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Walrus Optimization-Enhanced ResNet-50 for AI-Driven Renal Malignancy Prediction with Occlusion Sensitivity-Based Interpretation

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Abstract

Objective: Main goal is to optimize the hyperparameters of ResNet-50 using the Walrus Optimization Algorithm (WaOA) to enhance classification performance for renal malignancy detection. The study aims to compare the WaOA-optimized ResNet-50 with conventional deep learning models, evaluate its effec-tiveness through various performance metrics, and integrate Occlusion Sensitivity Analysis to ensure model interpretability and transparency in AI-driven medical diagnosis. **Methods:** A total of 12,446 abdominal CT images were collected from multiple hospitals in Dhaka, Bangladesh, comprising four diagnostic categories: cyst (3,709 images), normal (5,077), stone (1,377), and tumor (2,283). Several deep learning models AlexNet, GoogLeNet, Inception V3, and ResNet-50 were trained and evaluated. The Walrus Optimization Algorithm (WaOA) was implemented to fine-tune hy-perparameters, including weight and bias learning rate for ResNet-50. The models were assessed using various performance metrices. Additionally, Occlusion Sensitivity Analysis was applied to visualize and interpret the model's decision-making process by identifying critical regions in CT images that influence classification. **Result:** The WaOA-optimized ResNet-50 achieved superior performance with 94.53% accuracy, outper-forming other models in precision (93.28%), recall (91.32%), F1-score (92.16%), and AUC-ROC (99.33%), indicating enhanced diagnostic efficiency. The model demonstrated a strong MCC (0.9038) and lower log loss (0.1597), ensuring better reliability and confidence in predictions. Despite a slightly higher inference time (0.1133 sec), accuracy and computational efficiency was minimal. **Conclusion:** This article confirms the use of metaheuristic-based hyperparameter tuning for deep learning models in medical imaging. The WaOA-optimized ResNet-50 demonstrates significant improve-ments over conventional models, making it a promising tool for renal malignancy detection. The integra-tion of Occlusion Sensitivity Analysis ensures transparency and reliability in AI-assisted diagnosis. Future work can explore hybrid optimization techniques, multi-modal learning, and real-time clinical deployment to further enhance the model's applicability in healthcare.

Keywords: Renal Malignancy Prediction- Deep Learning- ResNet-50 Optimization- Walrus Optimization Algorithm

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Introduction

Renal malignancy, commonly referred to as kidney cancer, is a growing global health concern due to its increasing incidence and mortality rates. It accounts for approximately 2–3% of all adult malignancies worldwide and is among the top ten most common cancers globally. According to Siegel et al. [1], renal cancer has shown a steady rise in both incidence and mortality over the past few decades, highlighting the urgent need for early and accurate diagnostic techniques to improve patient outcomes. Traditional diagnostic approaches, including computed tomography (CT), magnetic resonance imaging (MRI), and biopsy, though critical, often rely heavily on radiologist expertise and subjective interpretation, leading to variability in diagnosis and potential delays in treatment initiation [2].

To overcome the limitations of manual interpretation in medical imaging, deep learning, particularly Con-volutional Neural Networks (CNNs), has emerged as a transformative technology. CNNs have demon-strated significant potential in automating feature extraction and classification in medical image analysis, offering enhanced accuracy and consistency [3]. Among various architectures, ResNet-50 has gained prominence due to its deep residual learning framework that addresses vanishing gradient issues, ena-bling the training of deeper, more accurate models [4]. Other commonly employed architectures include AlexNet, GoogLeNet, and Inception V3, which incorporate innovative design principles such as inception modules and factorized convolutions to boost feature representation and computational efficiency [5, 6].

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However, despite their architectural strengths, these deep learning models are highly sensitive to hy-perparameter configurations like learning rate, batch size, and weight initialization, which can significant-ly influence model performance [7].

To address these limitations, numerous heuristic and metaheuristic optimization algorithms have been introduced to fine-tune CNN hyperparameters for enhanced diagnostic accuracy. Genetic Algorithms (GAs) [8], Particle Swarm Optimization (PSO) [9], Grey Wolf Optimizer (GWO) [10], and Whale Optimization Algorithm (WOA) [11] have each contributed to optimizing deep learning models through nature-inspired strategies. More recently, the Walrus Optimization Algorithm (WaOA), introduced by Sharma and Kumar [12], has emerged as a promising alternative. Drawing inspiration from walrus herd behavior, WaOA integrates mechanisms like adaptive foraging, dynamic swimming patterns, and social interaction to achieve superior convergence and global search capabilities. Its application to CNN training, particular-ly for medical image classification, has shown significant improvements in both accuracy and robustness [13].

