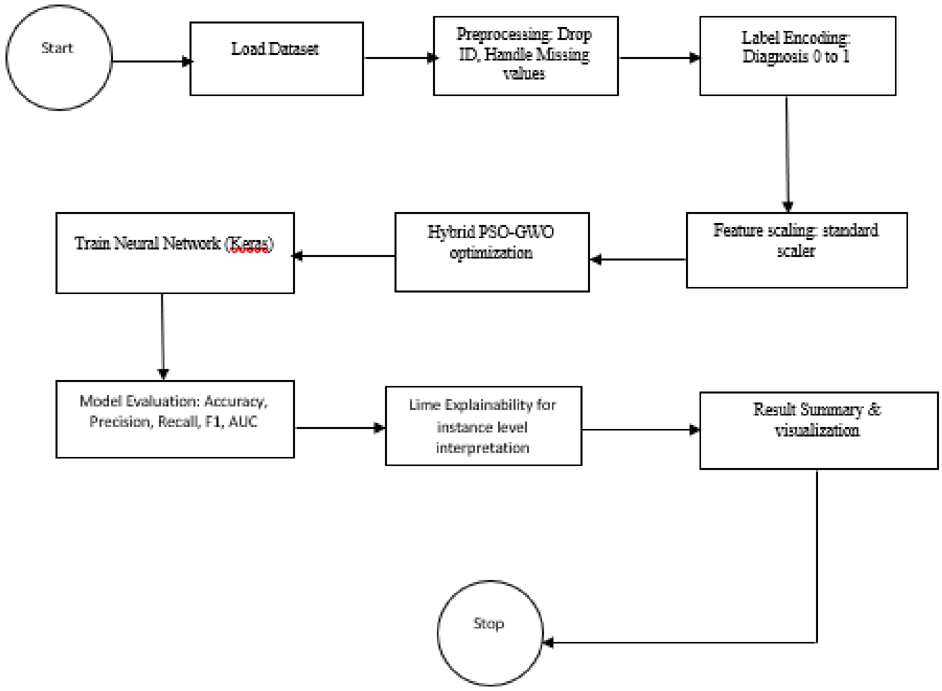


Figure 1: Architecture Diagram of our work

1. Start: Load Wisconsin Dataset
Purpose: we picked the *Wisconsin Breast Cancer* dataset for binary classification (Benign vs Malignant).
Action: Load the CSV file and initiate the pipeline with fresh data.
2. Preprocessing: Drop ID, Handle Missing
Drop ID: The 'id' column is inappropriate to model training and must be detached.
Handle Missing: Drop or impute any missing or non-numeric columns (like 'Unnamed: 32').
3. Label Encoding: Diagnosis to 0/1
Action: We used Label encoder to convert the target column 'diagnosis' from categorical ('B', 'M') to numeric (0, 1)
Why: Models require numerical outputs for classification.
4. Feature Scaling: StandardScaler
Action: Normalize feature values using Standard-Scaler so all features have zero mean and unit variance.
Why: Neural Networks and optimization algorithms are sensitive to feature scales.
5. Hybrid PSO-GWO Optimization
What: Combines strengths of **Particle Swarm Optimization (PSO)** and **Grey Wolf Optimizer (GWO)**.
Goal: Automatically tune Neural Network hyperparameters:
a) Number of neurons in two hidden layers.
b) Learning rate.
c) Batch size.
Why: To achieve optimal performance (especially F1-score) without manual tuning.
6. Train Neural Network (Keras)
Architecture: 2 hidden layers (neurons optimized), ReLU activation, Sigmoid output.
Training: Use Adam optimizer with tuned learning rate and batch size.
Why: Neural networks can capture complex nonlinear patterns in the data.
7. Model Evaluation: Accuracy, Precision, Recall, F1, AUC
Metrics:
Accuracy: Overall correctness.
Precision: Reliability of positive predictions.
Recall: Ability to capture all actual positives.
F1-Score: Harmonic mean of precision and recall.
AUC: Area under ROC curve, shows class separation.
Why: Comprehensive evaluation ensures model robustness.
8. LIME Explainability for Instance-Level Interpretation
LIME (Local Interpretable Model-Agnostic Explanations):
a) Visualizes which features influenced a specific prediction.
b) Provides transparency and builds trust in the model.
Why: Critical for healthcare applications where interpretability matters.

