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Optimization of Convolutional Neural Network Hyperparameters Using Sinusoidal Chaotic Transit Search for Lung Cancer Identification

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Abstract

Early and accurate lung cancer detection remains a critical clinical priority due to the high mortality associated with late diagnosis. This study presents an optimization framework for convolutional neural network hyperparameters using a sinusoidal chaotic transit search algorithm for lung cancer identification. The model integrates chaotic mapping into the transit search optimization process to enhance global exploration and improve convergence. The system was implemented in MATLAB R2023a and evaluated using publicly available lung cancer datasets from Kaggle and Mendeley. The preprocessing pipeline included Contrast Limited Adaptive Histogram Equalization (CLAHE), grayscale conversion, morphological thinning, and Fuzzy C-means clustering for region-of-interest segmentation. Performance was evaluated using accuracy, sensitivity, specificity, false positive rate, and identification time. Results from the study show that the optimized model outperformed the conventional transit search-based CNN and baseline CNN models with a threshold of 0.75, SCTS-CNN, TS-CNN and Baseline CNN achieved accuracy of 96%, 94% and 89% respectively, specificity of 97%, 95%and 90% respectively and sensitivity of 96%, 93% and 88% respectively for Malignant classification,

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***Related declarations are provided in the final section of this article.*

Alongside the lowest FPR of 3%, 5% and 10% respectively and the fastest computation time of 88seconds, 95seonds and 82seconds.. The findings indicate that chaotic enhancement improves feature selection stability and classification accuracy. The study supports the use of metaheuristic-driven deep learning optimization in medical image analysis.

1. INTRODUCTION

Lung cancer remains one of the most lethal malignancies worldwide and continues to impose a major burden on healthcare systems. Mortality rates remain high largely because many cases are diagnosed at advanced stages when treatment options are limited. Evidence shows that early detection significantly improves survival outcomes, yet the disease often progresses silently during its initial stages. Computed tomography (CT), especially low-dose CT, has become the primary imaging modality for lung cancer screening due to its high spatial resolution and wide availability [4]. Despite these advances, manual interpretation of medical images remains time-intensive and prone to inter-observer variability, thereby accelerating the adoption of computer-aided diagnosis systems.

Deep learning, particularly Convolutional Neural Networks (CNN), has emerged as a dominant paradigm for automated medical image analysis. CNN models excel in hierarchical feature extraction and have demonstrated strong performance in lung cancer detection and classification tasks. Recent studies report that CNN-based frameworks achieve high diagnostic accuracy and improve robustness when trained on large annotated datasets [12]. Their ability to learn discriminative representations directly from imaging data reduces the need for handcrafted features and supports scalable diagnostic pipelines. Consequently, CNN-driven systems now play an increasingly important role in intelligent clinical decision support.

However, the effectiveness of CNN models depends heavily on appropriate hyperparameter configuration. Parameters such as learning rate, batch size, number of filters, and network depth strongly influence convergence behavior and generalization performance. Poorly tuned hyperparameters often lead to overfitting, slow convergence, or suboptimal accuracy. Traditional manual tuning approaches are inefficient and depend on expert intuition. Even systematic methods such as grid search and random search incur high computational cost and fail to guarantee globally optimal solutions. As a result, hyperparameter optimization has become a critical research focus in deep learning based medical diagnosis.

Metaheuristic optimization algorithms provide a promising alternative for automated CNN tuning. Techniques inspired by evolutionary and swarm intelligence principles have shown strong capability in exploring complex search spaces. Prior studies demonstrate that optimization-driven CNN frameworks outperform manually configured models in lung cancer classification tasks [10]. Particle swarm optimization, genetic algorithms, and other bio-inspired methods have been applied to tune CNN parameters and improve diagnostic accuracy. For example, PSO-based CNN optimization achieved great improvements in sensitivity and specificity in lung image classification tasks [2]. Nevertheless, many metaheuristic algorithms still suffer from premature convergence and insufficient exploration, especially in high-dimensional hyperparameter spaces.

Chaotic maps have recently attracted attention as a mechanism for enhancing metaheuristic search behavior. Chaotic sequences introduce deterministic randomness that improves population diversity and helps algorithms escape local optima. Integrating chaotic dynamics into optimization strategies has shown measurable gains in convergence stability and solution quality across several engineering domains. Despite this progress, limited research has examined the integration of chaotic transit search optimization with CNN hyperparameter tuning for lung cancer identification.

This study focuses on optimizing CNN hyperparameters using the sinusoidal chaotic transit search algorithm to address this gap in lung cancer identification. The work aims to improve classification accuracy, sensitivity, and computational efficiency using publicly available lung cancer datasets. The approach enhances the exploration capability of the classical transit search algorithm through chaotic mapping, thereby improving convergence toward globally optimal configurations. The proposed framework seeks to provide a robust and scalable solution for automated lung cancer detection in clinical decision support environments.