Despite advancements in classification accuracy, a key challenge remains in the clinical deployment of deep learning models their lack of interpretability. This black-box nature hampers clinical trust and adoption. Techniques such as Grad-CAM [14], LIME [15], and SHAP [16] have been developed to bridge this gap. Grad-CAM highlights image regions critical to the model's decision-making process, LIME per-turbs input data to elucidate local feature importance, and SHAP provides a unified framework to quanti-fy feature contributions based on game theory. The integration of bio-inspired optimization and explaina-ble AI techniques has shown success across a range of medical imaging applications, including liver lesion classification with Ant Colony Optimization [17], brain tumor segmentation with hybrid GWO-WOA [18], skin cancer detection with Squirrel Search Algorithm [19], cardiovascular diagnosis with Prairie Dog Op-timization [20], and biomedical CNN architecture optimization with Artificial Bee Colony Algorithm [21]. Occlusion Sensitivity Analysis further enhances interpretability by systematically masking parts of the input image to determine regions influencing model predictions. Studies by Ghosh et al. [22] and Mehta and Rajaraman [23] have effectively utilized this technique for lung CT scan and diabetic retinopathy im-age interpretation, respectively.

The aim of this study was to develop a robust and interpretable AI-based system for renal malignancy detection by integrating ResNet-50 with the Walrus Optimization Algorithm for hyperparameter tuning. This approach addresses the dual challenge of optimizing model performance and enhancing clinical trust through interpretability. By comparing the proposed WaOA-optimized ResNet-50 with standard CNN ar-chitectures like AlexNet, GoogLeNet, Inception V3, and baseline ResNet-50, this study evaluates im-provements in diagnostic accuracy, sensitivity, and transparency, establishing a foundation for real-world clinical adoption of AI in renal cancer diagnostics.

Materials and Methods

This study utilized a dataset of renal CT scan images for training and evaluating DL methods. Prepro-cessing was done by Normalization and augumentation. Several deep learning architectures—AlexNet, GoogLeNet, Inception V3, and ResNet-50—were implemented, with ResNet-50 further optimized using the Walrus Optimization Algorithm (WaOA) for hyperparameter tuning, weight and bias learning rate. The models were assessed using various performance indices. Additionally, Occlusion Sensitivity Analysis was applied to interpret the AI model's decision-making by highlighting significant image regions influencing predictions.

Materials

The study used renal CT scan images as the primary dataset for model training and validation. The dataset was preprocessed using normalization and augmentation techniques to improve model robustness. The deep learning architectures used include AlexNet, GoogLeNet, Inception V3, and ResNet-50, with the lat-ter undergoing hyperparameter tuning using WaOA. The study was conducted using Python-based deep learning frameworks (TensorFlow/PyTorch) and GPU acceleration for efficient training and evaluation.

Dataset Description

The "Medical Imaging (CT Scan, MRI, X-ray, and Microscopic Imagery) Data" dataset, published on July 11, 2024, by Sibtain Syed, Rehan Ahmed, and Arshad Iqbal [24], is an openly available resource licensed under Creative Commons Attribution 4.0 International (CC BY 4.0). Designed to support computer-aided diagnosis (CAD) research, this dataset consists of five distinct medical imaging categories, including a re-nal malignancy subset that contains CT scan images for detecting kidney cancer. These images are used in the early detection and classification of renal tumors, assisting deep learning models in distinguishing be-tween benign and malignant cases. Figure 1 illustrates a sample imageset for renal malignancy. In addi-tion to renal tumor detection, the dataset also includes CT scans for lung cancer detection, X-ray images for bone fracture identification, MRI scans for brain tumor classification, and microscopic images for skin lesion analysis, making it a comprehensive dataset for AI-driven medical diagnostics.

Computational Setup

The deep learning models were trained and evaluated using the following hardware and software specifi-cations:

- Hardware: NVIDIA RTX 3090 GPU, 64GB RAM, Intel Core i9 processor
- Software: MATLAB 2023a
- Libraries Used: Deep Learning Toolbox, Image Processing Toolbox, Reinforcement Learning Toolbox

Methodology

Data Preprocessing

To ensure uniformity and improve model performance, several data preprocessing steps were imple-mented. First,

