HARMONY SEARCH-BASED XCEPTION MODEL FOR ENHANCED LUNG CANCER PREDICTION

Sabura Banu U

Professor, Department of Electrical and Electronics Engineering
Saveetha Engineering College, Saveetha Nagar, Thandalam, Chennai 602105
Tamilnadu, India

ABSTRACT

Lung cancer continues to be a major cause of cancer-related deaths globally, highlighting the importance of precise and effective diagnostic methods. Deep learning models, such as Xception, have shown promise in medical image classification, but their performance depends heavily on optimal hyperparameter selection. Traditional tuning methods often fail to achieve the best results efficiently, necessitating advanced optimization techniques. This study integrates the Harmony Search (HS) algorithm with the Xception model to optimize hyperparameters for improved lung cancer classification. The proposed HS-Xception model is evaluated against AlexNet, Inception V3, SqueezeNet, and standard Xception on a dataset containing four lung cancer categories. The models are assessed using multiple performance metrics. The experimental results demonstrate that HS-Xception outperforms all competing models, achieving a 97.18% accuracy, 97.37% precision, 97.33% recall, and a 99.95% AUC-ROC score, significantly improving upon standard Xception (93.22% accuracy). The optimization enhances model efficiency, reducing log loss and improving classification reliability across all lung cancer types. The integration of the Harmony Search algorithm with Xception enhances hyperparameter tuning, significantly improving lung cancer prediction accuracy. This study showcases the potential of metaheuristic optimization in Deep Learning (DL)-based medical image analysis, contributing to the development of more reliable and efficient diagnostic systems.

KEYWORDS

Lung Cancer Prediction, Deep Learning, Harmony Search Algorithm, Xception Network, Medical Image Classification, Metaheuristic Optimization, Hyperparameter Tuning

1. INTRODUCTION

Lung cancer is among the most aggressive and fatal types of cancer, responsible for a substantial share of cancer-related deaths globally. Early and precise detection is crucial for enhancing patient survival rates, as prompt diagnosis enables more effective treatment strategies. Traditional diagnostic techniques, such as histopathological examination and radiological imaging, often require extensive expertise and can be prone to subjective interpretation. In recent years, DL models have become highly effective tools for automated medical image analysis, offering promising results in lung cancer classification. However, the performance of these models heavily depends on the selection of optimal hyperparameters, which can significantly impact accuracy, generalization, and computational efficiency.

DL architectures have been widely used for medical image classification tasks, including lung cancer detection. Among these models, Xception, which is based on depthwise separable convolutions, has demonstrated superior feature extraction capabilities, making it a strong candidate for lung cancer classification. However, manually tuning Xception’s hyperparameters—such as learning rates are both time-intensive and computationally demanding. Conventional tuning techniques often struggle to effectively navigate the extensive hyperparameter space, resulting in suboptimal performance. To overcome these limitations, this study presents a metaheuristic-based approach utilizing the Harmony Search (HS) algorithm to fine tune the Xception model's hyperparameters, with the goal of improving classification accuracy and efficiency.

The Harmony Search (HS) algorithm mimics the improvisation steps of musicians searching for the best harmony. It is applied in numerous optimization problems, such as engineering design, scheduling, and machine learning. By integrating HS with Xception, this study aims to fine-tune hyperparameters more effectively, leading to improved lung cancer classification performance. The proposed HS-Xception model is trained and validated on a dataset containing four lung cancer types. The model’s performance is compared against AlexNet, Inception V3, SqueezeNet, and standard Xception, using various evaluation metrics.

Experimental results demonstrate that HS-Xception outperforms all competing models, achieving 97.18% accuracy, 97.37% precision, and a 99.95% AUC-ROC score, significantly surpassing the performance of standard Xception and other deep learning models. These findings highlight the effectiveness of using metaheuristic optimization to enhance deep learning architectures for medical image classification. The study outlines the use of HS-based hyperparameter tuning in improving the accuracy and reliability of lung cancer detection, laying the foundation for greater efficiency and automated diagnostic tools in clinical settings.

This article is organized as: Section 2 deals with an exhaustive review of related work, discussing existing deep learning approaches for lung cancer classification and the role of metaheuristic optimization techniques in enhancing model performance. Section 3 details the proposed methodology, including an overview of the HS algorithm, the architecture of the Xception model, and the integration of HS for hyperparameter tuning. Section 4 presents the experimental setup, including the dataset description, preprocessing steps, evaluation metrics, and implementation details. Section 5 reports and analyzes the results, comparing the performance of HS-Xception with other deep learning models based on various classification metrics. Section 6 discusses the findings, implications, and potential limitations of the study. The last section, Section 7 summarizes key takeaways and discusses the scope for future research.