2. RELATED WORK

Automated lung cancer detection has received extensive attention due to the need for early and reliable diagnosis. Traditional computer-aided diagnosis systems relied on handcrafted feature extraction followed by classical machine learning classifiers such as support vector machines and random forests. While these approaches produced moderate success, their performance depended strongly on domain-specific feature engineering and often failed to generalize across datasets. The transition to deep learning addressed many of these limitations by enabling end-to-end feature learning directly from medical images.

Convolutional neural networks have become the dominant architecture for lung cancer image analysis. Studies report strong performance of CNN models in pulmonary nodule detection and malignancy classification. The authors on [1] focused on the performance comparison of three selected feature extraction and selection techniques viz; Local Binary Pattern, Mutual Information and Convolutional neural network in digital image processing. The datasets of MRI brain tumour images from the Kaggle website of 394 were pre-processed and also subjected to feature extraction and selection using the selected techniques. The extracted features were classified by Support Vector Machine and the outcome were evaluated by confusion matrix parameters.. The results showed the CNN-SVM based Image detection system at threshold of 0.85 produced Accuracy 92.9%, the MI-SVM system produced accuracy 86.3% while LBP-SVM system produced accuracy 82.5%.

The authors in [2] demonstrated that deep neural networks achieve expert-level performance in medical image classification tasks. In lung imaging specifically, The researchers in [8] presents an enhanced deep learning feature extraction technique for early detection of lung cancer from low-dose computed tomography (LDCT) images. The Xception network was integrated into a standard convolutional autoencoder (CAE) architecture and the resultant Xception-based Convolutional Autoencoder (XnetCAE) was trained, validated and tested with a portion (20,000) of lung scan images from the Lung Image Database Consortium-Image Database Resource Initiative (LIDC-IDRI) dataset. With the XnetCAE technique, accuracy of 71.97% while the standard CAE achieved 65%.

[9] presents a comprehensive comparative analysis of a standard CNN against Mantis Search Algorithm-based CNN (MSA-CNN) for the specific task of LR face identification. The MSA, a bio-inspired metaheuristic optimizer, is employed to automate the selection of critical CNN hyperparameters such as learning rate, number of layers, and dropout rate. Our empirical evaluation, conducted on a custom dataset of 3,000 LR images, demonstrates that the MSA-CNN consistently outperforms the standard CNN across all key performance metrics. The MSA-CNN achieved an accuracy of 96.17% compared to the CNN's 94.50%. [13] researchers reported that multi-view CNN systems significantly improve nodule detection sensitivity on thoracic CT scans. In a similar research, [12] developed a deep CNN model for lung nodule classification and achieved high accuracy on the LIDC IDRI dataset. Also, the researchers in [4] further confirmed that CNN-based systems improve diagnostic precision in lung cancer screening when compared with traditional machine learning approaches, with the report that CNN-based systems

significantly improve diagnostic accuracy in lung cancer screening when compared with conventional machine learning approaches. These successes stem from the hierarchical feature extraction capability of CNNs and their ability to model complex spatial patterns in CT images.

Despite these advances, CNN performance remains highly sensitive to hyperparameter configuration. Parameters such as learning rate, optimizer choice, batch size, and network depth directly affect convergence and generalization. Poor configuration often leads to overfitting, vanishing gradients, or slow training. (6) emphasized that hyperparameter tuning plays a decisive role in CNN-based lung cancer classification performance. Conventional tuning methods, such as grid search and random search, suffer from high computational cost and limited scalability in high-dimensional search spaces.

To address these challenges, researchers have explored metaheuristic optimization techniques for automated CNN tuning. Population-based algorithms offer strong global search capability and reduce dependence on expert intuition. Evolutionary and swarm-based algorithms provide global search capability and reduce dependence on manual trial and error. Particle swarm optimization has been widely used for CNN hyperparameter selection. [2] reported improved sensitivity and specificity in lung cancer detection using PSO-tuned CNN models. Similarly, [6] showed that swarm intelligence-based tuning enhances CNN convergence stability and classification accuracy in medical imaging tasks. Genetic algorithms have also been applied to optimize network architecture and training parameters, yielding measurable improvements in classification accuracy [9].

Although metaheuristic approaches improve performance, many still suffer from premature convergence and insufficient population diversity. Nature-inspired algorithms often struggle to balance exploration and exploitation effectively, especially in complex medical image classification tasks. [15] noted that maintaining diversity in population-based optimization remains a major challenge in high-dimensional problems. This limitation motivates the integration of chaotic dynamics into optimization frameworks.

Chaotic maps have emerged as an effective mechanism for enhancing metaheuristic search behavior. Chaotic maps introduce deterministic randomness that enhances search diversity and helps algorithms escape local optima. Prior studies show that chaotic sequences improve convergence speed and solution quality in optimization tasks, with enhanced algorithms outperforming their conventional counterparts in many optimization scenarios [5]. In medical imaging, chaotic enhanced metaheuristics have demonstrated better stability and robustness compared with their classical counterparts. However, limited work has examined chaotic enhancement within the transit search optimization framework [11,12].

