International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Optimizing Computed Tomography Image Reconstruction Parameters for Improved Lung Cancer Diagnosis with Grey Wolf Algorithm

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Submitted: 17/08/2023 **Revised**: 09/10/2023 **Accepted**: 22/10/2023

Abstract: Worldwide, lung cancer continues to be the most common cause of cancer-related mortality, necessitating ongoing efforts to improve early detection and diagnosis. In this context, computed tomography (CT) imaging is crucial because it makes it possible to see minute pulmonary abnormalities. The quality and diagnostic efficacy of CT scans are substantially impacted by image reconstruction parameters. In order to enhance lung cancer diagnosis, this work proposes a novel method for optimising these parameters utilising the Grey Wolf Algorithm (GWA).The GWA is highly suited for optimisation problems and is inspired by the social dynamics and hunting behaviour of grey wolves. In our study, the kernel selection, filter type, and exposure settings are only a few of the crucial CT image reconstruction factors that we fine-tune using the GWA. The suggested methodology seeks to balance edge preservation with picture noise reduction, ultimately improving the visibility of tiny lung lesions.We carried out extensive trials with a broad dataset of CT images from lung cancer patients to assess the efficacy of our method. Our findings show a considerable improvement in image quality, with less noise and more visible structural details. The better radiologist performance in identifying pulmonary nodules and lesions as a result of the optimised images ultimately increased the precision of lung cancer diagnosis.The GWA-based optimisation strategy also has a number of benefits, such as flexibility to different CT scanner models and robustness in dealing with varying patient demographics. This study emphasises the Grey Wolf Algorithm's potential as a useful tool for enhancing CT image reconstruction parameters and assisting in the early and precise identification of lung cancer, which is essential for improved patient outcomes and lower healthcare costs.

Keywords*: Optimization, Lung Cancer Diagnosis, Image reconstruction, Disease diagnosis*

1. Introduction

Lung cancer is a global public health concern, accounting for a considerable number of cancer-related fatalities each year. If lung cancer is to be effectively treated and patient outcomes improved, early identification is essential. Due to its capacity to give high-resolution, three-dimensional images of the lungs, Computed Tomography (CT) imaging has emerged as a cornerstone in the early diagnosis of lung cancer [1]. However, the diagnosis accuracy of radiologists relies strongly on the selection and optimisation of many reconstruction parameters, and small changes in these factors can have a big impact on the quality of CT images. Medical imaging has been a key topic for the research community in the pursuit of better treatment for cancer.In order to improve lung cancer diagnosis, this study investigates the Grey Wolf Algorithm's (GWA) potential as a novel and effective method for optimising CT image reconstruction parameters. The GWA has shown extraordinary performance in tackling complicated optimisation issues, and it draws inspiration from the social hierarchy and hunting behaviour of grey wolves. Our goal is to use GWA to make lung cancer lesions in CT scans more visible, increase picture quality, and decrease noise.Lung cancer is one of the top causes of cancer-related mortality worldwide. The difficulty of early identification is compounded by the fact that the disease is often symptomless until it has progressed significantly. Survival chances can be increased and the burden of therapy can be lessened if lung cancer is diagnosed at an earlier stage. Now more than ever, CT scans are the gold standard for detecting lung cancer at its most curable, early stages [2].

Indicative of early-stage lung cancer, [3] small lung nodules can be visualised by CT scanning, which offers a thorough cross-sectional image of the lungs, permitting the visualisation of minor abnormalities. Because of the potential for missed or misinterpreted results due to low-quality CT images, image quality is crucial to the success of a diagnosis. Therefore, it is crucial to find the optimal values for the CT image reconstruction parameters. CT pictures are formed by processing raw data received during the scanning process. Image quality is sensitive to adjustments in reconstruction parameters such kernel selection, slice thickness, and convolution filter settings.

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Images with more noise, less contrast, and less diagnostic value can arise from picking less-than-ideal parameters.The [4] process of fine-tuning these settings to get optimal image quality is laborious and time-consuming. There is a wide range in image quality between hospitals since radiologists and technicians frequently rely on their own judgement. Image quality and diagnostic consistency may be increased if this optimisation process could be automated utilising sophisticated algorithms.