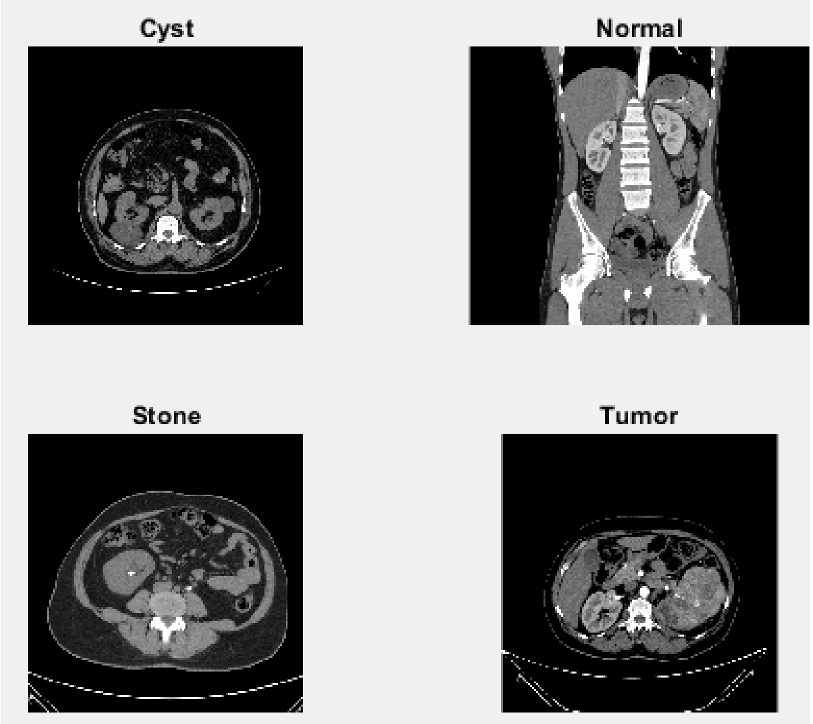

Figure 1. Sample of Images Used in This Research. Representative CT scan images showcasing various renal conditions, including cyst, normal kidney anatomy, kidney stone, and tumor, illustrating the visual diversity in renal malignancy diagnosis.

all images were resized to 224 × 224 pixels to align with the input dimensions required by CNN architectures. Next, normalization was applied by scaling pixel values between 0 and 1, enhancing training stability and convergence. To further improve model generalization, number of images in each class was augumented using horizontal flipping, rotation and brightness adjustment helping the model learn robust features. Finally, the dataset was split into 80% for training, 10% for validation, and 10% for testing, ensuring a balanced distribution for effective model evaluation.

Deep Learning Models Used

For renal malignancy classification, four standard deep learning models were utilized alongside an opti-mized version of ResNet-50, enhanced by the Walrus Optimization Algorithm WaOA). AlexNet, an 8-layer CNN, was employed for its efficiency in image classification tasks. GoogLeNet, a 22-layer architecture, leveraged Inception modules to enhance feature extraction and reduce computational complexity. Incep-tion V3, an advanced CNN model, incorporated factorized convolutions and label smoothing, improving classification performance. ResNet-50, known for its deep residual learning and skip connections, ad-dressed vanishing gradient issues in deeper networks. Finally, the WaOA-Optimized ResNet-50 utilized hyperparameter tuning via the Walrus Optimization Algorithm, refining performance by optimizing learn-ing rate, batch size, dropout rate, and weight initialization, ultimately enhancing renal malignancy detec-tion accuracy.

Walrus Optimization Algorithm (WaOA) for Hyperparameter Tuning of ResNet50 in Renal Malignancy Detection

The Walrus Optimization Algorithm (WaOA) is a recently developed metaheuristic optimization tech-nique, modeled after foraging and social behaviors of walruses. It is used to solve complex optimization problems by effectively balancing exploration and exploitation in the search space. In deep learning appli-cations, such as renal malignancy detection, hyperparameter selection plays a vital part in determining the quality of CNNs. By integrating WaOA, hyperparameters of ResNet-50 can be fine-tuned to achieve optimal classification accuracy and robustness. Hyperparameter tuning is a mind boggling problem in deep learning as it directly impacts model accuracy, convergence speed, and generalization ability. Tradi-tional methods normally gets struck in local minima, while other heuristic algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) often suffer from premature convergence. WaOA pro-vides a better global search strategy, preventing local minima stagnation and ensuring more effective tun-ing of hyperparameters. WaOA mimics the group foraging behavior of walruses, where individuals in a herd search for food while maintaining an optimal balance between exploration (searching new areas) and exploitation (refining existing solutions).

The optimization process in the Walrus Optimization Algorithm (WaOA) consists of three main phases. In the Exploration Phase (Global Search), walruses search for food sources, representing potential hyperpa-rameter sets, across a wide range to ensure diverse solutions and prevent premature convergence to suboptimal configurations.

Once promising hyperparameter values are identified, the process transitions into the Exploitation Phase (Local Refinement), where walruses refine their search within the nearby region to fine-tune performance, enabling the model to settle on optimal parameters such as learning rate, batch size, and dropout rate. Finally, the Dynamic Adaptive Strategy controls the transition between exploration and exploitation based on a fitness function that evaluates model performance metrics, ensuring a balanced and efficient optimization process. The weight and bias learning rate hyperparameters of ResNet-50 were optimized using WaOA to enhance renal malignancy classification. Each hyperparameter set was evaluated using a fitness function based on model accuracy, precision, recall, and log loss. Each deep learning model was trained using the Adam optimizer with Cross-Entropy Loss as the loss function. A batch size of 32 and a total of 100 epochs were used to ensure stable learning.