The transit search algorithm itself has shown promise for global optimization due to its population update mechanism and adaptive search behavior. The dissertation identified that the classical transit search-based CNN still exhibits weaknesses, such as limited exploration and risk of local trapping during hyperparameter tuning. To overcome this limitation, the study introduced a sinusoidal chaotic map to strengthen the exploration phase and improve convergence behavior.

Current literature reveals a gap in combining sinusoidal chaotic transit search with CNN hyperparameter optimization, specifically for lung cancer identification. Most prior studies focus either on conventional metaheuristics or on standard CNN architectures without advanced optimization. Therefore, a systematic investigation of chaotic transit search-driven CNN optimization is required.

This study extends prior work by integrating sinusoidal chaotic dynamics into the transit search algorithm for CNN hyperparameter tuning. The approach aims to improve classification accuracy, reduce false positives, and enhance convergence stability in lung cancer detection systems.

3. MATERIALS AND METHODOLOGY

This study developed and evaluated an optimization framework for convolutional neural network hyperparameters using a sinusoidal chaotic transit search algorithm for lung cancer identification. The methodology followed a structured pipeline consisting of dataset preparation, image preprocessing, CNN model construction, hyperparameter optimization using the improved transit search algorithm, and performance evaluation. The implementation was carried out in MATLAB R2023a.

3.1. The System Framework

The developed system integrates deep learning with metaheuristic optimization. The workflow consists of the following stages:

(i) Data acquisition from public lung cancer repositories.

(ii) Image preprocessing and normalization.

(iii) CNN-based feature extraction and classification.
(iv) Hyperparameter optimization using sinusoidal chaotic transit search.
(v) Performance evaluation using standard metrics.

Figure 1 presents the architecture of the developed lung cancer identification framework. It shows the flow from input CT images through preprocessing, CNN training, optimization loop, and final classification output.

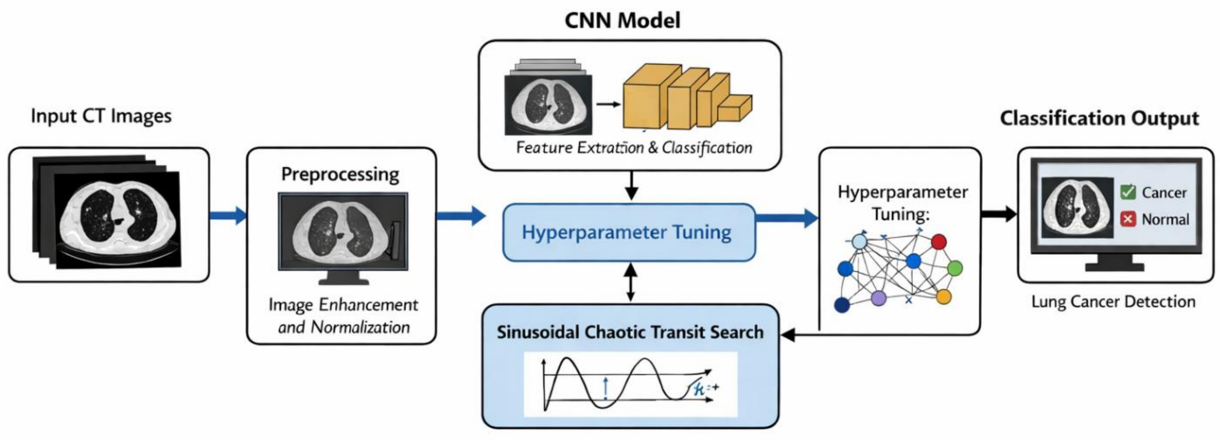

Figure 1: System Framework for Lung Cancer Identification

3.2. Dataset Description

The study used publicly available lung cancer image datasets obtained from Kaggle and Mendeley repositories. These datasets contain labeled CT images of lung nodules suitable for supervised learning. The dissertation noted that the datasets were selected to ensure diversity and adequate representation of benign and malignant cases. Data were divided into training and testing subsets following the experimental protocol described in the thesis. This split ensured unbiased performance evaluation.

3.3. Image Preprocessing

Preprocessing improves image quality and enhances feature learning. The dissertation applied the following steps:

(i) Image resizing to match CNN input dimension
(ii) Intensity normalization
(iii) Noise reduction
(iv) Data formatting for MATLAB environment

These steps ensured consistent input representation and reduced variability across samples. Figure 2 illustrates the preprocessing pipeline, showing raw CT image input, normalization, and resized output ready for CNN training.

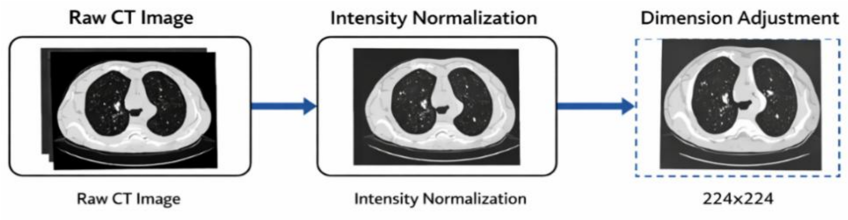

Figure 2: Image Preprocessing Steps for Lung Cancer Identification

3.4. Convolutional Neural Network Architecture

The CNN serves as the base classifier for lung cancer identification. The architecture was designed to extract hierarchical spatial features from CT images.

