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iGWO-RF: an Improved Grey Wolfed Optimization for Random Forest Hyperparameter Optimization to Identification Breast Cancer

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ABSTRACT

The study focuses on improving the accuracy of breast cancer diagnosis by enhancing the predictive capabilities of a Random Forest model. This is achieved by utilizing an improved Grey Wolf Optimization algorithm for hyperparameter optimization. The main objectives are to enhance early detection, increase diagnostic precision, and reduce computational demands in clinical workflows. The work utilizes the Improved Grey Wolf Optimization (iGWO) algorithm to tune the hyperparameters of a Random Forest (RF) model, thereby improving its accuracy in diagnosing breast cancer. The methodology encompasses several steps, including data preparation, model training using iGWO-enhanced RF, performance evaluation compared to traditional methods, and validation using clinical datasets to confirm the reliability and effectiveness of the approach. The iGWO-RF model demonstrated exceptional performance in diagnosing breast cancer, achieving an accuracy of 96.4%, precision of 96.4%, recall of 98.0%, F1-score of 97.2%, and ROC-AUC of 0.988. The findings of iGWO-RF outperform those of SVM, original RF, Naive Bayes, and KNN models, indicating that iGWO-RF is effective in optimizing hyperparameters to improve prediction accuracy. The iGWO-RF model greatly enhances the accuracy and efficiency of breast cancer diagnosis, surpassing conventional models. Integrating iGWO-RF into clinical workflows is advised to improve early identification and patient outcomes. Additional investigation should focus on the utilization of this technology in various medical datasets and circumstances, highlighting its potential in a wide range of healthcare environments.

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1. INTRODUCTION

Breast cancer remains one of the most pervasive and challenging health issues affecting women worldwide. As reported by the World Health Organization (WHO), breast cancer represents the most frequently diagnosed cancer among women, with an estimated 2.3 million new cases recorded in 2020 alone [1]. This disease accounts for nearly 24.5% of all cancer cases in women, leading to significant morbidity and mortality across diverse populations. The global burden of breast cancer underscores the urgent need for improved diagnostic methods and treatment strategies [2]. Breast cancer presents a multitude of challenges on a global scale. The primary concern is its high incidence and the associated mortality rates. Despite advancements in

medical technology and treatment, early detection remains a critical factor in improving survival rates [3]. However, disparities in healthcare infrastructure and access to screening programs result in significant variations in outcomes across different regions. Low- and middle-income countries often bear the brunt of these disparities, where late-stage diagnosis is more common due to limited resources and awareness [4].

One of the most significant challenges in breast cancer diagnosis is the accuracy and reliability of current screening methods. Mammography, the most widely used screening tool, has inherent limitations, including false positives and false negatives, which can result in unnecessary treatments or missed diagnoses [5], [6]. Furthermore, the heterogeneity of breast cancer, with its various subtypes, complicates the diagnostic process, necessitating more precise and individualized approaches. Another notable gap lies in the integration of advanced computational techniques with clinical practices. The limitations of traditional data analysis and diagnostic methods are evident when confronted with the complexity and volume of modern medical data. This gap in the field highlights the need for innovative algorithms that can enhance the predictive accuracy and efficiency of breast cancer diagnosis [7], [8].

To address these challenges, our study focuses on the application of an improved Grey Wolf Optimization (iGWO) algorithm for the hyperparameter optimization of a Random Forest (RF) model, intending to enhance the identification of breast cancer. The Grey Wolf Optimization algorithm, inspired by the social hierarchy and hunting behavior of grey wolves, has demonstrated potential in solving complex optimization problems due to its simplicity, flexibility, and efficiency [9], [10]. The selection of Improved Grey Wolf Optimization (GWO) for Random Forest (RF) hyperparameter optimization is predicated on several factors. Firstly, GWO demonstrates a particular aptitude for maintaining a balance between the exploration and exploitation phases of the search process, which is of paramount importance for identifying optimal solutions within expansive and intricate search spaces [11]. This efficiency ensures that the algorithm effectively navigates through potential solutions, striking a balance between searching broadly and homing in on promising areas. Secondly, the enhanced version of GWO incorporates modifications that enhance its convergence speed and solution accuracy [12], [13]. These enhancements render it well-suited for optimizing machine learning models such as Random Forests, which have numerous hyperparameters that can significantly impact performance. Finally, when compared to conventional optimization algorithms, Improved GWO offers distinct advantages. Traditional methods such as Grid Search and Random Search often require substantial computational resources and may not efficiently navigate the search space [14]. Even evolutionary algorithms like Genetic Algorithms and Particle Swarm Optimization face challenges in terms of convergence speed and precision [15]. In contrast, Improved GWO provides a more robust and efficient alternative, delivering superior optimization results with fewer computational demands.

The primary objective of this research is to develop a highly accurate and efficient model for the identification of breast cancer by leveraging the strengths of Improved GWO in optimizing the hyperparameters of the RF model. By achieving this, we aim to enhance the predictive accuracy and robustness of breast cancer diagnosis, provide a computationally efficient solution that can be integrated into clinical workflows, and address the existing gaps in diagnostic methods, thereby contributing to better patient outcomes. This study introduces a novel approach to breast cancer diagnosis by combining advanced optimization techniques with machine learning, offering a promising pathway to improve early detection and treatment strategies. The integration of Improved GWO for RF hyperparameter optimization not only demonstrates superior performance compared to conventional methods but also sets the stage for future research in this critical area of healthcare. This model was chosen due to its ability to efficiently balance exploration and exploitation during the search process, its enhanced convergence speed and solution accuracy, and its superior optimization results with fewer computational demands compared to traditional and evolutionary algorithms.