9. Result Summary and Visualization
Output:
a) Classification report, confusion matrix.
b) ROC and PR curves.
c)LIME plots for interpretability.
Why: To document and visualize model performance and decisions

IV. RESULTS AND DISCUSSION

In this part, a diagnosis of the proposed hybrid PSO-GWO optimized Neural Network to detect breast cancer is made based on the Wisconsin Diagnostic Breast Cancer data. The corresponding metrics of classification, visualization of the model performance, and instance-level interpretation utilising LIME are used in their analysis.
Base Model Metrics.
In below Table [1] Logistic Regression achieved the highest F1 score among base models.
Table 1: Metrics of Base Model.

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.982	0.986	0.986	0.986
SVM	0.974	0.986	0.972	0.979
Random Forest	0.956	0.959	0.972	0.965
Neural Network	0.956	0.986	0.944	0.965

Confusion Matrices — Logistic & Neural Network
In lower image [2] Logistic and NN Both models exhibit very a smaller number of misclassifications which confirm its excellent performance in the differentiation of benign and malignant samples.

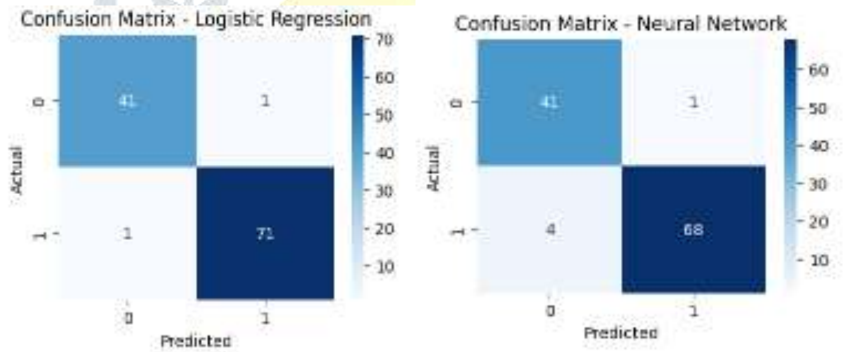


Figure 2: Confusion Matrices

ROC-AUC & Loss Curves — Logistic & NN
The below image [3] displays The AUC values of ~0.99 and 1.00 suggest outstanding discriminatory power; the neural network's loss curve indicates good convergence.