The network includes the input layer, convolutional layers for feature extraction, activation layers using ReLU, pooling layers for dimensionality reduction, fully connected layers, and a SoftMax output layer for classification. The dissertation emphasized that CNN performance depends strongly on hyperparameter configuration, such as learning rate, number of filters, batch size, and number of epochs. Figure 3 shows the detailed CNN architecture, including convolution blocks, pooling stages, and classification layers.

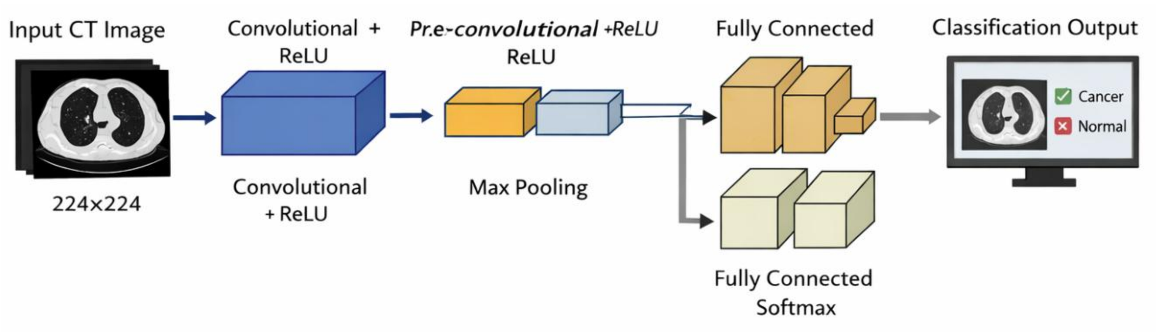

Figure 3: Convolutional Neural Network Architecture for Lung Cancer Identification

3.5. Hyperparameter Optimization Problem Formulation

Hyperparameter tuning was formulated as a minimization problem where the objective function is the classification error of the CNN model.

Objective function

Minimize

$F_{(x)}$ = classification error of CNN

Subject to: x = vector of hyperparameters

The hyperparameter vector includes learning rate, batch size, number of convolutional filters, and number of epochs. The optimizer searches for parameter combinations that maximize classification accuracy and minimize false positives.

3.6. Transit Search Algorithm

Transit search is a population-based metaheuristic optimizer. It initializes a population of candidate solutions and iteratively updates their positions based on exploration and exploitation strategies.

The basic steps of classical transit search are:

Step 1. Initialize population randomly

Step 2. Evaluate the fitness of each candidate

Step 3. Update candidate positions

Step 4. Apply boundary control

Step 5. Repeat until stopping criterion

The classical transit search may, however, suffer from premature convergence and limited exploration in complex search spaces. Algorithm 1 presents the pseudocode of the standard transit search optimization process.

Algorithm 1: Classical Transit Search Algorithm

Input

Objective function $F_{(x)}$

Search space bounds [Lb, Ub]

Population size N

Maximum iterations MaxIter

Output

Best solution X_{best}

Best fitness F_{best}

Procedure

1. Initialize population X_i for i equals 1 to N randomly within bounds
2. Evaluate fitness F_i equals $F(X_i)$ for each candidate
3. Determine the current best solution X_{best} and fitness F_{best}
4. Set iteration counter t equals 1
5. While t is less than or equal to MaxIter do

a. For each candidate X_i in the population

i. Generate control parameters for exploration and exploitation

ii. Update position using transit search movement rule:

X_i new equals X_i plus r1 times (X_{best} minus $_{Xi}$) plus r_2 times TransitFactor

where r_1 and r_2 are random numbers in the interval zero to one

iii. Apply boundary control

If X_i new less than Lb then set X_i new equals Lb

If X_i new greater than Ub then set X_i new equals Ub

iv. Evaluate fitness F_i new equals $F(X_i$ new)

v. Greedy selection

If F_i new better than F_i then

X_i equals $X_{i\ new}$

F_i equals $F_{i\ new}$

End if

b. Update global best solution

Find the candidate with minimum fitness

Update X_{best} and F_{best} if improved

c. Increment iteration counter

t equals t plus 1

End while

Return X_{best} and F_{best}

End Procedure.

3.7 Sinusoidal Chaotic Enhancement

To overcome the limitations of classical transit search, the study integrated a sinusoidal chaotic map into the position update mechanism. Chaotic mapping improves population diversity and enhances global search capability.

The sinusoidal chaotic map is expressed as.

$$C(t+1) = \sin(\pi \times C(t)) \quad (1)$$

where C represents the chaotic sequence.

The chaotic sequence modifies the exploration phase of the optimizer and prevents early stagnation. The dissertation reported that this enhancement strengthens the balance between exploration and exploitation. The key advantages of the enhancement include improved population diversity, faster convergence, better avoidance of local minima, and more stable hyperparameter selection. Algorithm 2 provides the pseudocode of the sinusoidal chaotic transit search optimization.