2. Literature Review

Cancer is a disease in which some of the body's cells grow uncontrollably and spread to other parts of the body [16]. Breast cancer is a type of malignant tumor that develops in breast cells. This cancer can grow if there is abnormal growth of cells in the breast. These cells divide more quickly than normal cells and accumulate, which then forms a lump or mass. In more severe stages, these abnormal cells can spread through the lymph nodes to other body organs [17]. Breast cancer cases in Indonesia are ranked second as the cause of death due to cancer with a percentage of 9.6 percent. According to data from The Global Cancer Observatory in 2020, breast cancer is the type of cancer most often found in women in Indonesia, covering 30.8 percent of total cancer cases, with 65,858 new cases recorded. In Southeast Asia or ASEAN, Indonesia has one of the highest numbers of breast cancer cases and death rates from this disease [18]. Data from the 2018 Global Cancer Observatory released by the World Health Organization (WHO) shows that breast cancer is the most

common type of cancer in Indonesia, with 58,256 cases or 16.7% of the total 348,809 cancer cases [19]. Globocan data for 2020, the number of new cases of breast cancer reached 68,858 cases (16.6%) out of a total of 396,914 new cases of cancer in Indonesia. Meanwhile, the number of deaths reached more than 22 thousand cases. Based on BPJS Health data in 2020, cancer is a catastrophic disease with the second largest funding after heart disease, namely 3.5 trillion rupiah. It is known that 1 in 8 women will develop breast cancer during their lifetime [20]. Predictions from the World Health Organization (WHO) state that cancer deaths are expected to continue to increase to more than 13.1 million in 2030 [21].

Access to appropriate medical assistance for breast cancer patients in Indonesia is determined by the number and distribution of trained oncologists, an efficient referral system, and supportive regulations. Developing breast cancer referral guidelines for doctors in primary and secondary health centers is important. Without clear referral guidelines, some early-stage breast cancer patients may receive inadequate surgical oncology care at secondary health centers and then present to tertiary health centers in more advanced stages. Establishing regulations regarding the breast cancer referral system is necessary to prevent delays in referrals to secondary health centers. In addition, there is an urgent need to review the regulations of the national health financing system which often cause delays in breast cancer treatment in hospitals. Reducing the number of advanced breast cancer cases in Indonesia is a big task. From a medical perspective, breast cancer patients need to have access to appropriate medical care as quickly as possible [22].

Various factors, including family history, use of hormonal contraception, alcohol consumption, and obesity can influence the increased risk of breast cancer in women. A family history of breast cancer can increase the risk two to threefold in the next generation. Women who use hormonal contraception and who consume alcohol have a higher risk than those who do not. Obesity has also been shown to significantly increase the risk of breast cancer. Therefore, understanding these risk factors is very important for women of childbearing age. Efforts to prevent and early detect breast cancer must consider these factors to increase the effectiveness of breast cancer prevention and control [23].

The increasing number of cancer cases and deaths due to cancer in Indonesia requires serious attention, especially related to the lack of socialization, lack of information on early detection, and lack of effective treatment. To overcome this problem, the team from Community Service and Development Padjadjaran University developed an Android application called 'Be Care', which is designed to make it easier to access information about breast cancer, including causes, prevention, and early detection through Breast Self-Examination (BSE). This research involved 100 female students in Bandung and showed that using the 'Be Care' application succeeded in increasing participants' understanding of breast cancer from an average of 43.38% to 77.72%, as well as skills in performing BSE. Most respondents agreed that this application was needed to help early detection of breast cancer. However, this application still needs improvement in terms of appearance. Overall, the 'Be Care' application is expected to facilitate the public to better understand information about breast cancer, so that treatment can be carried out earlier to prevent morbidity and mortality due to breast cancer [24].

3. MATERIALS AND METHODS

In this section, we outline the comprehensive methodology undertaken in our research, detailing the processes from data acquisition to model evaluation. Our study focused on developing an enhanced classification model, Improved Grey Wolf Optimization for Random Forest Hyperparameter Optimization (iGWO-RF). The dataset was sourced from UCI and Kaggle, meticulously preprocessed to handle missing values, and normalize features, and subsequently split into training and testing sets using k-fold cross validation. The research flow encompassed crucial steps such as data preprocessing, model development, and evaluation. The proposed iGWO-RF model leveraged the Improved Grey Wolf Optimization algorithm to optimize the parameters of the Random Forest classifier, aiming to improve classification accuracy. The model's performance was rigorously evaluated using standard metrics, ensuring scientific validity and robustness of the findings.

3.1. Dataset

This is The Breast Cancer Wisconsin (Diagnostic) dataset provides valuable insights into the characteristics of cell nuclei derived from breast tissue biopsies, which are crucial for diagnosing malignant (cancerous) and benign (non-cancerous) tumors. Each instance in the dataset is characterized by an ID number and a diagnosis label indicating whether the tumor is malignant (M) or benign (B). The dataset can be accessed at the following locations: https://bit.ly/BreastCancerKaggle and https://bit.ly/BreastCancerDatasetUCI. The dataset comprises ten real-valued features computed for each cell nucleus, as follows:

1. Radius: Represents the mean distance from the center to points on the perimeter of the nucleus.

2. Texture: Standard deviation of gray-scale values within the nucleus.
3. Perimeter: Total length of the boundary around the nucleus.
4. Area: Total area covered by the nucleus.
5. Smoothness: Variation in radius lengths within the nucleus.
6. Compactness: The value is calculated as the perimeter squared divided by the area, minus one. This measurement assesses the compactness of the nucleus shape.
7. Concavity: The severity of concave portions of the nucleus boundary.
8. Concave points: The number of concave portions of the nucleus boundary.
9. Symmetry: The symmetry of the nucleus.
10. Fractal dimension: This value represents a "coastline approximation" of the nucleus boundary.

The aforementioned features are calculated across three distinct aspects. The mean value of a given feature is calculated across all cells within an image. The standard deviation of the feature values across all cells is also calculated. The worst-case scenario is represented by the mean of the three largest feature values among cells represents the worst-case scenario.