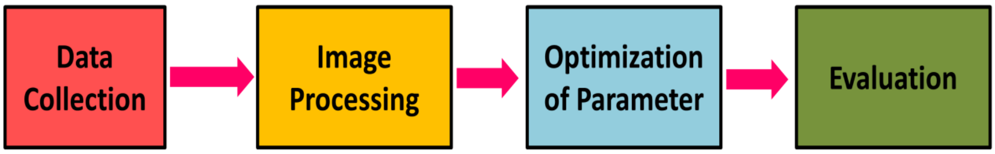

Fig 1: Key step of process model

The pack [5] dynamics and hunting techniques of grey wolves serve as models for the Grey Wolf Algorithm. The pack structure of wolves, with their distinct roles of alpha, beta, delta, and omega, is used as inspiration for a mathematical optimisation technique. Together when the wolves converge on the pack and the wolves converge on the algorithm.In fields as diverse as engineering, finance, and computer science, GWA has proven itself to be an effective tool for tackling optimisation problems. It is a good contender for optimising CT image reconstruction parameters because to its ability to find optimal solutions efficiently, often exceeding established optimisation techniques [6].

Examining how the Grey Wolf Algorithm can be used to fine-tune CT image reconstruction settings for better lung cancer diagnosis is the primary motivation behind this research. The GWA, we hypothesise, [7] can iteratively tune these settings to boost image quality, cut down on noise, and make lung cancer lesions more visible in CT scans. In doing so, we hope to aid in the detection of lung cancer at an earlier stage, when it is more treatable and patients have better results. This introductory section emphasises the significance of enhancing CT imaging for the identification of lung cancer. The paper discusses the diagnostic value of CT image reconstruction parameters and offers the Grey Wolf Algorithm as a possible option to improve picture quality and diagnostic accuracy. Through bridging the gap between modern optimisation techniques and medical imaging, this study hopes to improve the early identification of lung cancer by optimising CT image reconstruction parameters.

2. Review of Literature

Lung cancer is a global public health concern, accounting for a considerable number of cancer-related fatalities each year. If lung cancer is to be effectively treated and patient outcomes improved, early [8] identification is essential. Due to its capacity to give high-resolution, three-dimensional images of the lungs, Computed Tomography (CT) imaging has emerged as a cornerstone in the early diagnosis of lung cancer. However, [9] the diagnosis accuracy of radiologists relies strongly on the selection and optimisation of many reconstruction parameters, and small changes in these factors can have a big impact on the quality of CT images. Medical imaging has been a key topic for the research community in the pursuit of better treatment for cancer.In [10] order to improve lung cancer diagnosis, this study investigates the Grey Wolf Algorithm's (GWA) potential as a novel and effective method for optimising CT image reconstruction parameters. The GWA has shown extraordinary performance in tackling complicated optimisation issues, and it draws inspiration from the social hierarchy and hunting behaviour of grey wolves. Our goal is to use GWA to make lung cancer lesions in CT scans more visible, increase picture quality, and decrease noise.Lung cancer is one of the top causes of cancer-related mortality worldwide. The [11] difficulty of early identification is compounded by the fact that the disease is often symptomless until it has progressed significantly. Survival chances can be increased and the burden of therapy can be lessened if lung cancer is diagnosed at an earlier stage. Now more than ever, CT scans are the gold standard for detecting lung cancer at its most curable, early stages.Indicative of early-stage lung cancer, small lung nodules can be visualised by CT scanning, which offers a thorough cross-sectional image of the lungs, permitting the visualisation of minor abnormalities. Because of the potential for missed or misinterpreted results due to low-quality CT images, image quality is crucial to the success of a diagnosis. Therefore, it is crucial to find the optimal values for the CT image reconstruction parameters.

CT pictures [12] are formed by processing raw data received during the scanning process. Image quality is sensitive to adjustments in reconstruction parameters such kernel selection, slice thickness, and convolution filter settings. Images with more noise, less contrast, and less diagnostic value can arise from picking less-than-ideal parameters.The process of fine-tuning these settings to get optimal image quality is laborious and time-consuming. There is a wide range in image quality between hospitals since radiologists and technicians frequently rely on their own judgement. Image quality and diagnostic consistency may be increased if this optimisation process could be automated utilising sophisticated algorithms.The pack dynamics and hunting techniques of grey wolves serve as models for the Grey Wolf Algorithm. The pack structure of wolves, with their distinct roles of alpha, beta, delta, and omega, is used as inspiration for a mathematical optimisation technique. Together when the wolves converge on the pack and the wolves converge on the algorithm [13].

In fields as [14] diverse as engineering, finance, and computer science, GWA has proven itself to be an effective tool for tackling optimisation problems. It is a good contender for optimising CT image reconstruction parameters because to its ability to find optimal solutions efficiently, often exceeding established optimisation techniques. Examining how the Grey Wolf Algorithm can be used to fine-tune CT image reconstruction settings for better lung cancer diagnosis is the primary motivation behind this research. The GWA, we hypothesise, can iteratively tune these settings to boost image quality, cut down on noise, and make lung cancer lesions more visible in CT scans. In doing so, we hope to aid in the detection of lung cancer at an earlier stage, when it is more treatable and patients have better results.