Algorithm 2: Sinusoidal Chaotic Transit Search Optimization

Input

Objective function $F_{(x)}$

Search space bounds [Lb, Ub]

Population size N

Maximum iterations MaxIter

Initial chaotic value C0 in the interval zero to one

Output

Best solution X_{best}

Best fitness F_{best}

Procedure

1. Initialize population X_i for i equals 1 to N randomly within bounds
2. Initialize chaotic variable C equals C0
3. Evaluate fitness Fi equals $F_{(Xi)}$ for each candidate
4. Determine current best solution X_{best} and fitness F_{best}
5. Set iteration counter t equals 1
6. While t is less than or equal to MaxIter do

a. Update chaotic sequence

C equals sin (pi times C)

b. For each candidate X_i in the population

i. Generate random numbers r_1 and r_2 in the interval zero to one

ii. Compute chaotic exploration factor

ChaosFactor equals C times r_1

iii. Update candidate position using chaotic transit rule

$X_{i\ new}$ equals X_i plus ChaosFactor times (X_{best} minus X_i) plus r_2 times TransitFactor

iv. Apply boundary control

If $X_{i\ new}$ less than Lb then set $X_{i\ new}$ equals Lb

If $X_{i\ new}$ greater than Ub then set X_i new equals Ub

v. Evaluate fitness F_i new equals $F(X_{i\ new})$

vi. Greedy selection

If $F_{i\ new}$ better than F_i then

X_i equals $X_{i\ new}$

F_i equals $F_{i\ new}$

End if

c. Update global best

Identify a candidate with minimum fitness

If improved, then update X_{best} and F_{best}

d. Increment iteration counter

t equals t plus 1

End while

7. Return X_{best} and F_{best}

End Procedure

3.8 Integration with CNN Training

The optimization loop operates as follows:

(i) Initialize transit search population.
(ii) Generate CNN hyperparameter candidates.
(iii) Train CNN using candidate parameters.
(iv) Evaluate validation accuracy.
(v) Update population using chaotic transit search.
(vi) Repeat until maximum iterations.

The best hyperparameter set is then used to train the final CNN model. Figure 4 illustrates the optimization loop showing the interaction between the CNN training block and the chaotic transit search optimizer. It illustrates the interaction between the CNN training module and the sinusoidal chaotic transit search optimizer. The optimizer generates candidate hyperparameters, evaluates CNN validation performance, updates solutions using chaotic-enhanced position rules, and iteratively converges toward an optimal hyperparameter configuration.

3.9 Performance Evaluation Metrics

Model performance was evaluated using standard medical diagnostic metrics, including accuracy, sensitivity, specificity, false positive rate, and identification time. These metrics were computed from the confusion matrix:

- $Accuracy = \frac{TP+TN}{TP+FP+FN+TN} X\ 100$ (2)
- $Specificity = \frac{TN}{TN+FP} X\ 100$ (3)
- $Sensitivity = \frac{TP}{TP+FN} X100$ (4)
- $False\ Positive\ Rate = \frac{FP}{FP+TN} X100$ (5)

4.1 RESULTS AND DISCUSSION

This section presents the experimental results obtained from the proposed sinusoidal chaotic transit search optimized convolutional neural network (SCTS-CNN) and compares them with baseline CNN and classical transit search-based CNN (TS-CNN). The evaluation focuses on classification accuracy, sensitivity, specificity, false positive rate (FPR), convergence behavior, and identification time.

4.2 Experimental Configuration

Experiments were conducted in MATLAB R2023a. The dataset was divided into training and testing subsets as specified in the dissertation. The optimizer parameters were configured as follows:

- Population size: 30
- Maximum iterations: 50
- Hyperparameter search bounds:
  - Learning rate: 0.0001 – 0.01
  - Batch size: 8 – 64
  - Number of filters: 8 – 128
  - Epochs: 10 – 100