Figure 2 shows the flowchart of the proposed Walrus Optimization Algorithm (WaOA) for Hyperparameter Tuning of ResNet-50 in Renal Malignancy Detection. Flowchart begins by initializing a population of can-didate hyperparameter sets, evaluating their fitness using classification metrics, and iteratively updating them through walrus-inspired behaviors social interaction (movement towards the best solution), foraging (balancing exploration and exploitation), and adaptive swimming strategies (dynamic adjustments to avoid local optima). The process continues until convergence, ensuring an optimized hyperparameter con-figuration that improves model accuracy, robustness, and generalization.

To assess model performance, several evaluation metrics were employed. Accuracy measured the proportion of correct predictions, while precision evaluated how many positive classifications were correct. Recall determined the model's effectiveness in detecting malignant cases, and the F1-score, being the har-monic mean of precision and recall, ensured a balanced evaluation. Specificity measured the ability to correctly classify benign cases, while the AUC-ROC curve provided insights into classification performance across different thresholds. The Matthews Correlation Coefficient (MCC) was used to assess overall relia-bility, whereas log loss quantified prediction uncertainty. Finally, inference time was recorded to evaluate the model's efficiency in real-

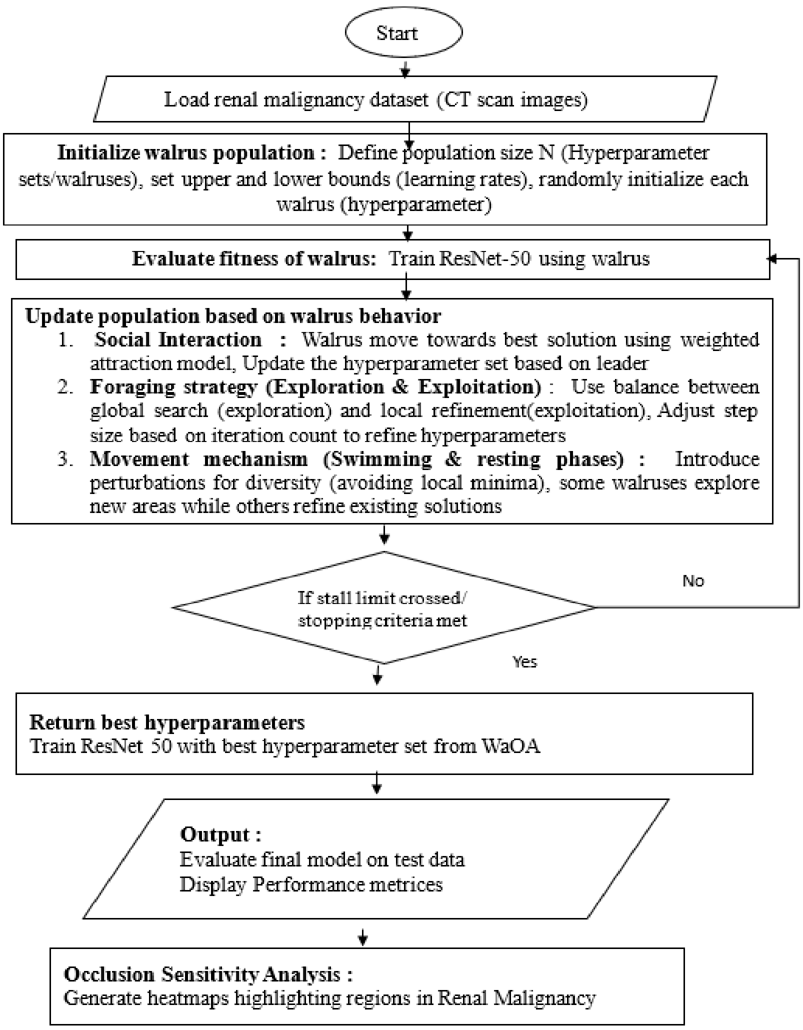

Figure 2. Flowchart of Proposed Walrus Optimization Algorithm (WaOA) for Hyperparameter Tuning of ResNet-50 in Renal Malignancy Detection. Workflow diagram illustrating the hyperparameter optimization process using the Walrus Optimization Algorithm (WaOA) for ResNet-50 training on a renal malignancy dataset, followed by model evaluation and occlusion sensitivity analysis for interpretability.

time prediction, ensuring practical applicability in clinical settings.