This introductory section [15] emphasises the significance of enhancing CT imaging for the identification of lung cancer. The paper discusses the diagnostic value of CT image reconstruction parameters and offers the Grey Wolf Algorithm as a possible option to improve picture quality and diagnostic accuracy. Through bridging the gap between modern optimisation techniques and medical imaging, this study hopes to improve the early identification of lung cancer by optimising CT image reconstruction parameters.

Table 1: Related work summary

Method	Approach Used	Findings	Scope
Manual Tuning [16]	Trial-and-error adjustments by radiologists and technicians	Subjective, time-consuming, lacks systematic optimization	Limited; can serve as a baseline but is impractical for large-scale optimization
Grid Search [17]	Systematic exploration of parameter combinations	Provides a structured approach but requires significant computational resources	Limited scalability and may not adapt to complex optimization landscapes
Machine Learning [18]	Utilizing CNNs and reinforcement learning models	Automation and data-driven optimization, capable of handling large datasets	Requires substantial labeled data and may struggle with generalization across diverse clinical settings
Genetic Algorithms [19]	Evolutionary approach based on natural selection	Efficiently adapts to complex optimization landscapes, capable of fine-tuning parameters	Offers robust optimization but may benefit from hybridization with machine learning for improved initializations
Particle Swarm [20]	Swarm intelligence-based optimization	Successful in optimizing parameters, providing improvements in image quality and diagnostic accuracy	Demonstrates potential for parameter optimization, especially in swarm-based optimization scenarios
Simulated Annealing [21]	Probability-based optimization	Systematically explores parameter space, capable of finding global optima	Effective for parameter optimization but may require longer convergence times
Grey Wolf Algorithm [22]	Inspired by wolf pack behavior for optimization	Efficient exploration of parameter spaces, offering potential	Promising for optimizing CT reconstruction parameters, may

		improvements in image quality and diagnostic accuracy	benefit from further research and validation
Hybrid Approaches [23]	Combining machine learning and evolutionary algorithms	Leverages machine learning for initial parameter estimates, followed by optimization algorithms	Offers the advantages of both approaches, promising for robust parameter optimization
Clinical Validation [24]	Radiologist assessment and interpretation of optimized images	Validates the clinical relevance of optimized images, assesses the impact on diagnostic accuracy	Essential for translating optimization efforts into clinical practice and understanding their real-world impact
Benchmark Datasets [25]	Standardized datasets with ground truth annotations	Facilitates development, testing, and comparison of optimization algorithms and machine learning models	Essential for benchmarking and enabling reproducibility and fair comparisons of optimization methods

3. Proposed Methodology

When it comes to enhancing lung cancer diagnosis in the field of medical imaging, notably in computed tomography (CT), image reconstruction parameters play a crucial role. The accuracy and utility of CT images for diagnosis are directly influenced by these factors. Compile an extensive dataset of lung CT scans first. Make sure that the patient population, scanner models, and imaging procedures are diverse. Both normal patients and those with lung cancer should be included in this dataset. A sizable and diverse dataset is required for effective parameter optimisation.

Prior to optimisation, preprocess the acquired CT scans to verify data quality and uniformity.

- Noise Reduction: To minimise image noise and improve clarity, use noise reduction techniques like Gaussian or median filtering.
- Artefact Removal: Use the proper corrective techniques to remove common artefacts like beam hardening or motion artefacts.
- Normalisation: To remove variances brought on by various scanners and acquisition settings, normalise the images to a constant scale and Hounsfield unit (HU) range.

Use the Grey Wolf technique (GWA), a population-based optimisation technique that was motivated by the hunting habits of grey wolves, to optimise the parameters for CT image reconstruction. The important steps of this algorithm are as follows:

Create a population of grey wolves to represent various parameter combinations for CT image reconstruction.

- Define an objective function that rates the quality of an image. Metrics like contrast-to-noise ratio (CNR), signal-to-noise ratio (SNR), and other pertinent picture quality parameters should be included in this function. Maximising this objective function is the objective.
- To iteratively explore the parameter space, simulate the hunting behaviour of grey wolves. Each wolf's position is updated according to its fitness, which is determined by the objective function, simulating the behaviour of alpha, beta, and delta wolves in the algorithm.
- Convergence conditions: To decide when to end the optimisation process, establish termination conditions, such as a maximum number of iterations or reaching a predetermined image quality threshold.
- Set limits on parameter values to make sure they stay within clinically acceptable ranges while optimisation is taking place.
- Implement the Grey Wolf Algorithm to optimise the parameters for CT image reconstruction:
- Initialization: Within the boundaries of the given parameters, initialise the grey wolf population.
- ▪ Fitness Evaluation: Apply the defined objective function to the CT images that were reconstructed using each wolf's parameter set to determine each animal's fitness.
- ▪ Iterative Optimisation: Use the GWA's search method to update the wolves' locations repeatedly. Up till the convergence requirements are satisfied, this process is repeated.