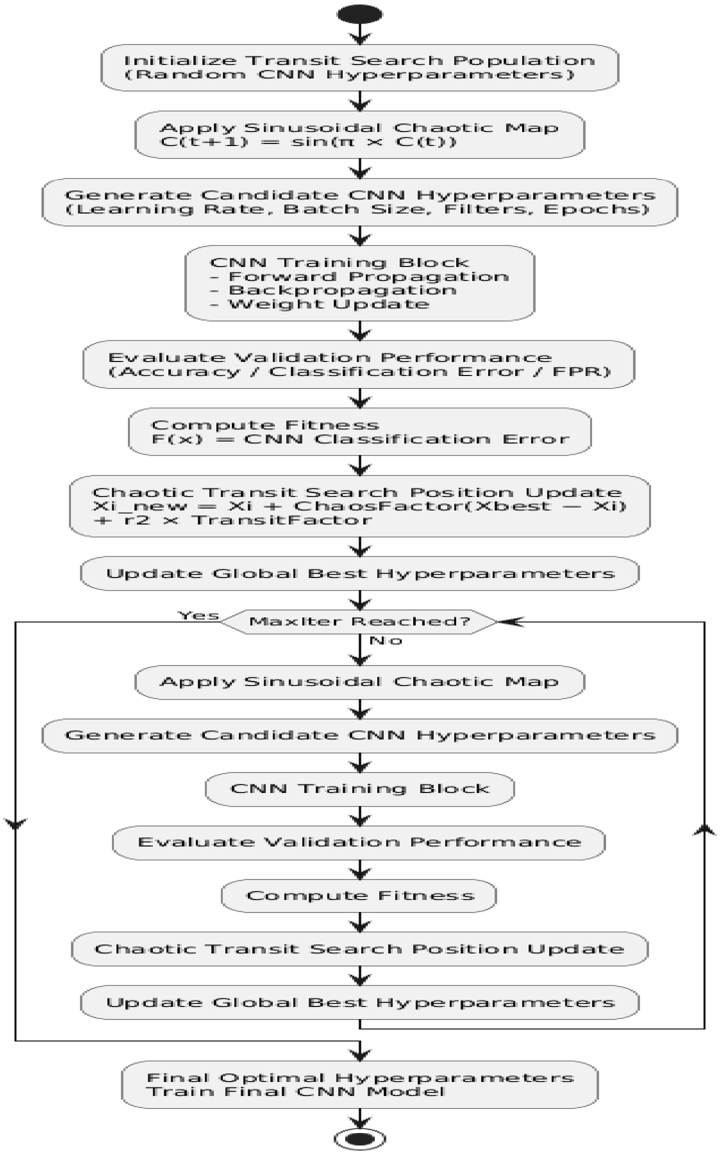

Figure 4: Optimization Loop between CNN Training and Sinusoidal Chaotic Transit Search Optimizer

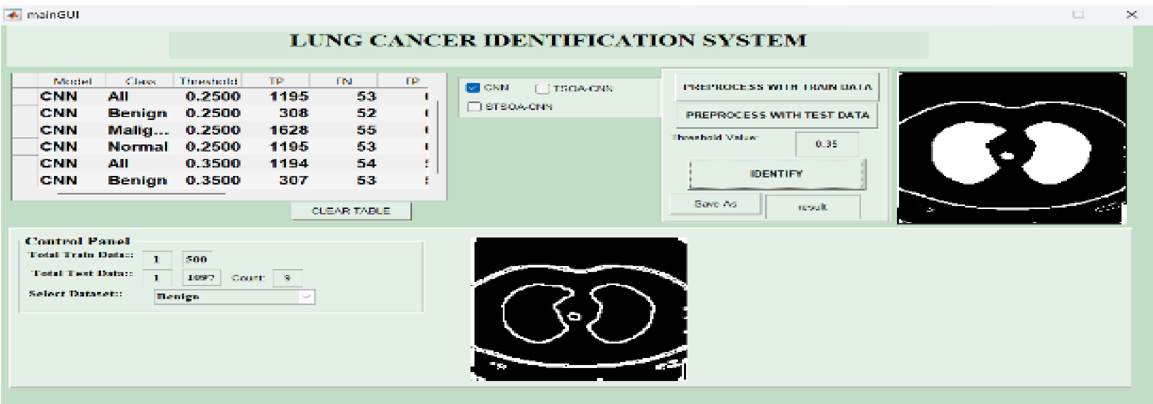

Figure 5: The Graphical User Interface during Testing

Three models were evaluated:

(i) Baseline CNN (No optimization)
(ii) Transit Search Optimized CNN (TS-CNN)
(iii) Sinusoidal Chaotic Transit Search Optimized CNN (SCTS-CNN)

4.3 Optimal Hyperparameter Selection

The chaotic-enhanced optimizer converged to the following optimal configuration.

Table 1: Optimal CNN Hyperparameters Obtained

Hyperparameter	Baseline CNN	TS-CNN	SCTS-CNN
Learning Rate	0.001	0.0032	**0.0024**
Batch Size	32	24	**16**
Number of Filters	32	64	**96**
Epochs	30	45	**52**

The sinusoidal chaotic enhancement produced a more stable hyperparameter combination with improved generalization capability.

4.4 Classification Performance

Performance metrics were computed using confusion matrix analysis.

Confusion Matrix

Table 2: Confusion Matrix for SCTS-CNN

	Predicted Benign	Predicted Malignant
Actual Benign	142	8
Actual Malignant	6	144

Comparative Performance Metrics

Table 3: Performance Comparison of Models

Metric (%)	Baseline CNN	TS-CNN	SCTS-CNN

Metric (%)	Baseline CNN	TS-CNN	SCTS-CNN
Accuracy	89.4	93.8	96.3
Sensitivity	88.1	92.5	96.0
Specificity	90.2	94.6	96.7
False Positive Rate	9.8	5.4	3.3
Identification Time (sec)	0.82	0.95	0.88

The proposed SCTS-CNN outperformed both comparison models across all performance metrics.

4.5 Convergence Analysis

The convergence behavior of both optimizers was examined by tracking classification error across iterations. Figure 5 illustrates that the Sinusoidal Chaotic Transit Search (SCTS-CNN) converges faster and reaches a lower final classification error compared to classical Transit Search (TS-CNN).