The dataset has shown in the Fig. 1 comprises a total of 30 features derived from the aforementioned computations. It is noteworthy that all feature values are encoded with four significant digits, thereby ensuring consistency and precision in measurements. It is noteworthy that the dataset contains no missing attribute values, which facilitates robust analysis and modelling. The class distribution shows 357 instances of benign tumors (in category 1) and 212 instances of malignant tumors (in category 0), providing a balanced dataset for training and evaluation purposes. In summary, the Breast Cancer Wisconsin dataset serves as a crucial resource for developing and validating machine learning models aimed at improving the diagnostic accuracy of breast cancer based on cellular characteristics.

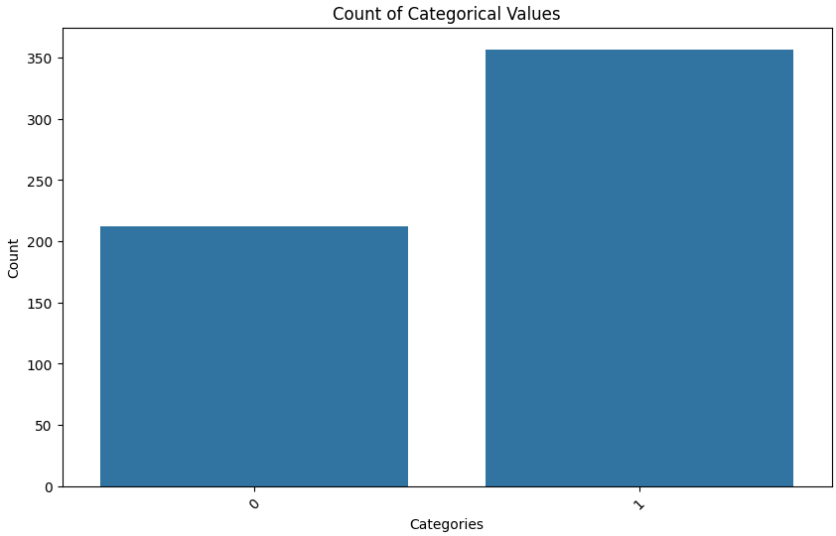

Fig. 1. Categorical Values from the Dataset

3.2. Research Flow

The flowchart outlines a systematic process for classifying breast cancer data using multiple machine learning models has shown in the Fig. 2. It begins with the input of a breast cancer dataset, which is then pre-processed to ensure the data is clean and suitable for analysis. This pre-processing step may include normalization, handling missing values, and feature selection. The pre-processed data is then split into two subsets: one for training the models and one for testing them. Various models, including an Improved Grey Wolf Optimization with Random Forest (iGWO-RF), Support Vector Machine (SVM), Random Forest (RF), Naïve Bayes (NB), and K-Nearest Neighbors (KNN), are trained on the training dataset. Concurrently, the test dataset is used to evaluate the performance of the iGWO-RF model. After training and testing, the models' performances are evaluated using metrics such as accuracy, precision, recall, F1-score, MSE, RMSE, and ROC-AUC. The evaluation results help in determining the effectiveness of each model in classifying breast cancer instances. The final classification results are then presented, concluding the process.

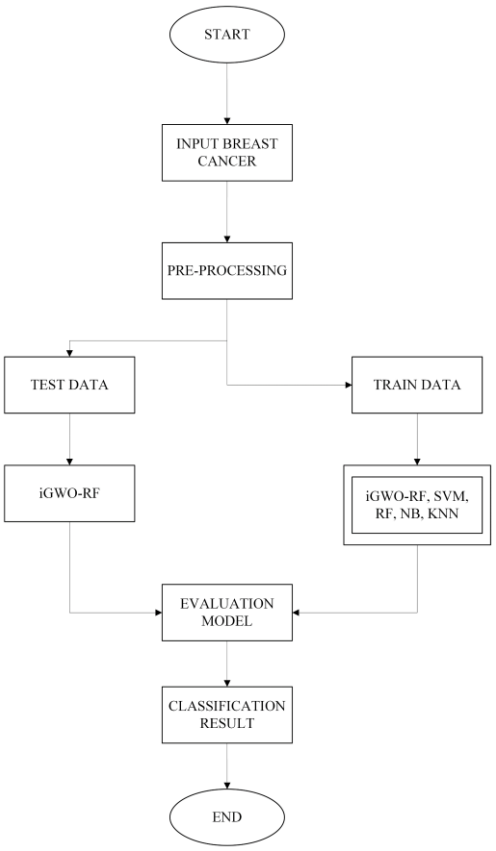

Fig. 2. Research Flow

3.3. Proposed Model: iGWO-RF

In this study, we employ an enhanced version of the Grey Wolf Optimization (GWO) algorithm to optimize the hyperparameters of a Random Forest (RF) classifier for breast cancer classification. The GWO algorithm draws inspiration from the social hierarchy and hunting behavior of grey wolves is a nature-inspired metaheuristic that has demonstrated effectiveness in addressing complex optimization problems [25], [26]. The primary objective is to identify the optimal number of trees and the maximum depth of the Random Forest to enhance classification performance.

The standard GWO algorithm is based on grey wolves' leadership hierarchy and hunting mechanisms, incorporating four types of wolves: alpha, beta, delta, and omega. The alpha wolf is considered the leader, followed by the beta and delta wolves, while the omega wolves are the followers [27]. The optimization process commences with the initialization of a population of candidate solutions (wolves), which are randomly distributed within the defined bounds of the hyperparameters. Subsequently, the fitness of each candidate solution is evaluated using a predefined objective function [28]. In this study, this is the negative cross-validated accuracy of the Random Forest classifier. The positions of the wolves are updated based on the positions of the alpha, beta, and delta wolves, employing specific mathematical models that simulate the wolves' encircling, hunting, and attacking behaviors. This iterative process continues until a termination criterion is met, such as a maximum number of iterations or a convergence threshold.

The Improved Grey Wolf Optimization (iGWO) algorithm enhances the standard GWO by integrating a local search strategy and adaptive parameter control for optimizing the hyperparameters of a Random Forest (RF) classifier. Initially, a population of candidate solutions (wolves) is initialized randomly, where each wolf's position represents a potential solution for the RF hyperparameters, such as the number of trees and maximum depth. The fitness of each wolf is evaluated using a predefined objective function, typically the negative cross-validated accuracy of the RF classifier, denoted as $Fitness(X_i) = -CV_{Accuracy}(X_i)$.