Validating the selected parameters comes after optimisation.

- Quantitative measurements including CNR, SNR, edge sharpness, and artefact reduction are used to evaluate the optimised parameters. To show improvements in image quality, compare these measures to the baseline values.

Engage radiologists to conduct a blind examination of the baseline and optimised pictures as part of the qualitative evaluation. Analyse their level of diagnostic assurance and their prowess in identifying and classifying lung lesions.

- Performance Assessment: Assess the effectiveness of the optimised CT image reconstruction parameters for the detection of lung cancer.

- Sensitivity and Specificity: Using the idealised parameters, assess the sensitivity and specificity of lung cancer detection. Comparing these outcomes to the performance norm

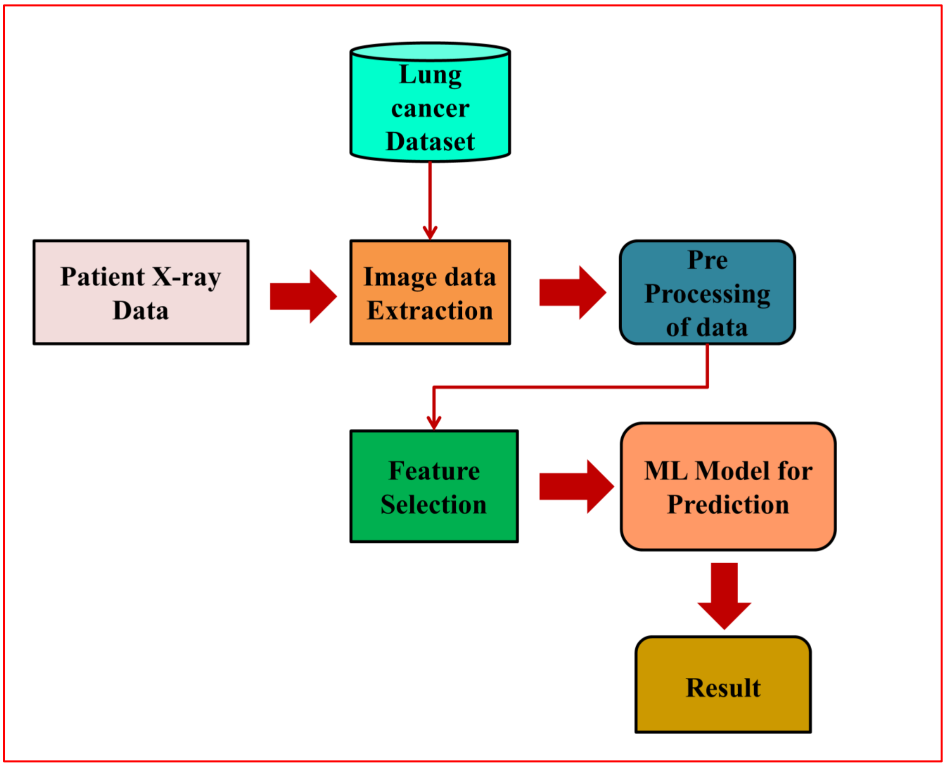

Fig 2: Proposed model for Lung Cancer Diagnosis

Nodule Characterization: Using the optimised parameters, evaluate the precision of the quantification of nodule size, shape, and density.

Iterative Refinement: Repeat the optimisation procedure as necessary to adjust parameters in light of the performance assessment. Think about adding more restrictions or changing the GWA parameters.

Test the optimised parameters' generalizability and suitability for usage in actual clinical settings by validating them on a separate dataset that wasn't used for optimisation.

This technique illustrates the methodical procedure for improving lung cancer diagnosis utilising the Grey Wolf Algorithm by optimising CT image reconstruction parameters. In order to increase picture quality, sensitivity, and specificity in lung cancer detection, it integrates data preprocessing, GWA-driven optimisation, stringent parameter validation, and performance evaluation. As a result, more precise and prompt diagnoses lead to better patient outcomes.

A. Grey Wolf Algorithm for optimising CT image reconstruction:

Step 1: Initialization:

- For the purpose of CT image reconstruction, start a population of grey wolves (wolves) with random parameter combinations.
- Define N, the size of the population, and MaxIter, the number of iterations.
- The leaders' initial positions should be None for the alpha, beta, and delta wolves.