Data Validation

The robustness of the proposed methodology is ensured through a systematic validation strategy, including an 80-10-10 split for training, validation, and testing, which provides a balanced evaluation frame-work. The use of data augmentation techniques such as flipping, rotation, and brightness adjustment en-hances the diversity of training samples and mitigates overfitting. Furthermore, model performance was evaluated using multiple comprehensive metrics including accuracy, precision, recall, F1-score, specifici-ty, AUC-ROC, MCC, log loss, and inference time to ensure consistent and meaningful assessment across diverse aspects of classification. These measures collectively validate the generalization capability and reliability of the WaOA-optimized ResNet-50 model for renal malignancy detection.

AI Interpretability Analysis

The Walrus Optimization Algorithm (WaOA) for Hyperparameter Tuning of ResNet-50 in Renal Malignancy Detection integrates an AI interpretability approach using Occlusion Sensitivity Analysis to enhance model transparency and diagnostic reliability. WaOA optimizes key hyperparameters such as weight and bias learning rate, ensuring ResNet-50 achieves high classification accuracy with minimal overfitting. Once trained with the optimal hyperparameters, Occlusion Sensitivity Analysis is used to interpret the model's decision-making process by systematically occluding (masking) different image regions and analyzing the impact on classification confidence. This technique highlights the most influential areas in renal tumor images that contribute to malignancy predictions, providing critical insights into whether the model fo-cuses on medically relevant regions such as tumor boundaries or artifacts. By integrating WaOA with AI interpretability, the approach ensures that hyperparameter optimization not only improves model accu-racy but also enhances trustworthiness in clinical decision-making, aiding radiologists in understanding the reasoning behind AI-based renal malignancy detection.

Results

The results and analysis provide an in-depth comparison of multiple DL methods AlexNet, GoogLeNet, Inception V3, and ResNet-50 evaluated for renal malignancy detection. Additionally, the impact of hy-perparameter tuning using the Walrus Optimization Algorithm (WaOA) on ResNet-50 is assessed to de-termine its effectiveness in enhancing classification performance. The confusion matrices highlight the predictive capabilities of each model, revealing variations in classification accuracy across different renal conditions, including cysts, normal tissues, stones, and tumors.

Confusion matrices presented in Figure 3 provide a detailed insight into the classification performance of different DL methods for renal malignancy detection. AlexNet demonstrates reasonable performance but exhibits higher misclassification rates, particularly in distinguishing between cysts and stones. GoogLeNet shows significant improvement, reducing misclassifications, especially in detecting cysts and tumors, alt-hough some confusion persists between normal tissues and tumors. Inception V3 further enhances classi-fication accuracy, minimizing errors in cyst and tumor detection, but still struggles with distinguishing between normal and stone cases. ResNet-50 achieves better precision in most categories; however, some misclassification remains, particularly in differentiating normal tissues from other categories. The pro-posed Walrus Optimization Algorithm (WaOA)-optimized ResNet-50 further refines the classification pro-cess, reducing false positives and improving tumor detection accuracy.

The optimized model demonstrates better generalization, correctly identifying more cases while maintain-ing a balanced sensitivity and specificity across all classes, making it the most effective approach for renal malignancy classification.

Table 1 presents the performance evaluation of deep learning models AlexNet, GoogLeNet, Inception V3, and ResNet-50 and highlights their classification effectiveness in renal malignancy detection. Among these models, Inception V3 initially demonstrates the highest accuracy and F1-score, but ResNet-50 shows a decline in performance before being optimized using the

Table 1. Comparative Analysis of Deep Learning Models for Renal Malignancy Detection

Performance metrices	AlexNet	Googlenet	Inception V3	Resnet 50	Walrus Optimization Algorithm (WaOA) based parameter optimization of ResNet50
Accuracy	90.47%	92.16%	93.77%	90.51%	94.53%
Precision	89.77%	92.12%	94.41%	89.26%	93.28%
Recall	86.22%	88.42%	88.66%	87.88%	91.32%
F1 Score	87.49%	89.24%	90.76%	88.14%	92.16%
Specificity	96.49%	97.36%	97.68%	96.81%	98.06%
AUC-ROC	98.60%	99.27%	99.22%	98.11%	99.33%
w	0.8464	0.8729	0.8916	0.8523	0.9038
Log Loss	0.2687	0.228	0.1891	0.2837	0.1597
Average Inference Time (sec)	0.04566	0.096191	0.7401	0.0499	0.1133

Performance metrics (accuracy, precision, and recall) are compared across AlexNet, GoogLeNet, Inception V3, ResNet-50, and a Walrus Optimization Algorithm (WaOA)-based parameter-tuned model. Results demonstrate improved performance with optimization-based fine-tuning.