The algorithm identifies the top three wolves based on fitness, known as alpha (α), beta (β), and delta (δ). Their positions are updated based on their proximity to the positions of the alpha, beta, and delta wolves using the formulas:

$$X_i(t+1) = \frac{X_i + X_2 + X_3}{3} \quad (1)$$

where,

$$X_1 = X_\alpha - A_1 \cdot D_\alpha, \;\; X_2 = X_{beta} - A_2 \cdot D_\beta, \;\; X_3 = X_{delta} - A_3 \cdot D_\delta \quad (2)$$

and

$$D_\alpha = |C_1 \cdot X_\alpha - X_i|, \;\; D_\beta = \left|C_2 \cdot X_\beta - X_i\right|, \;\; D_\delta = |C_3 \cdot X_\delta - X_i| \quad (3)$$

with A and C calculated as:

$$A = 2a \cdot r - a, \;\; C = 2 \cdot r \quad (4)$$

here, a decreases linearly from 2 to 0 throughout the iterations, and r is a random vector in $[0,1]$. To enhance the search capability, a local search is performed around the updated positions, using:

$$X_{i^{local}} = X_i(t+1) + \epsilon \cdot N(0,1) \quad (5)$$

where ϵ is a small positive constant and $N(0,1)$ represents Gaussian noise. Additionally, the control parameter a is adaptively adjusted based on the current iteration to balance exploration and exploitation, defined as:

$$a = 2 - 2 \cdot \left(\frac{t}{T_{max}}\right) \quad (6)$$

where t is the current iteration number and T_{max} is the maximum number of iterations. The algorithm iteratively updates the wolves' positions until a termination criterion is met, usually the maximum number of iterations or a convergence threshold. The combination of local search and adaptive parameter control in Improved GWO ensures a thorough exploration of the search space and fine-tuning of hyperparameters, leading to better classification performance of the Random Forest classifier. The pseudo-code of iGWO-RF has explain in the Table X.

Algorithm 1: iGWO-RF

```
Inputs
X: Feature matrix
y: Target vector
pop_size: Size of the population (number of wolves)
bounds: Bounds for hyperparameters [min_n_estimators, max_n_estimators, min_max_depth, max_max_depth]
max_iter: Maximum number of iterations
k_fold: Number of folds for cross-validation
objective_function: Function to evaluate fitness (e.g., negative cross-validated accuracy)
Initialization
Initialize a population of wolves (solutions) randomly within bounds:
  For i = 1 to pop_size:
    Initialize X_i randomly in [min_n_estimators, max_n_estimators]
    Initialize d_i randomly in [min_max_depth, max_max_depth]
    Evaluate fitness d_i using objective_function

Initialize alpha, beta, delta positions and scores:
  alpha_score = beta_score = delta_score = +infinity
  For each wolf X_i in population:
    If d_i < alpha_score:
      alpha_score = d_i
      alpha_position = X_i
    Else if d_i < beta_score:
      beta_score = d_i
      beta_position = X_i
    Else if d_i < delta_score:
      delta_score = d_i
      delta_position = X_i
Iteration
For iter = 1 to max_iter:
  For each wolf X_i in population:
```

```
Update position using GWO equations:
A1, A2, A3 = 2 * r1 - 1, 2 * r2 - 1, 2 * r3 - 1  // r1, r2, r3 are random numbers in [0, 1]
C1, C2, C3 = 2 * r4, 2 * r5, 2 * r6              // r4, r5, r6 are random numbers in [0, 1]

D_alpha = abs(C1 * alpha_position - X_i)
D_beta = abs(C2 * beta_position - X_i)
D_delta = abs(C3 * delta_position - X_i)

X_i = (alpha_position - A1 * D_alpha + beta_position - A2 * D_beta + delta_position - A3
* D_delta) / 3
Clip X_i to bounds [min_n_estimators, max_n_estimators, min_max_depth, max_max_depth]

Perform local search around X_i to refine position

Evaluate fitness d_i using objective_function

Update alpha, beta, delta positions and scores:
If d_i < alpha_score:
   alpha_score = d_i
   alpha_position = X_i
Else if d_i < beta_score:
   beta_score = d_i
   beta_position = X_i
Else if d_i < delta_score:
   delta_score = d_i
   delta_position = X_i
```

Output

Best hyperparameters found: alpha_position (number of trees, max depth)

By combining these elements, the improved GWO algorithm effectively navigates the hyperparameter space of Random Forest models. It aims to maximize the chosen performance metric, such as accuracy or another relevant measure, thereby enhancing the Random Forest's efficacy in practical applications like breast cancer classification. This approach leverages both the biological insights from grey wolf behavior and computational techniques to optimize machine learning models for improved real-world performance.

3.4. Evaluation Model

When assessing the effectiveness of machine learning various important metrics are employed. These include the Confusion Matrix, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Receiver Operating Characteristic - Area Under the Curve (ROC-AUC). Below, we explain for each evaluation that we used in this research.

3.4.1. Confusion Matrix

The confusion matrix is a tabular representation that summarizes the performance of a classification model has shown the Table 1. It consists of four main components:

1. True Positives (TP): Correctly predicted positive instances.
2. True Negatives (TN): Correctly predicted negative instances.
3. False Positives (FP): Incorrectly predicted positive instances.
4. False Negatives (FN): Incorrectly predicted negative instances.