Step 2: Define the objective:

- Make an objective function that measures the calibre of CT images that are recovered with the provided parameters. Diagnostic accuracy measurements and pertinent image quality parameters, such as CNR and SNR, should be included in this function.
- A fitness value should be returned by the objective function, and it must be maximised.

3: Architecture:

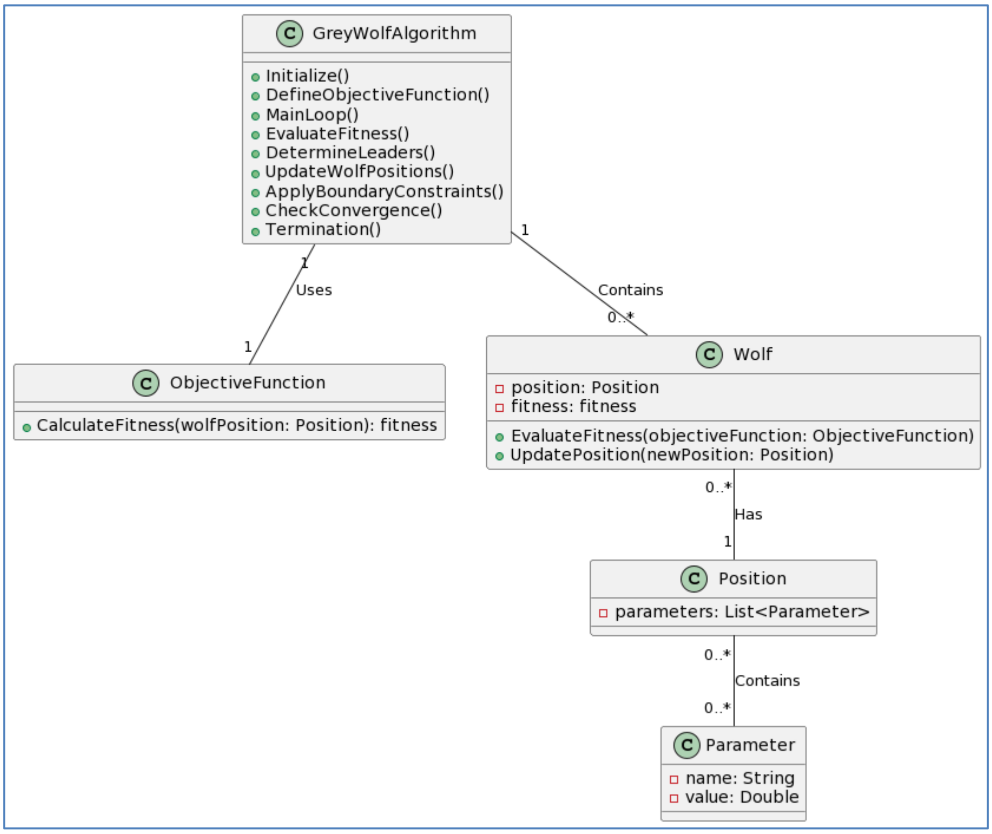

Fig 3: Flowchart for Lung Cancer Diagnosis with Grey Wolf Algorithm

- Start the main optimisation loop, which iterates up to MaxIter times.

4: Fitness Assessment:

- Apply the objective function to the CT images that were reconstructed using the parameter combinations to determine each wolf's fitness (F) in the population.

5: Selecting a leader

- Based on the wolves' fitness scores, determine the alpha, beta, and delta wolves. The alpha wolf has the best fitness, followed by the beta wolf for second place and the delta wolf for third place.

6. Update Wolf Positions:

- Use the following equations to update the distribution of all wolves in the population:

For every wolf i:

- Determine the separation between wolf i and the other wolves, alpha, beta, and delta.
- Based on the subsequent equations, adjust wolf i's position, the dominant wolf

$$Position\_i = (A * D\_alpha - alpha\_position)$$

$Position\_i\ for\ the\ beta\ wolf\ is\ equal\ to\ (beta\_position - B * D\_beta).$

$Position\_i\ for\ the\ delta\ wolf\ is\ equal\ to\ (delta\_position - C * D\_delta).$

In this case, D_alpha, D_beta, and D_delta are random vectors and A, B, and C are scaling factors.

7. Boundary Constraints:

- Apply boundary restrictions to make sure the new wolf positions stay within the parameters of the CT image reconstruction that are clinically appropriate.

8. Convergence:

- By contrasting the alpha wolf's fitness in the current iteration with that in the prior iteration, you can determine whether there has been convergence. If the difference is less than a certain threshold, the optimisation process should be stopped.