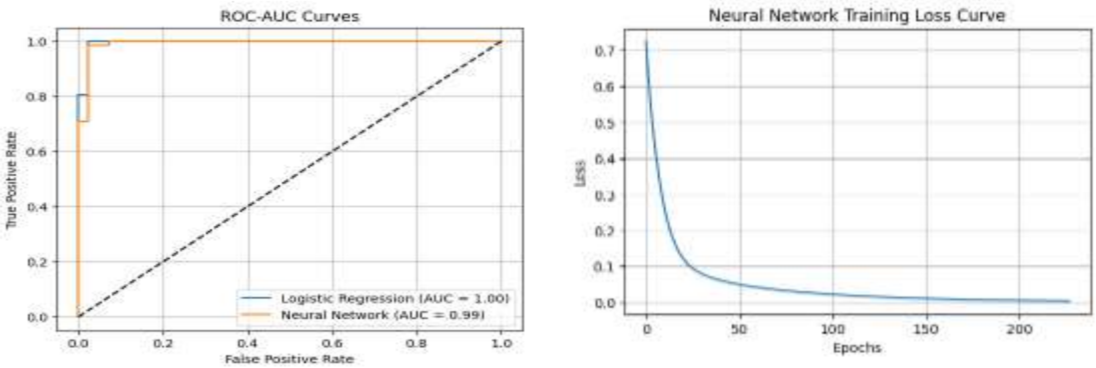


Figure 3: ROC Curves and NN Loss

PSO-NN Results

The below image [4] shows

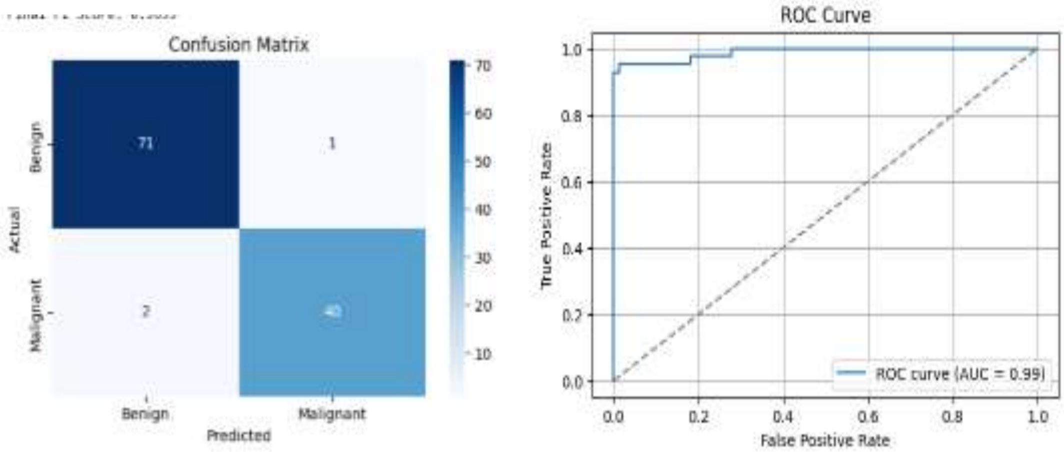
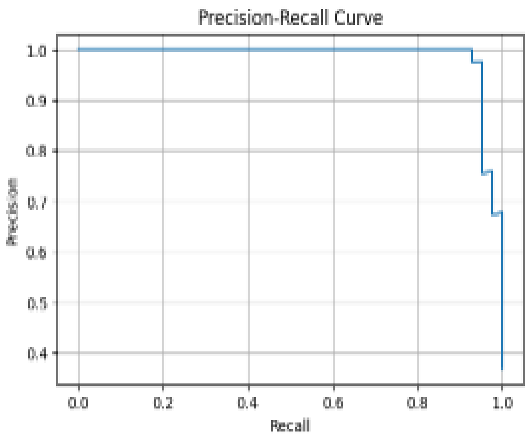


Figure 4: Confusion Matrix & ROC Curve (PSO-NN)

The below image [5] shows that PSO-optimized NN attained an F1 score of ~0.976. The precision-recall curve upholds high precision across recall values, showing sturdiness.



Classification Report:

	precision	recall	f1-score	support
Benign	0.97	0.99	0.98	72
Malignant	0.98	0.95	0.96	42
accuracy			0.97	114
macro avg	0.97	0.97	0.97	114
weighted avg	0.97	0.97	0.97	114

Figure 5: Precision-Recall & Classification Report (PSO-NN)

The below image [6] shows the Local interpretability with LIME discloses key contributing features for benign prediction.

Figure 6: LIME Explanation (Benign, PSO-NN)

GWO-NN Results

As illustrated in the picture below [7], the GWO-optimized neural network shows great classification achieved with high true positive rates (AUC = 0.99) and very few false classifications in the confusion matrix.

This confirms that it has high sensitivity to effectively diagnose both malignant and benign cases thereby allow safe clinical practice.