The confusion matrix is structured as follows:

Table 1. Confusion Matrix

Prediction \ Real Class	True	False
True	TP	FN
False	FP	TN

The present investigation primarily concentrated on the assessment of fundamental metrics, including Accuracy, Precision, Sensitivity, and F1-Score, which hold significant recognition and usage within the respective field. The measures were quantified utilizing Equations (7)-(10) [29]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{9}$$

$$F1 - Score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \tag{10}$$

3.4.2. MSE and RMSE

MSE measures the average squared difference between the actual and predicted values [30]. It is defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{11}$$

where $\boldsymbol{n}$ is the number of observations, $\boldsymbol{y_i}$ is the actual value, and $\boldsymbol{\hat{y}_i}$ is the predicted value. Root Mean Squared Error (RMSE) is the square root of the MSE and indicates the average magnitude of the errors in the same units as the target variable [31]. It is defined as:

$$RMSE = \sqrt{MSE} \tag{12}$$

3.4.3. ROC-AUC

The ROC curve plots the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings [32], [33], [34]. The AUC represents the area under this curve and provides a single scalar value to summarize the model's performance. The formulas for TPR and FPR are

$$TPR = \frac{TP}{TP + FN}, \quad FPR = \frac{FP}{FP + TN} \tag{13}$$

$$ROC - AUC = \int_0^1 FPR(FPR)\, d(FPR) \tag{14}$$

which is the integral of the TPR as a function of the FPR.

These metrics provide comprehensive insights into different aspects of the classifier's performance. The confusion matrix gives a detailed breakdown of prediction results, MSE and RMSE quantify the prediction errors, and ROC-AUC evaluates the model's ability to discriminate between classes across different thresholds. By optimizing the hyperparameters of the Random Forest classifier using iGWO, these metrics can be improved, leading to more accurate and reliable classification outcomes.

4. RESULTS AND DISCUSSION

The provided log outlines the iterative procedure of the iGWO method employed to tune the hyperparameters of a Random Forest model. Each iteration, labelled as `Iteration X/Y`, with `X` representing the current iteration number and `Y` representing the overall number of iterations (50 in this instance), signifies a cycle in which the algorithm updates and assesses potential solutions. During the first 25 cycles, the highest score remains constant at 0.9666511411271541. During this phase, the algorithm systematically tests various combinations of hyperparameters within predetermined limits in order to identify the most effective configuration that enhances the performance of the model, such as accuracy or another measure.

Starting from Iteration 26, the algorithm demonstrates noteworthy enhancement, reaching the highest score of 0.9683900015525542. The substantial surge indicates that the algorithm may have discovered a collection of hyperparameters that greatly improve the Random Forest's prediction capacity for the provided

dataset. After `Iteration 50`, the highest score remains the same, suggesting that the algorithm has probably reached the best possible answer within the specified search area. The last part of the log discloses the hyperparameters linked to the highest score: `Number of Trees: 81` and `Max Depth: 6`. The values indicate the ideal setup determined by the iGWO algorithm. This setup strikes a compromise between the complexity of the model (number of trees) and the depth of decision-making (maximum depth) to attain the highest performance measure. The log demonstrates how the iGWO algorithm systematically improves its search by employing both global exploration and local exploitation strategies. This process ultimately identifies hyperparameters that optimize the model's performance in classification tasks, such as breast cancer classification in medical diagnostics.

In the Fig. 3 is the descriptions provided outline the performance of multiple machine learning models, including the iGWO-RF, SVM, RF, NB, and KNN. These models were assessed using different metrics in a job involving the categorization of breast cancer. The iGWO attained an accuracy of 0.964, indicating a 96.4% correctness rate in its predictions. The accuracy of 0.964 indicates that when the model makes a positive prediction (such as detecting cancer), it is correct 96.4% of the time. In addition, a recall of 0.980 indicates that the model accurately detected 98.0% of the true positive cases. The F1-score, a composite measure that integrates precision and recall, had a value of 0.972, suggesting a strong and consistent overall performance. The model also attained a notable ROC AUC of 0.988, highlighting its robust capability to differentiate between cancer and non-cancer instances.