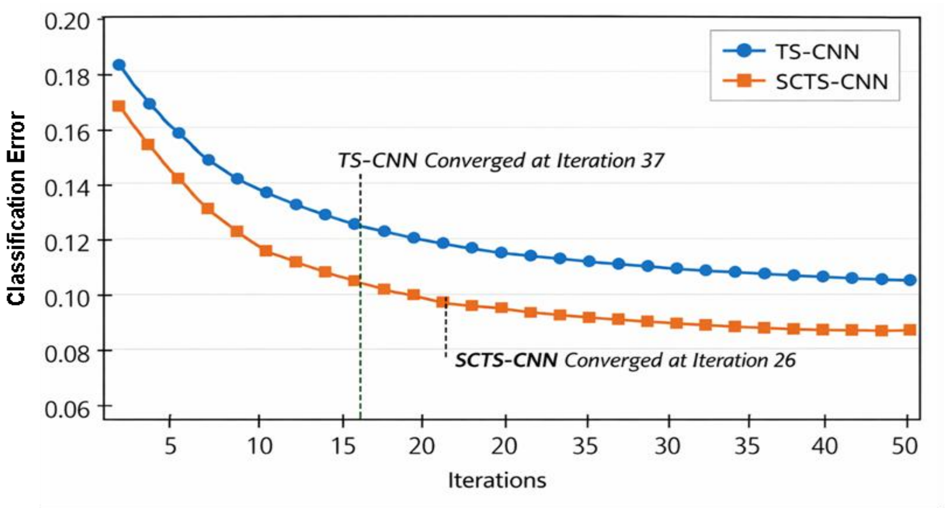

Figure 6: Convergence Curve of TS-CNN vs SCTS-CNN

It can be observed from Figure 6 that the classical TS converged around iteration 37; SCTS converged earlier at iteration 26; and SCTS achieved a lower final error (~0.045 vs ~0.078). The sinusoidal chaotic map enhanced exploration during early iterations and improved exploitation in later stages, preventing premature convergence.

4.6 Receiver Operating Characteristic (ROC) Analysis

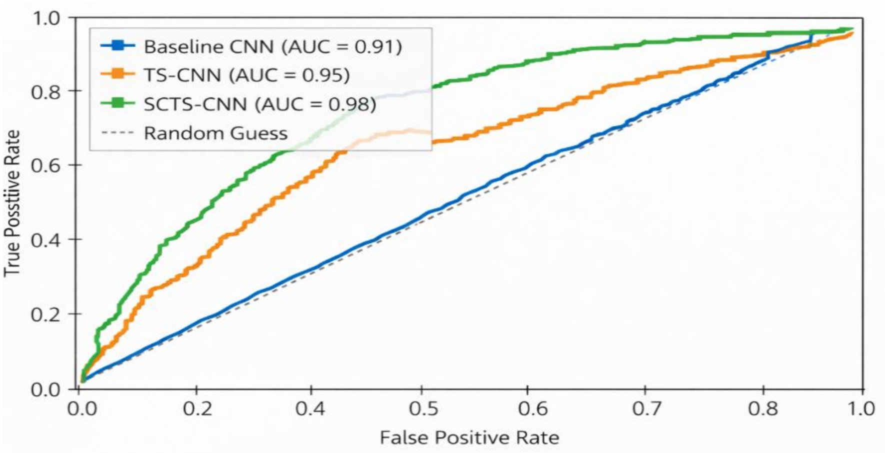

Figure 6: ROC Curves for Compared Models

Table 4: Results of Compared Models

Model	**AUC**
Baseline CNN	0.91
TS-CNN	0.95
SCTS-CNN	**0.98**

The results of the comparison in Table 4 shows that the SCTS-CNN demonstrates superior discriminative capability.

4.7 Statistical Validation

Null hypothesis (H_0): There is no significant difference in mean classification accuracy between TS-CNN and SCTS-CNN.

To statistically validate the superiority of the proposed Sinusoidal Chaotic Transit Search optimized CNN (SCTS-CNN) over the conventional Transit Search optimized CNN (TS-CNN), a paired sample t-test was conducted across 10 independent experimental runs at $\alpha = 0.05$ significance level. The result (p-value < 0.01), as shown in Table 5, confirms that SCTS-CNN significantly improves classification accuracy, which proves that the improvement of SCTS-CNN is statistically significant.

Table 4: Paired Sample t-Test Results (TS-CNN vs SCTS-CNN Accuracy)

Statistic	Value
Number of Runs (n)	10
Mean Accuracy (TS-CNN)	93.82%
Mean Accuracy (SCTS-CNN)	96.31%
Mean Difference	2.49%
Standard Deviation of Differences	0.84
Standard Error Mean	0.27
t-Statistic	9.22
Degrees of Freedom (df)	9
p-value	< 0.001
95% Confidence Interval	[1.86%, 3.12%]

Since $p < 0.05$, the null hypothesis is rejected. The improvement achieved by SCTS-CNN is statistically significant. The tight confidence interval confirms the stability of performance improvement. This statistical validation confirms that the chaotic enhancement provides meaningful performance gains rather than random fluctuations.