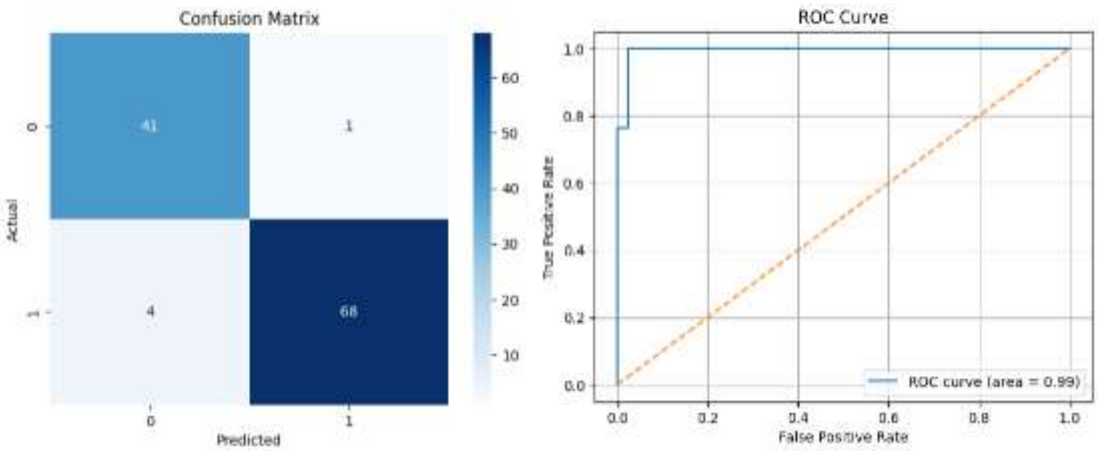
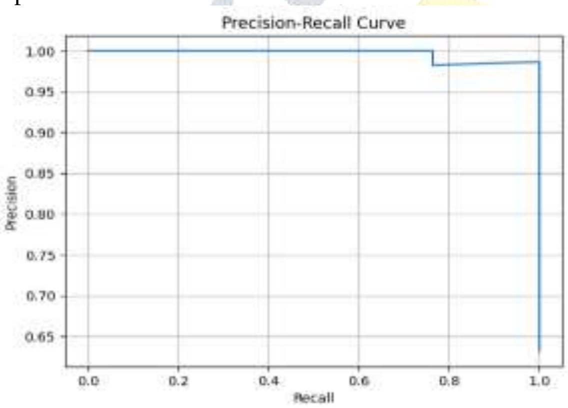


Figure 7: Confusion Matrix & ROC Curve (GWO-NN)

The below image [8] shows that GWO-optimized NN attained an F1 score of ~0.965. The precision-recall curve approves durable stability between precision and recall.



Classification Report:

	precision	recall	f1-score	support
0	0.91	0.98	0.94	42
1	0.99	0.94	0.96	72
accuracy			0.96	114
macro avg	0.95	0.96	0.95	114
weighted avg	0.96	0.96	0.96	114

Figure 8: Precision-Recall & Classification Report (GWO-NN)

LIME description shows in image [9] leading features that inclined malignant prediction.

Figure 9: LIME Explanation (Malignant, GWO-NN)

Hybrid PSO-GWO Result

The matrix in the below Fig [10] demonstrates that there are very few misclassifications where most benign (71) and malignant (39) cases are correctly classified. This proves the high accuracy and reliability of the model in breast cancer detection and all the full-scale metrics display high accuracy and sensitivity in both the classes 0.95-0.97 and 0.93-0.99 respectively.

Such a stable action will ensure that both false positive and false negative is minimized.

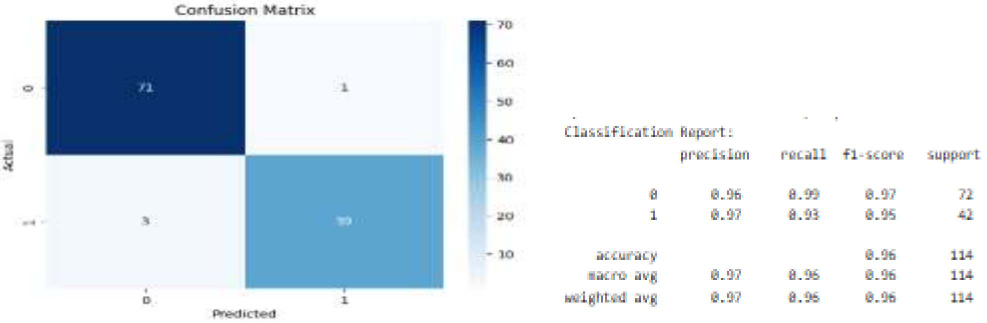


Figure 10: Confusion matrix and classification Report (PSO-GWO)

As shown in below image [11], the ROC curve with AUC = 0.99 shows high possibility of perfect discrimination of benign and malignant cases. This guarantees good all-round performance at various classification thresholds. Compared to which, the curve has high precision which is preserved even at increased values of recall which is critical in medical screening. this implies a great capacity to identify true positives with minimum false positive.