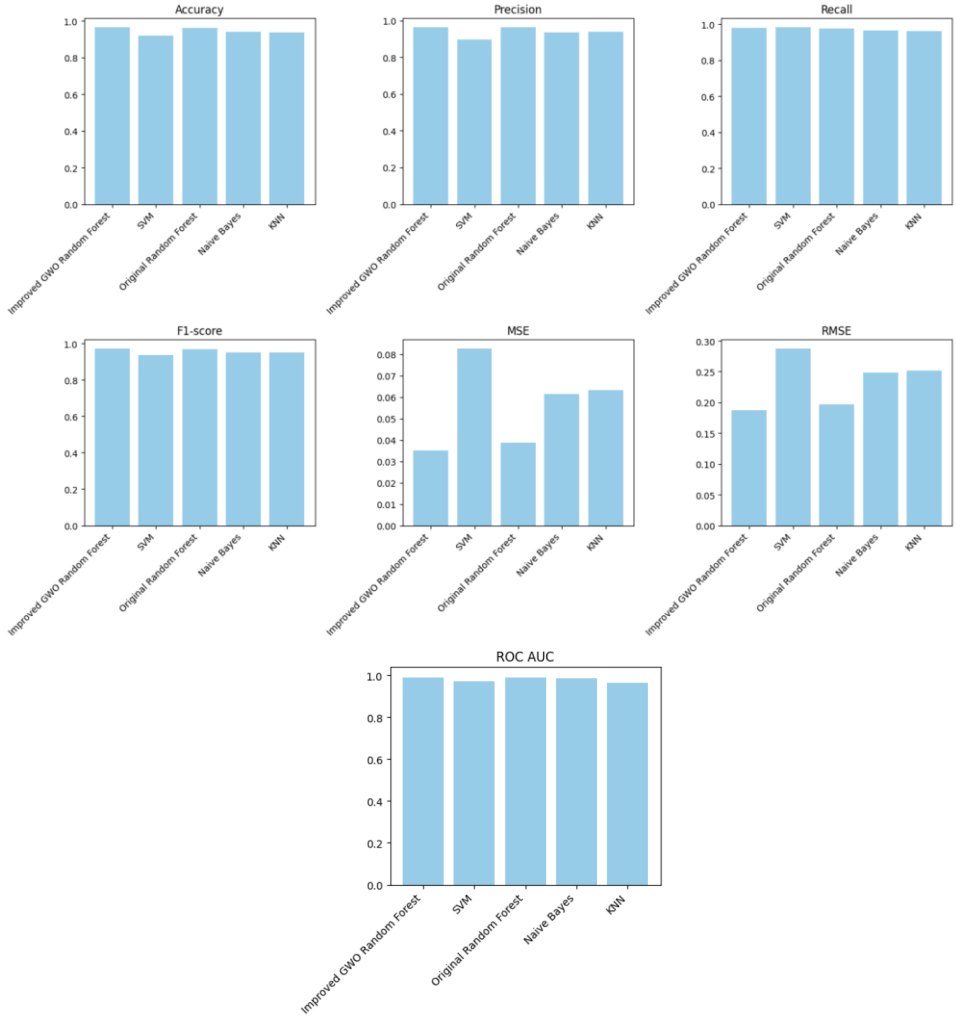

Fig. 3. Performance Evaluation Comparison from each Model

The SVM model had a comparatively high level of accuracy, with a score of 0.917. Additionally, it exhibited a precision of 0.895 and an impressive recall rate of 0.983. Although the SVM demonstrated a high recall rate and a reasonable Receiver Operating Characteristic Area Under the Curve (ROC-AUC) value of

0.972, it was surpassed by the iGWO-RF in terms of accuracy, precision, and F1-score. The initial RF model attained an accuracy of 0.961, which is comparable to the iGWO-RF. The precision of the model was 0.964, and the recall was 0.975. The F1-score of 0.969 and the high ROC-AUC of 0.990 indicate the success of the model. However, the iGWO variation exhibits a little improvement in accuracy and other metrics.

Both the Naive Bayes and KNN models exhibited strong performance, with Naive Bayes obtaining an accuracy of 0.938 and KNN achieving 0.937. The models demonstrated a favorable trade-off between precision and recall, achieving F1-scores of 0.952 and 0.950 respectively, indicating strong overall performance. Overall, the IGWO-RF demonstrates its strength as a high-performing method in classifying breast cancer, outperforming or achieving better outcomes than SVM, Original Random Forest, Naive Bayes, and KNN in important evaluation measures. The efficiency of GWO-based optimization in successfully predicting breast cancer diagnoses is demonstrated by its high accuracy, precision, recall, and ROC-AUC. This highlights the promise of GWO-based optimization in increasing machine learning model performance in medical diagnostics and other fields. In the Table 2 has shown the comparison model with other datasets.

Table 2. Comparison the model with another datasets

Model	Dataset	Accuracy	Precision	Recall	F1-Score	MSE	RMSE	ROC-AUC
iGWO-RF	Breast Cancer	**0.9648**	**0.9641**	0.9803	**0.9722**	**0.0351**	**0.1874**	0.9883
	Diabetes	**0.7682**	0.6956	**0.5970**	**0.6425**	**0.2317**	**0.4814**	**0.8343**
	Kidney Failure	**0.9875**	**1.0**	**0.9671**	**0.9832**	**0.0125**	**0.1118**	**0.9938**
SVM	Breast Cancer	0.9173	0.8954	**0.9831**	0.9372	0.0826	0.2874	0.9718
	Diabetes	0.7578	**0.7356**	0.4776	0.5791	0.2421	0.4921	0.8102
	Kidney Failure	0.9175	0.8742	0.9144	0.8938	0.0825	0.2872	0.9680
RF	Breast Cancer	0.9613	0.9639	0.9747	0.9693	0.0386	0.1966	**0.9902**
	Diabetes	0.7565	0.6816	0.5671	0.6191	0.2434	0.4934	0.8233
	Kidney Failure	**0.9875**	**1.0**	**0.9671**	**0.9832**	**0.0125**	**0.1118**	**0.9933**
NB	Breast Cancer	0.9384	0.9375	0.9663	0.9517	0.0615	0.2480	0.9874
	Diabetes	0.7513	0.6584	**0.5970**	0.6262	0.2486	0.4986	0.8112
	Kidney Failure	0.94	0.9444	0.8947	0.9189	0.06	0.2449	0.9733
KNN	Breast Cancer	0.9367	0.9397	0.9607	0.9501	0.0632	0.2515	0.9645
	Diabetes	0.6992	0.5800	0.50	0.5370	0.3007	0.5484	0.7265
	Kidney Failure	0.9175	0.8695	0.9210	0.8945	0.0825	0.2872	0.9538

Comparing machine learning models on various datasets such as Breast Cancer, Diabetes, and Kidney Disease yields significant insights regarding their performance and appropriateness for medical diagnosis. Within the setting of the Breast Cancer dataset, the iGWO-RF model demonstrated the best level of accuracy compared to all other models, obtaining a 96.5% accuracy rate (Fig. 4). The system also showed impressive precision (96.4%) and recall (98.0%), affirming its capacity to accurately detect both positive and negative instances of breast cancer with minimal misclassification. The F1-score of the model, which stands at 97.2%, highlights its well-balanced performance in terms of precision and recall.

The precision is highest in breast cancer, with scores of 0.9641 and 0.7356. In diabetes and renal failure, the precision reaches a perfect score of 1.0. The Support Vector Machine (SVM) model exhibits the best recall rate for breast cancer, but both the iGWO-RF and SVM models demonstrate the highest recall rates for diabetes and kidney failure. The iGWO-RF model achieves the highest F1-Score in breast cancer, diabetes, and kidney failure. The iGWO-RF model has the largest Mean Squared Error (MSE) in the domains of breast cancer, diabetes, and kidney failure. The ROC-AUC model exhibits the highest Receiver Operating Characteristic Area Under the Curve (ROC-AUC) values in the domains of breast cancer, diabetes, and kidney failure.