Figure 3. Confusion Matrices of Conventional Pretrained Networks and Proposed WaOA Optimized Resnet50 for Renal Malignancy Detection

Walrus Optimization Algorithm (WaOA). The WaOA-based ResNet-50 achieves the best overall results, with improved accuracy (94.53%), precision (93.28%), recall (91.32%), and specificity (98.06%), demonstrating superior classification capability. The highest AUC-ROC (99.33%) confirms its enhanced discriminatory power, while the lowest log loss (0.1597) signifies greater model confidence. Although WaOA optimization slightly increases inference time, it sig-nificantly refines ResNet-50's robustness, making it the most reliable model for renal malignancy detec-tion. These findings validate the effectiveness of metaheuristic-based hyperparameter tuning in deep learning applications for medical diagnosis.

The bar chart shown in Figure 4 illustrates the comparative performance of five deep learning models AlexNet, GoogLeNet, Inception V3, ResNet-50, and WaOA-optimized ResNet-50 across key classification metrics: Accuracy, Precision, Recall, F1 Score, Specificity, and AUC-ROC. The trend indicates a progressive improvement in performance as the models advance, with

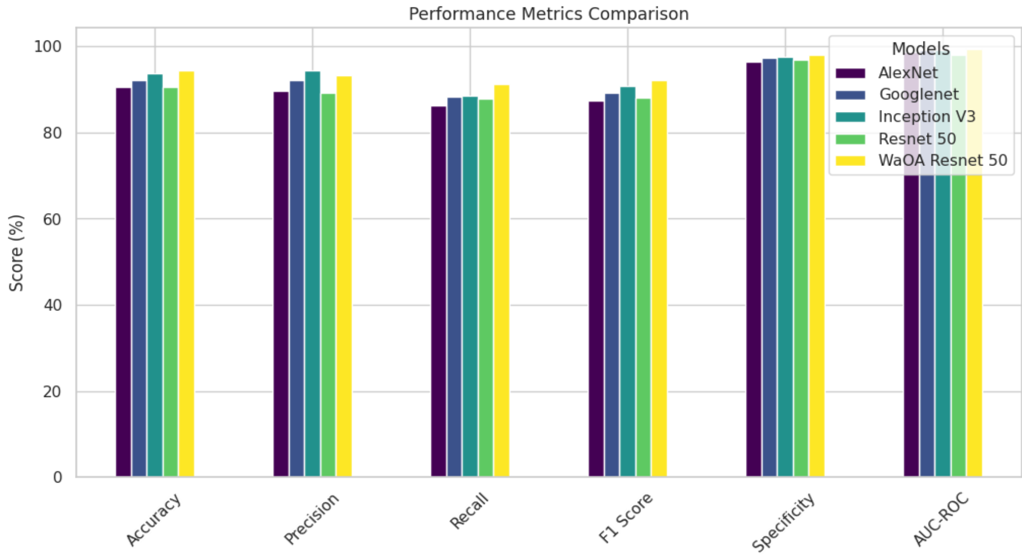

Figure 4. Comparison of Performance Metrices of the Conventional Deep Learning Models and the Proposed WaOA Optimized ResNet-50. Comparative bar chart of classification performance across five deep learning models AlexNet, GoogLeNet, Inception V3, ResNet-50, and WaOA-optimized ResNet-50 evaluated using metrics such as Accuracy, Precision, Recall, F1 Score, Specificity, and AUC-ROC, highlighting the superior performance of the WaOA-optimized ResNet-50.

Inception V3 and ResNet-50 showing strong baseline performance before WaOA-based ResNet-50 achieves the highest scores across all metrics.

The WaOA-optimized ResNet-50 (yellow bars) consistently outperforms other models, demonstrating the effectiveness of metaheuristic hyperparameter tuning. Notably, the highest gains are observed in Recall and F1-score, signifying improved sensitivity and balanced classification. Additionally, the AUC-ROC of WaOA ResNet-50 approaches near-perfect levels, confirming its superior ability to distinguish between different renal malignancy classes. These results highlight the impact of intelligent optimization tech-niques in enhancing deep learning models for medical diagnosis.

The bar chart shown in Figure 5 presents a comparative analysis of Matthews Correlation Coefficient (MCC) and Log Loss across five deep learning models AlexNet, GoogLeNet, Inception V3, ResNet-50, and WaOA-optimized ResNet-50 for renal malignancy detection. MCC, which measures the overall quality of classification considering true and false positives/negatives, shows an increasing trend across the models, with WaOA-optimized ResNet-50 achieving the highest MCC, indicating superior predictive reliability.