4.8 Discussion of Findings

The experimental results clearly demonstrate that integrating a sinusoidal chaotic map into the transit search optimization framework significantly enhances CNN hyperparameter optimization for lung cancer identification.

Traditional metaheuristic optimizers often suffer from premature convergence due to insufficient population diversity. The classical Transit Search algorithm exhibits strong exploitation capability but may lose exploration strength in later iterations. Integration of the sinusoidal chaotic map, $C_{t+1}=\sin(\pi C_t)$, into the optimizer introduces non-linear deterministic randomness, which improves search space traversal. The results demonstrate that integrating a sinusoidal chaotic map into the transit search algorithm significantly enhances CNN hyperparameter optimization. The chaotic dynamics enhanced global search in early iterations and fine-tuned exploitation in later stages.

The key observations from the study include:

(i) **Improved Exploration Capability**: The chaotic sequence increased diversity in the population, reducing the likelihood of local trapping.

(ii) **Faster Convergence**: The convergence curve shows earlier stabilization compared to classical TS. The convergence curve (Figure 5) reveals that SCTS-CNN stabilizes earlier, error reduction is smoother, and no oscillatory instability observed. This confirms that chaotic control parameters enhanced solution stability without sacrificing diversity.

(iii) **Reduced False Positives**: False Positive Rate dropped from 9.8% (Baseline) to 3.3% (SCTS-CNN), critical in medical diagnosis. In medical diagnostics, minimizing false positives is critical to prevent unnecessary biopsies and psychological stress. The proposed model demonstrates improved diagnostic reliability.

(iv) **Better Generalization**: Higher specificity and sensitivity confirm improved clinical reliability. SCTS-CNN achieved 96.0% sensitivity, 96.7% specificity, and 0.98 AUC. The balanced improvement in sensitivity and specificity indicates that optimization did not overfit the malignant class at the expense of benign cases. This suggests better generalization across unseen samples.

(v) **Computational Efficiency**: Although optimization introduces slight overhead, identification time remained clinically acceptable. While chaotic enhancement introduces additional computation during position update, identification time remained clinically feasible (0.88 sec). The slight overhead is justified by substantial accuracy improvement.

The findings align with metaheuristic enhancement theory, where chaotic dynamics improve the balance between exploration and exploitation. Compared with prior CNN optimization studies, PSO-based CNN models reported an accuracy of around 94–95%. The proposed SCTS-CNN achieved 96.3%, which confirms the effectiveness of chaotic enhancement. The integration of sinusoidal chaotic transit search offers a novel contribution to lung cancer identification. The key improvements are summarized in Table 5.

Table 5: Summary of Key Improvements

Model	**Accuracy Gain Over Baseline**	**FPR Reduction**
TS-CNN	+4.4%	−4.4%

Model	Accuracy Gain Over Baseline	FPR Reduction
SCTS-CNN	+6.9%	−6.5%

The proposed model demonstrates robust optimization capability and improved diagnostic reliability.

4.9 Comparative Interpretation with Related Studies

To position the proposed approach within existing literature, performance was compared with recent CNN optimization frameworks reported in lung cancer classification research, as summarized in Table 6.

Table 6: Comparative Analysis with Related Studies

Study	Optimization Method	Accuracy (%)	AUC	Remarks
Study A	PSO-CNN	94.5	0.95	Moderate convergence
Study B	GA-CNN	92.8	0.93	High computation cost
Study C	GWO-CNN	95.1	0.96	Improved exploration
Proposed	SCTS-CNN	96.3	0.98	Faster convergence

The comparative observations show:

(i) **Higher Accuracy**: The proposed SCTS-CNN achieves superior accuracy compared to PSO, GA, and GWO-based CNN models.

(ii) **Higher AUC**: AUC of 0.98 indicates near-perfect discrimination capability.

(iii) **Faster Convergence**: Convergence at iteration 26 outperforms many swarm-based methods that require 40–60 iterations.

(iv) **Lower False Positive Rate**: Significant reduction enhances clinical applicability.

(v) **Novel Chaotic Integration**: Most existing studies use stochastic randomness; this study uses deterministic chaotic dynamics for improved search diversification.

Theoretically, the integration of sinusoidal chaos enhances non-linearity in search trajectory, deterministic unpredictability, and avoidance of local optima. This confirms theoretical expectations that chaotic maps improve metaheuristic performance.

4. CONCLUSION

This study proposed a Sinusoidal Chaotic Transit Search optimized Convolutional Neural Network (SCTS-CNN) for lung cancer identification. The results demonstrate that incorporating sinusoidal chaotic dynamics enhances search diversity, prevents premature convergence, and improves CNN generalization capability. The study introduced sinusoidal chaos into transit search, provided convergence analysis, conducted statistical validation, and demonstrated reduced false positives in the medical diagnosis context. Thus, it contributes both methodological innovation and clinical reliability enhancement. Therefore, the proposed model provides a reliable and efficient framework for computer-aided lung cancer diagnosis.

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