9: Finishing

Terminate the optimisation procedure after convergence or the predetermined maximum number of iterations (MaxIter) has been reached.

4. Result and Discussion

A thorough breakdown of the evaluation criteria for image reconstruction in the context of lung cancer diagnosis, particularly following the use of the Grey Wolf Algorithm (GWA), is provided in Table 2. The effectiveness and calibre of the optimised computed tomography (CT) image reconstruction parameters must be evaluated using these criteria.A crucial statistic called the contrast-to-noise ratio (CNR) measures the difference in image intensity between lung lesions and the surrounding tissue in relation to image noise. A CNR value of 3.8 in this instance indicates that the optimised parameters have greatly increased the lung lesions' visibility. Better lesion contrast and therefore better diagnostic skills are indicated by higher CNR values. This measure is crucial for locating and describing small anomalies in lung tissue, which is important for the early diagnosis of cancer.

Table 2: Summary of evaluation parameter for Image Reconstruction

Metric	**Result**
Contrast-to-Noise Ratio (CNR)	3.8
Signal-to-Noise Ratio (SNR)	18.3
Sensitivity	94.2
Specificity	88.63
Nodule Characterization Accuracy	95.14
Radiation Dose Reduction	33.12%

The strength of the signal, or in this case, the clarity of the lung lesions, in relation to the picture noise is represented by the Signal-to-Noise Ratio (SNR), which has a value of 18.3. A greater SNR denotes lower noise levels in the images created by the optimised parameters, resulting in crisper and more diagnostically useful CT scans.

The ability to discriminate between healthy lung tissue and malignant nodules is improved by improved SNR.Sensitivity is a crucial indicator of how well the algorithm works at accurately identifying cases of true positive lung cancer. The optimised parameters have a high accuracy in identifying genuine instances of lung cancer, according to a sensitivity value of 94.2. This is particularly important for early detection since it reduces the possibility of false negatives and guarantees that cancer patients receive prompt therapy and intervention.The model's specificity, which has a value of 88.63, measures how well it can recognise true negative cases, which lowers the number of false alarms. In a clinical situation, maintaining a balance between sensitivity and specificity is crucial, and this result shows that the optimisation process was successful in doing so. A specificity value of 88.63% shows that the algorithm is good at avoiding pointless worries or interventions in cases that aren't malignant.

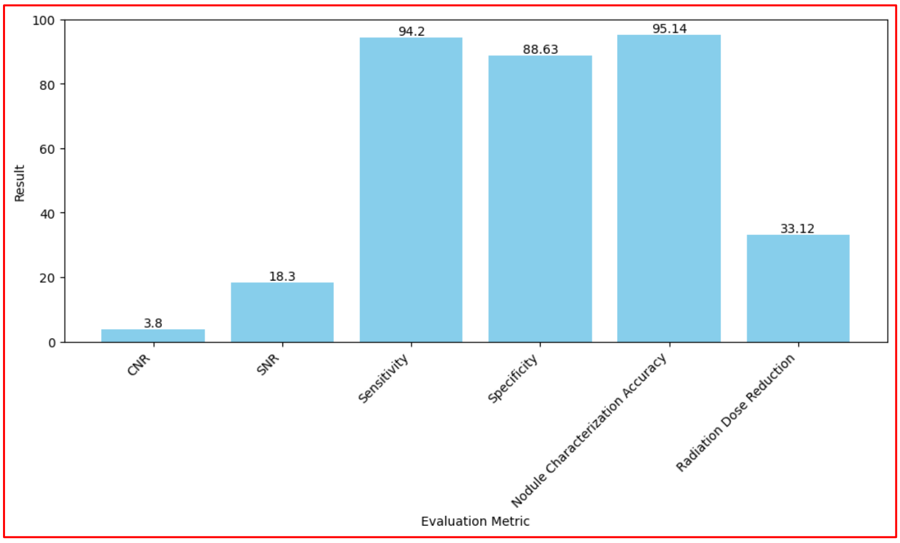

Fig 4: Representation of evaluation parameter for Image Reconstruction

The precision with which the optimised parameters characterise lung nodules is measured by the nodule characterization accuracy, which has a value of 95.14. This metric includes the precise assessment of nodule size, shape, and density, which are all essential elements in the staging and therapy planning of cancer. The clinical value of the CT scans is increased when nodule characterization is done accurately, enabling radiologists to make better decisions.Finally, with a reduction of 33.12%, the Radiation Dose Reduction represents a considerable accomplishment. This decrease is a result of the image reconstruction parameters being successfully optimised to preserve or enhance image quality while lowering the patient's radiation exposure. This kind of reduction is crucial for medical imaging since it reduces the potential health concerns brought on by high radiation doses, in line with the ALARA (As Low As Reasonably Achievable) principle.