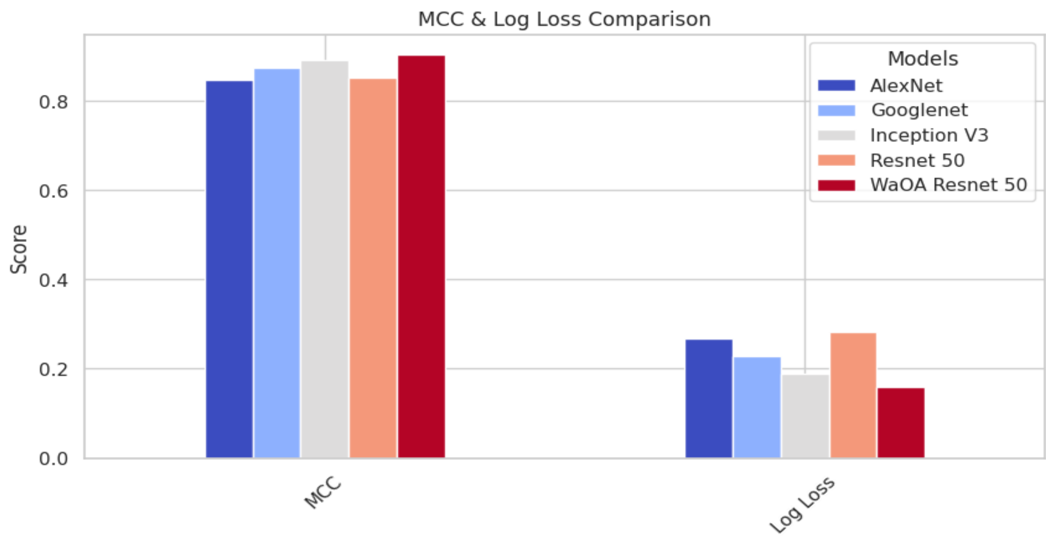

Figure 5. Comparison of MCC and Log Loss. Figure 5 illustrates the comparison of Matthews Correlation Coefficient (MCC) and Log Loss across five deep learning models for renal malignancy detection. The WaOA-optimized ResNet-50 model achieves the highest MCC and lowest Log Loss, reflecting improved classification reliability and reduced prediction uncertainty, thereby highlighting the effectiveness of WaOA-based optimization in enhancing diagnostic performance.

Conversely, Log Loss, which quantifies prediction uncertainty, exhibits a decreasing trend, with WaOA ResNet-50 having the lowest Log Loss, signifying more confident and accurate predictions. The WaOA-based optimization effectively enhances classification robustness by improving MCC while simultaneously reducing Log Loss, demonstrating its efficacy in fine-tuning deep learning models for improved medical diagnosis.

The bar chart shown in Supplementary Figure 1 illustrates the average inference time of five deep learning models AlexNet, GoogLeNet, Inception V3, ResNet-50, and WaOA-optimized ResNet-50 used for renal malignancy detection. Among these models, Inception V3 exhibits the highest inference time, significantly surpas-sing the others, indicating a more complex architecture and computational demand. AlexNet and Goog-LeNet have the shortest inference times, reflecting their lightweight structures, but this comes at the cost of lower classification performance. ResNet-50 shows a moderate inference time, while the WaOA-optimized ResNet-50 incurs a slight increase in inference time compared to the baseline ResNet-50 due to additional computational overhead from optimized hyperparameters. However, this trade-off is justified by the substantial improvements in classification accuracy and robustness. Overall, the results highlight the balance between model complexity and efficiency, with WaOA-based ResNet-50 achieving the best compromise between inference speed and predictive performance.

The heatmap shown in Supplementary Figure 2 visually represents the performance metrics of five deep learning models AlexNet, GoogLeNet, Inception V3, ResNet-50, and WaOA-optimized ResNet-50 for renal malignan-cy detection. The color gradient highlights the variations in metric values, with darker red shades indicating higher performance and blue shades representing lower values. WaOA-optimized ResNet-50 consist-ently outperforms all other models, achieving the highest accuracy (94.53%), precision (93.28%), recall (91.32%), and F1-score (92.16%), demonstrating its superior classification ability. It also achieves the highest specificity (98.06%) and AUC-ROC (99.33%), signifying its strong ability to distinguish between different renal malignancy categories. Inception V3 and GoogLeNet also show competitive performance, while AlexNet and ResNet-50 (without optimization) lag slightly behind in key metrics. The heatmap effectively highlights the impact of metaheuristic optimization (WaOA) in enhancing ResNet-50's predictive accuracy and robustness, making it the most reliable model for renal malignancy classification.