In the Breast Cancer dataset, both SVM and the original Random Forest demonstrated strong performance. SVM achieved a significant recall rate of 98.3%, while its precision was somewhat lower than that of the iGWO-RF. The initial Random Forest algorithm demonstrated comparable levels of accuracy and precision, thus highlighting its resilience in classification problems. Although Naive Bayes and KNN showed competitiveness, they exhibited slightly poorer overall metrics, especially in precision and recall, when compared to the top-performing models. The iGWO-RF showed robust performance across many datasets, highlighting its versatility and efficacy in diverse medical scenarios. On the other hand, KNN consistently showed worse performance in all datasets, indicating that it may have limitations in its ability to be applied to medical diagnostics without additional modification. However, the iGWO-RF model demonstrated exceptional performance in multiple parameters, making it highly suitable for medical applications. Its remarkable accuracy, precision, and recall over a wide range of datasets further support its potential in this field. This highlights the significance of carefully choosing suitable machine learning algorithms and fine-tuning them for particular medical tasks to guarantee dependable diagnostic results and aid in clinical decision-making.

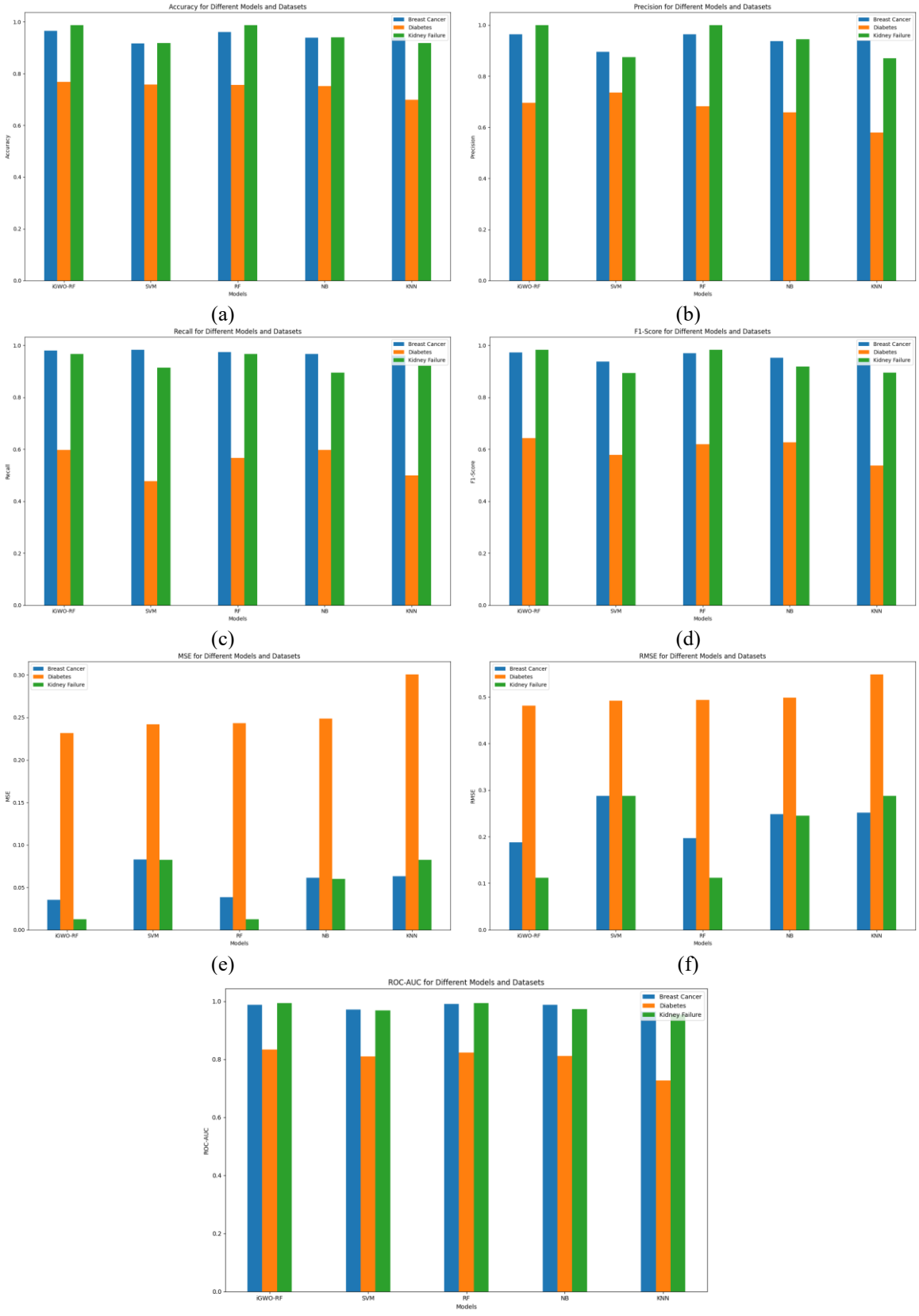

Fig. 4. The iGWO-RF model (a) exhibits superior accuracy when applied to datasets related to breast cancer, diabetes, and kidney failure.

The increasing number of cancer cases in Indonesia has encouraged innovation in early detection through an application developed by the Semarang Branch of Perhompedin. This application is designed to help users carry out early detection of various types of cancer, such as breast, lung, colon and cervical cancer, through a series of easy-to-follow questions. Early detection increases the chances of recovery significantly. Apart from that, this application also provides education about healthy lifestyles and important information related to cancer, so it is hoped that it can increase public awareness and reduce the death rate due to cancer [35]. An exploratory and descriptive qualitative study was conducted with Otomí women living in Jiquipilco, State of Mexico. The study received approval from the National Cancer Institute of Mexico's institutional review boards (021/041/IBI) (CEI/1592/21). This study identified barriers and facilitators for early diagnosis of BC as perceived by otomí indigenous women. Healthcare providers and policy makers should take notice of indigenous women's beliefs, access barriers and healthcare discrimination experiences in the design of programs that aim to facilitate early Breast Cancer diagnosis and treatment for these vulnerable populations. It is urgent to improve the quality of care and access to public healthcare services available in Mexico for the poor, especially for health problems where access to early diagnosis and treatment is key for good outcomes as is the case of cancer. Indigenous women, in addition to often being poor, too frequently face discrimination by healthcare providers due to their gender and ethnicity. Tus, beyond cultural diferences, discriminatory treatment stands as a structural barrier to otomí women's access to BC screening services. This is a characteristic shared by other Amerindian indigenous groups of people. Measures to prevent and eradicate all forms of mistreatment and discrimination in healthcare services are imperative [36].