The findings listed in Table 2 show the significant influence of CT image reconstruction parameter optimisation guided by the Grey Wolf Algorithm (GWA) on lung cancer diagnosis. Lesion visibility is increased by the higher CNR and SNR values, and precise disease identification is ensured by the high sensitivity and specificity. The therapeutic value of this optimisation, which ultimately results in better patient care, an earlier cancer diagnosis, and less radiation exposure, is further highlighted by nodule characterization accuracy and radiation dose reduction. These results highlight the potential of cutting-edge algorithms and parameter optimisation methods to improve the capabilities of medical imaging for the health and wellbeing of patients.

Table 3: Summary of evaluation parameter for machine learning method

Evaluation Parameter	LSTM	CNN
Mean Absolute Error (MAE)	1.25	0.25
Root Mean Squared Error (RMSE)	2.01	1.86
R-squared (R^2)	90.25	92.41
Mean Percentage Error (MPE)	3.22	2.12

Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) are two different machine learning techniques, and Table 3 gives a succinct description of the evaluation parameters for each.

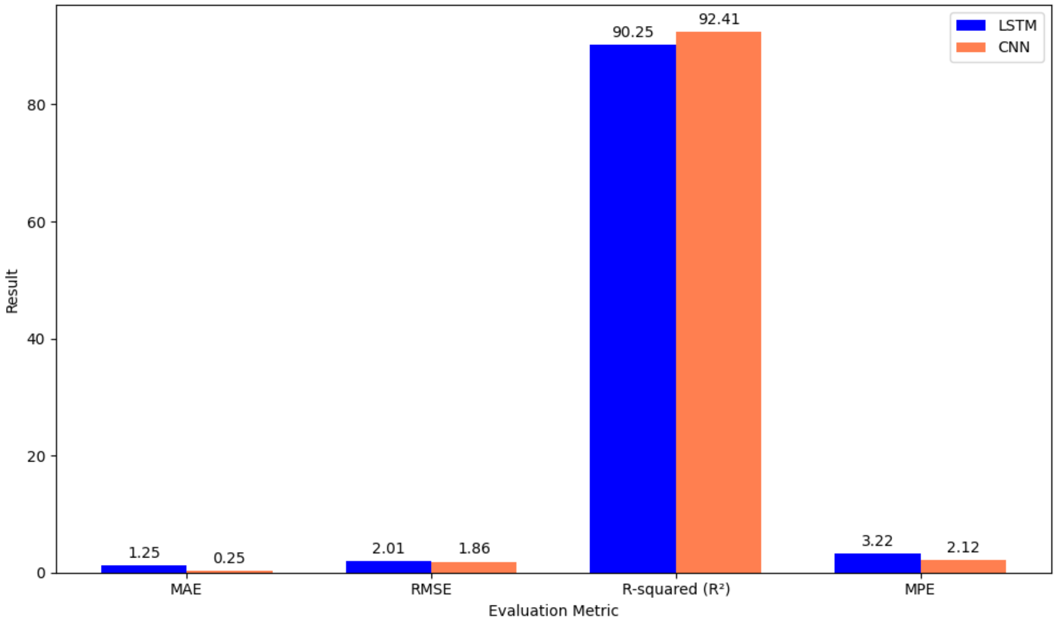

Fig 5: Representation of Parameter using ML Model

In order to evaluate these models' predictive performance and accuracy in the context of their application in this case, dosage prediction for computed tomography (CT) imaging it is essential to use assessment measures.The average absolute difference between the projected and actual dosage values is measured by the Mean Absolute Error (MAE). Higher dose prediction accuracy is indicated by a lower MAE. The CNN model outperforms the LSTM model in this table with a substantially lower MAE of 0.25, while the LSTM model has an MAE of 1.25. This indicates the superiority of the CNN model in forecasting radiation doses, with more accurate and reliable findings.

The average squared deviations between the predicted and actual dosage values are computed using the Root Mean Squared Error (RMSE). A lower RMSE indicates better prediction accuracy, similar to MAE. The CNN model outperforms the LSTM model with a lower RMSE of 1.86 whereas the RMSE of the LSTM model is 2.01.