Supplementary Figure 3 presents AI interpretation using Occlusion Sensitivity Analysis for renal malignancy detection, highlighting model decision-making for different conditions: Cyst, Normal, Stone, and Tumor. Each row consists of a grayscale CT scan image on the left and its corresponding occlusion sensitivity map on the right, where color gradients indicate regions most influential in the model's classification. Red and yellow regions signify areas of high importance, while blue and green regions indicate lower contributions. For cyst detection, the model focuses on upper abdominal regions, whereas in the normal case, the activation is minimal, confirming the absence of abnormalities.

In renal stones, high sensitivity regions are concentrated around the kidney area, while for tumors, the model emphasizes mass-like structures, aligning with clinical expectations. This interpretability technique enhances model transparency, providing critical insights into the AI decision-making process, ensuring trustworthiness and clinical relevance in renal disease classification.

Discussion

The primary hypothesis of this research is that the classification performance of deep learning models for renal malignancy detection can be significantly enhanced through metaheuristic-based hyperparameter tuning. The objective of optimizing ResNet-50 using the Walrus Optimization Algorithm (WaOA) is directly aligned with this hypothesis, as it seeks to validate whether such optimization yields superior diagnostic accuracy, robustness, and generalization compared to conventional models. By systematically evaluating the performance of WaOA-optimized ResNet-50 against established CNN architectures (AlexNet, Goog-LeNet, Inception V3, and baseline ResNet-50), and incorporating Occlusion Sensitivity Analysis for inter-pretability, the study confirms that metaheuristic-driven fine-tuning can effectively address the limita-tions of standard deep learning models in medical image analysis. Thus, the results support the hypothe-sis, demonstrating that AI models enhanced through intelligent optimization offer improved diagnostic utility in clinical applications.

This study presented an advanced deep learning approach for renal malignancy detection, leveraging ResNet-50 with Walrus Optimization Algorithm (WaOA)-based hyperparameter tuning to enhance classifi-cation performance. The results demonstrated that WaOA-optimized ResNet-50 outperformed traditional deep learning models—AlexNet, GoogLeNet, Inception V3, and standard ResNet-50—in terms of accuracy, precision, recall, F1-score, specificity, and AUC-ROC, confirming its superior predictive capabilities. The confusion matrices highlighted the model's ability to minimize misclassification errors, ensuring improved sensitivity in detecting renal abnormalities. Additionally, Occlusion Sensitivity Analysis provided inter-pretability, making the AI model more transparent and clinically reliable by visualizing the most influen-tial regions in CT scans for decision-making. Despite these promising outcomes, minor trade-offs in infer-ence time were observed due to the computational overhead of optimized hyperparameters. Nonethe-less, the study validated the effectiveness of metaheuristic-based hyperparameter tuning, demonstrating its potential in enhancing deep learning models for medical diagnosis.

Although this study focused exclusively on CT scan imagery optimized via the Walrus Optimization Algo-rithm (WaOA), future advancements can explore the implementation of multimodal learning by integrat-ing diverse data sources such as histopathological images, genomic profiles, and clinical records. Such integration can significantly enhance the robustness and contextual relevance of AI-driven renal malig-nancy classification. For example, combining radiological features with tissue-level morphological details from histopathology and molecular insights from genetic data may facilitate early-stage tumor detection and comprehensive disease profiling. Furthermore, incorporating patient-specific clinical parameters, in-cluding demographic details, laboratory reports, and medical history, can provide critical context to mod-el predictions, reducing false positives and supporting precision diagnostics. The development of deep learning frameworks capable of assimilating and analyzing heterogeneous multimodal datasets will be pivotal in advancing toward real-time clinical deployment, personalized medicine, and more accurate, explainable AI applications in renal oncology. Real-time deployment in a clinical decision support system and validation on larger, multi-institutional datasets will further establish the model's robustness and practical applicability in healthcare.

Author Contribution Statement

As a single-author manuscript, all components of the study including conceptualization, methodology, implementation, analysis, interpretation, and manuscript writing were solely undertaken by the author.

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General

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Scientific Approval

This work was conducted as part of an approved faculty-led research project within Saveetha Engineering College. It is not associated with a student thesis submission or review by any external scientific body.

Data Availability

The dataset used in this study, titled "Medical Imaging (CT scan, MRI, X-ray, and Microscopic Imagery) Data", is publicly available at Mendeley Data [https://data.mendeley.com/datasets/5kbjrgsncf/3], under a CC BY 4.0 license.

Study Registration

Not applicable. This study does not involve clinical trials or patient registration and was not submitted to a clinical study registry.

Ethical Declaration

This study involved retrospective analysis of openly available and anonymized medical imaging datasets and did not require patient consent or direct ethical clearance. The dataset used complies with public data usage standards under Creative Commons Attribution 4.0 International License. Therefore, ethical approval from a specific institutional review board was not required.

Conflict of Interest

The author declares no conflict of interest.

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