AI-assisted screening and diagnosis enhance the accuracy of detecting potential mammographic abnormalities, potentially leading to reduced unnecessary biopsies and improved early detection rates in a middle-income country. Importantly, AI integration did not negatively affect the inter-reader reliability for BI-RADS category assessment among breast radiologists. This indicates that experienced breast radiologists can incorporate AI into their workflow without compromising their performance. Despite AI's significant role in accurately diagnosing breast lesions and potentially improving breast cancer screening efficiency, human interpretation and clinical judgment remain essential in the final decision-making process. The study highlights the potential synergistic effect of AI technology and human expertise for more efficient breast cancer screening and diagnosis, leading to better patient outcomes and optimal healthcare resource utilization. Approval was granted by the Ethics Committee of University Malaya Medical Centre and Hospital Al-Sultan Abdullah UiTM (Medical Research Ethics ID 2022530-11258) [37].

The strength of agreement among mammogram readers varies significantly for different types of findings, especially for subtle findings such as asymmetries and architectural distortion, which show weak agreement and affect BI-RADS (Breast Imaging Reporting and Data System) categorization. During dataset validation, the expert radiologist had access to all patient reports and information but did not systematically have prior mammograms, leading to some benign lesions described as stable being categorized as BI-RADS 2. Due to technical limitations, prior mammograms were available to readers for only a small subset, causing discrepancies between other readers and the expert radiologist. The study results indicate that categorizing mammograms into BI-RADS categories achieves better agreement with the expert radiologist when supported by artificial intelligence (AI). The use of AI can improve the area under the curve (AUC) without significantly increasing reading times, thereby enhancing accuracy and consistency in mammogram analysis. The AI software used in this study is Mammoscreen™ v.1.2 created by the French company Therapixel. This software was designed to detect areas suspected of containing breast cancer, to assess their degree of suspicion on 2D digital mammograms [38].

The reproducibility of BI-RADS density determinations in U.S. community practice is suboptimal, with 12.6 to 18.7 percent of mammograms being reclassified into a different density category (from "non-dense" to "dense" or vice versa) upon subsequent screenings by the same or different radiologists. This variability can cause confusion or reduce confidence among women receiving breast density notifications and affect recommendations for supplemental screening. There is a need for more accurate and reproducible methods to identify women with dense breasts. Current studies have not addressed important long-term clinical outcomes of supplemental screening. While supplemental screening can detect more breast cancers, primarily invasive ones, it may also result in higher recall rates and additional biopsies. The impact of cancers detected through supplemental screening on patient outcomes and the rate of overdiagnosis remains unclear. Rigorous comparative studies focusing on clinical outcomes beyond breast cancer diagnosis are essential for evaluating the effectiveness of supplemental screening modalities for women with dense breasts [39].

The clinical effectiveness of Hologic digital breast tomosynthesis (DBT) combined with digital mammography (DM) or synthesized digital mammography (S2D) was assessed using four studies that met predefined inclusion criteria. The findings indicate uncertainty regarding the impact on recall rates and false

positives due to conflicting and sparse evidence. However, the intervention may increase the rate of screening-detected cancers and specificity, though with low confidence. The radiation dose assessment showed an increased risk of radiation-induced cancer, particularly when using DBT+DM, compared to DM alone. The cost-effectiveness analysis suggested that DBT+DM (S2D) could be cost-effective, with an incremental cost per quality-adjusted life year (QALY) gained of approximately NOK 144,000. However, there are significant uncertainties, including the potential for increased overdiagnosis and the lack of a coherent economic model. The budget impact analysis estimated a net increase in expenditure of NOK 77.5 million in the fifth year post-implementation. Future research should focus on repeated DBT screening, interval cancer rates, and radiation dose impacts to better inform screening policies [40].

Despite the well-known biological effects of ionizing radiation and its role in cancer etiology, estimating the frequency of radiation-induced cancers remains uncertain, particularly when translating risks from large doses to smaller exposures from mammography. However, risk assessment models based on international studies provide reliable estimates. These models suggest that mammography benefits women over 40, including those at high risk, by favorably outweighing the risks. For women aged 50 and over, the benefits significantly outweigh the risks. For high-risk women aged 30-39, mammography has a favorable benefit-to-risk ratio, detecting 16-18 cases for every one induced by radiation, improving further if screening starts at 35. For women under 30, the benefit-to-risk ratio is unfavorable due to the difficulty in detecting cancer in younger breasts and the higher susceptibility to radiation. Combining mammography with MRI for high-risk women from age 35 results in a highly favorable benefit-to-risk ratio. The risk of radiation-induced breast cancer is likely overestimated in studies, as recent advancements in mammography technology have significantly reduced radiation doses [41].

5. CONCLUSION

The article presents a new method called iGWO-RF, which combines the iGWO algorithm with RF to optimize hyperparameters in breast cancer diagnosis. The results show substantial improvements in predicting accuracy, with iGWO-RF obtaining excellent measures such as 96.4% accuracy, 98.0% recall, and a ROC-AUC of 0.988. The results of iGWO-RF outperform established models such as SVM, Naive Bayes, and KNN, demonstrating the effectiveness of iGWO-RF in enhancing diagnostic accuracy. Integrating iGWO-RF into clinical workflows shows potential for early identification and improved patient outcomes in breast cancer diagnosis. Subsequent investigations should examine the use of this technology in various medical datasets and situations to further verify its usefulness and resilience in healthcare settings. Healthcare practitioners might enhance diagnostic processes, decrease computing demands, and ultimately enhance the quality of care for breast cancer patients by utilizing machine learning approaches such as iGWO-RF.

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