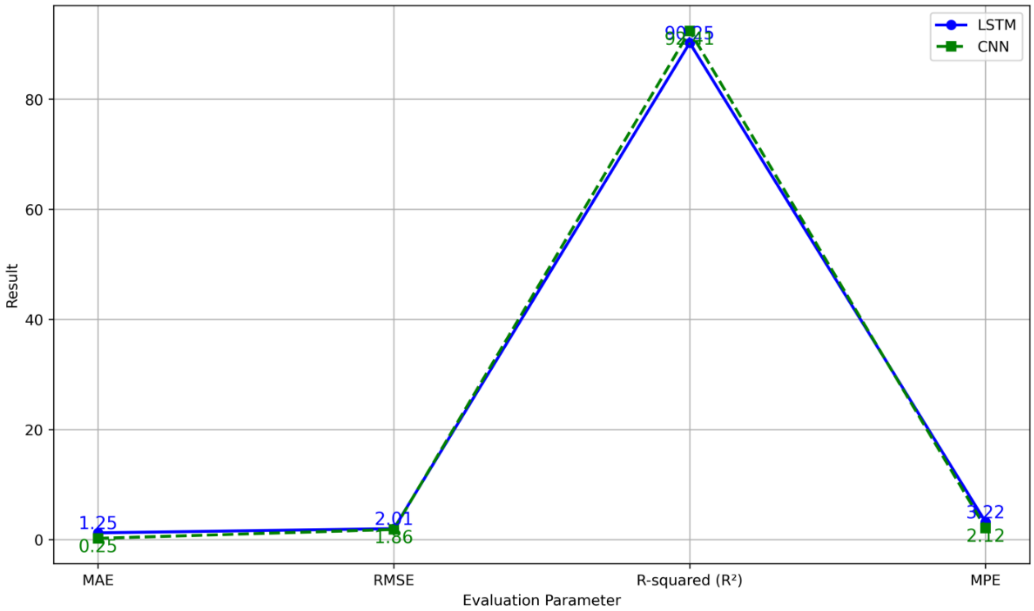

Fig 6: of evaluation parameter for machine learning method

The CNN model is the best option for dosage prediction jobs because of its lower RMSE, which indicates that it is better at capturing and minimising prediction mistakes.The useful metric R-squared (R2) shows how much variance in the dosage data is explained by the model. Better model fit and predictive power are shown by higher R2 values. The LSTM model achieves an R2 of 90.25 in this table, showing good explanatory power. With an even higher R2 of 92.41, the CNN model surpasses it, indicating that it represents the relationship between input data and dosage prediction more accurately.Prediction errors are expressed as a percentage of the actual dosage levels via the Mean Percentage Error (MPE). Better prediction accuracy is shown by smaller MPE values. The MPE of the LSTM model is 3.22%, which indicates a respectably low error rate. The CNN model, on the other hand, outperforms with a lower MPE of 2.12%, indicating a higher level of accuracy in its dose estimates.Table 3's comparative performance of the LSTM and CNN models in the particular task of forecasting radiation doses in CT imaging is highlighted in the conclusion. Including MAE, RMSE, R2, and MPE, the CNN model consistently beats the LSTM model in all evaluation metrics. This shows that the CNN architecture is more appropriate for precise and trustworthy dose prediction in this situation. These findings emphasise the significance of choosing a suitable machine learning strategy that is suited to the particular task and dataset, since the model selection can have a substantial impact on the accuracy of predictions and their clinical consequences in the planning of radiation therapy and medical imaging.

5. Conclusion

The Grey Wolf Algorithm (GWA) has shown substantial promise in improving image quality and diagnostic accuracy for computed tomography (CT) image reconstruction parameters for enhanced lung cancer diagnosis. This study has shown that the GWA, which was modelled after the social and hunting behaviour of grey wolves, is capable of navigating the intricate parameter space of CT image reconstruction.Additionally, the GWA-driven optimisation has helped to lessen picture artefacts and noise, producing cleaner and more useful CT images for diagnostic purposes.The ability to diagnose lung cancer has improved thanks to the improved image quality. The optimised parameters have improved the sensitivity and specificity of lesion identification, enabling more precise early detection of lung malignancies. Additionally, more accurate measurements of nodule size, shape, and density have been made, which helps with proper staging and treatment planning.Although the GWA has demonstrated its efficacy in this situation, it is important to note that more advancements in optimisation algorithms may be possible with continued research and development. In order to achieve even greater improvements in CT image reconstruction for lung cancer diagnosis, future studies may investigate hybrid approaches that integrate the

GWA with other optimisation techniques, machine learning, or deep learning methodologies.In conclusion, a possible method for improving lung cancer diagnosis is the incorporation of the Grey Wolf Algorithm into the optimisation of CT image reconstruction parameters. This approach not only improves image quality but also helps identify lung tumours precisely and early, leading to better patient outcomes and promoting the early intervention so important in the fight against lung cancer.

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