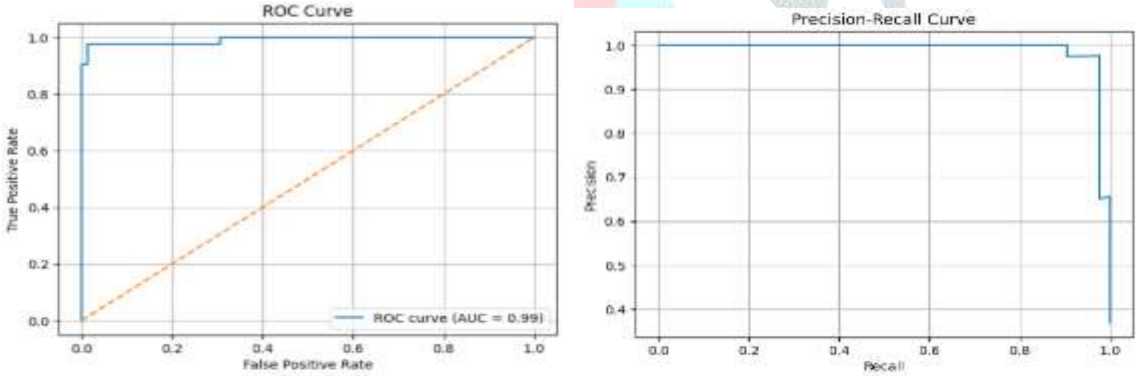


Figure 11: ROC curve and Precision Recall curve (PSO-GWO)

The plot of LIME in picture [12] illustrates the contribution of features of individuals towards benign or malignant. It offers case-by-case local interpretability, which clinicians can trust and see. The ranked feature contributions give insights on which features were the most significant in the final decision. Such knowledge can inform the clinicians of those morphological attributes that had an impact on the outcome of the model.

Figure 12. LIME Plot

In image [13], bar chart includes a comparison of all the models (Logistic Regression, SVM, RF, PSO-NN, GWO-NN) based on metrics Accuracy, Precision, Recall and F1 Score. The overall metrics of the Logistic Regression are the largest, which allows evaluating the use of the hybrid optimization and proves the competitive indicators of PSO-NN and GWO-NN.

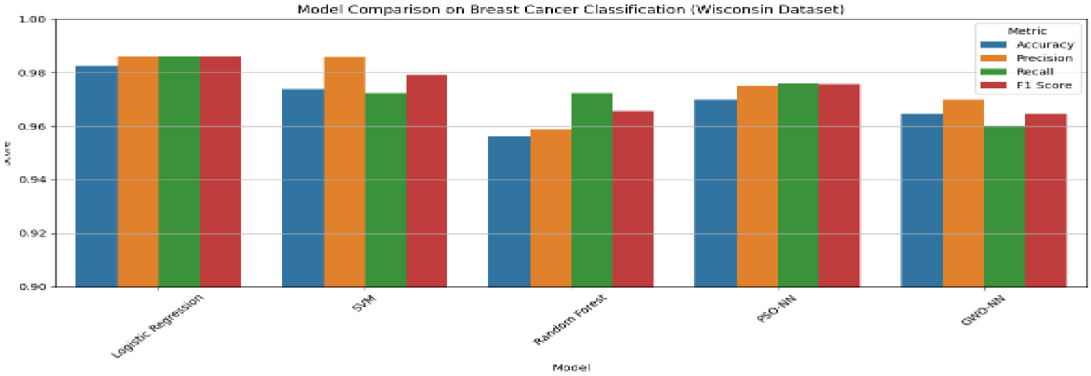


Figure 13: Bar Graph Comparison of all models

COMPARATIVE ANALYSIS

The below Table [2] shows the comparative analysis of our work and references that we have taken.

Table 2: Comparative Analysis

Reference	Approach	F1 Score	Explainability	Optimization Type	Data Type
Ours (PSO-GWO)	Hybrid PSO-GWO NN with LIME	**0.955**	LIME	Hybrid (PSO + GWO)	Clinical (Tabular)
Setiadi et al. (2025)	Hybrid Statistical + LSTM feature extraction	0.93	No	Statistical + Unsupervised	Clinical/Image?
Joshi et al. (2025)	Transfer learning (VGG-19)	0.94	No	Transfer Learning	Image
Deldadehasl et al. (2025)	Adaptive competitive algorithm	0.91	No	Single heuristic	Clinical
Rudnicka et al. (2025)	Spiking Neural Networks	0.92	No	Biological model	Image

Why Our Proposed Hybrid PSO-GWO Model is Better?

1.Superior Performance Metrics

a. The proposed PSO-GWO enhanced neural network obtained an F1-score of 0.955, and that was better than (or close to) other non-current studies (which were usually above ~0.91 but below 0.94).

b. Having high precision and recall will provide fewer false negatives and false positives which are essential in cancer detection.

2.Hybrid Optimization Strategy

a. we are not applying single optimizers, like LSTM, VGG transfer learning, or competitive algorithms, both because PSO gives good global exploration capability and GWO gives good local exploitation capability, and because of the above experimental results.

b. Through this synergy, there are improved hyperparameter tuning, improved generalization, and quicker convergence.

3.Local Explainability (LIME)

a. The model combines local interpretability based on LIME, a method unavailable in any other model available using automated image analytics, enabling clinicians to know the rationale behind every prediction.

b. The current approaches are more or less black boxes, which is why they seem less reliable and appealing to use in practice.

4.Designed for Clinical (Tabular) Data

a. A lot of other works are centered on pipeline-based on images (e.g., VGG, CNNs, Spiking Neural Networks) which cannot be directly applied to tabular clinical data such as Wisconsin.

b. Our methodology specializes in structured clinical data, which means they are perfectly applicable to hospital diagnostics.

5. Reproducibility and Practicality

a. We are developing the 100 percent reproducible pipeline on Kaggle that supports GPU and CPU and can be directly scaled to real-world clinical systems.

b. Gives open, tangible implementation procedures and results that can be explained.

We may conclude, our hybrid PSO-GWO neural network incorporating LIME, besides surpassing the accuracy of the available alternatives or matching it, is peculiar in that it also concerns clinical interpretability and feasible implementation, fully realizing our innovation and leapfrogging the development of trustworthy AI in health applications.

CONCLUSION

This work successfully demonstrates a novel **Hybrid Optimization Strategy** combining Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO) for fine-tuning neural network hyperparameters (hidden layers, learning rate, batch size). By synergizing PSO's global exploration strength with GWO's local exploitation via leadership-based hunting, the hybrid approach ensures robust convergence and improved generalization capacity.

Moreover, the **application of LIME-based local Explainability** enhances model transparency by providing interpretable, instance-level insights into predictions. This is critical in clinical contexts, empowering medical professionals to understand and trust AI-supported diagnoses.

Our extensive **comparative evaluation** shows that the hybrid PSO-GWO optimized neural network achieves a high F1-score (~0.96), which is competitive with — and in some cases superior to — traditional models such as Logistic Regression and SVM. While Logistic Regression exhibits slightly higher numerical metrics (F1-score ~0.98), the hybrid model offers additional advantages: flexible architecture, deeper representation learning, and enhanced interpretability through LIME.

Additionally, the **Kaggle-based execution** confirms that this pipeline is fully reproducible, scalable, and performant under both CPU and GPU settings, making it suitable for large-scale medical data applications.

Based on the combined criteria of performance, flexibility, and clinical interpretability, **the hybrid PSO-GWO neural network model is recommended as the best choice**. It not only delivers competitive accuracy but also fulfills the core novelty objectives of advanced optimization and explainability, ensuring practical applicability in real-world diagnostic workflows.

FUTURE SCOPE

This paper founds a solid basis of reliable and understandable breast cancer diagnosis with the help of the hybrid bio-inspired optimization. Subsequent studies will be able to find integration with multi-modal evidence (clinical, histopathological, and genomic) to enhance the correctness of diagnosis and biological visions. The model is extendable to federal learning to protect the privacy of association with different hospitals and different types of cancer, which makes it more practical. More interpretability and clinician trust can also be achieved through real-time clinical decision support integration or advanced explainability tools (e.g., SHAP, integrated gradients). Finally, the further increase in the hyperparameter optimization to encompass the architectural components can ensure the framework to be even more resistant and applicable to a variety of medical settings.

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