2. RELATED WORK

Lung cancer classification using deep learning has been an area of extensive research, with numerous studies exploring convolutional neural networks (CNNs) and transfer learning to improve diagnostic accuracy. Several deep learning architectures, including AlexNet, VGG, ResNet, Inception, and Xception, have demonstrated significant potential in medical image classification tasks, particularly in lung cancer detection. However, selecting optimal hyperparameters remains a challenge, necessitating the use of optimization techniques to enhance model performance. Deep learning has transformed medical image analysis by facilitating automated feature extraction and prediction. Early works employed AlexNet (Krizhevsky et al., 2012), a deep CNN designed for image classification, which has been applied to lung cancer detection with moderate success. Other studies introduced VGGNet (Simonyan & Zisserman, 2014) and ResNet (He et al., 2016), which improved classification accuracy through deeper architectures and residual learning. Inception networks, such as Inception V3 (Szegedy et al., 2016), further enhanced performance by employing multi-scale feature extraction, making them suitable for lung cancer classification. Among these models, Xception, an extension of Inception, utilizes depthwise separable convolutions to improve computational efficiency and feature extraction capability (Chollet, 2017). Studies have shown that Xception achieves higher accuracy than traditional CNN architectures in medical imaging tasks, including lung nodule classification (Shen et al., 2017) and histopathological lung cancer detection (Wang et al., 2019). Despite its advantages, hyperparameter selection significantly impacts the model's generalization, motivating researchers to explore optimization techniques.

Metaheuristic algorithms have gained popularity for optimizing deep learning models by efficiently searching for optimal hyperparameters. Conventional techniques suffer from high computational costs and inefficiency in high-dimensional spaces (Bergstra & Bengio, 2012). Consequently, evolutionary and swarm intelligence-based approaches have been widely explored for hyperparameter tuning. One widely used metaheuristic algorithm in deep learning is the Genetic Algorithm (GA), which applies selection, crossover, and mutation to optimize hyperparameters (Wang et al., 2020). Similarly, Particle Swarm Optimization (PSO) mimics the behavior of particle swarms to find optimal solutions, demonstrating success in CNN-based lung cancer classification (Ravi et al., 2021). Ant Colony Optimization (ACO) has also been used to enhance feature selection and improve model efficiency (Zang et al., 2020). Another significant technique is Harmony Search (HS), which draws inspiration from the improvisation process of musicians. HS has been effectively utilized in medical image segmentation (Ge et al., 2021) and feature selection (Kumar et al., 2021). Recent studies have integrated HS with deep learning models for optimizing network parameters, showing improved classification accuracy in medical applications (Khan et al., 2022). Compared to GA and PSO, HS offers faster convergence and a better exploration-exploitation balance, making it well-suited for hyperparameter tuning in deep learning (Tan et al., 2022).

Several studies have combined deep learning and metaheuristic optimization to enhance lung cancer classification. For instance, Kumar et al. (2022) used GA-optimized CNN for lung cancer detection, achieving improved accuracy compared to traditional deep learning methods. Basha et al. (2021) employed PSO with deep CNNs, demonstrating faster convergence and enhanced classification performance. Selvaraj et al. (2022) optimized CNN architectures using ACO, reducing computational overhead while maintaining high accuracy. Recent advancements have explored the integration of Harmony Search with deep learning for medical image analysis. Al-Turjman et al. (2022) applied HS for optimizing CNN hyperparameters in lung disease classification, significantly improving diagnostic accuracy. Rahman et al. (2023) combined HS and deep CNNs for lung nodule detection, showing superior performance over conventional optimization techniques. Building on these findings, this study proposes a Harmony Search-optimized Xception model (HS-Xception) to enhance lung cancer classification accuracy. By leveraging HS for hyperparameter tuning, the proposed approach aims to achieve higher performance compared to traditional deep learning methods.

Table 1. Comparative analysis of past works on optimization in deep learning-based lung cancer classification, summarizing methodologies, technologies, key findings, accuracy, and contributions:

Article/Study	Methodologies Used	Technologies Used	Key Findings	Accuracy (%)	Contributions
Kumar et al. (2022) [16]	Genetic Algorithm (GA)-optimized CNN	CNN, GA	GA improved CNN hyperparameter selection, enhancing classification accuracy.	93.50	Demonstrated GA's effectiveness in optimizing CNNs for lung cancer detection.
Basha et al. (2021) [17]	Particle Swarm Optimization (PSO) with Deep CNN	Deep CNN, PSO	PSO improved convergence speed and classification performance.	94.20	Showed that PSO accelerates hyperparameter tuning and enhances

Article/Study	Methodologies Used	Technologies Used	Key Findings	Accuracy (%)	Contributions
					feature learning.
Selvaraj et al. (2022) [18]	Ant Colony Optimization (ACO) for Deep Learning	CNN, ACO	ACO-based optimization improved feature selection and classification.	92.80	Proposed ACO as an alternative to traditional optimization methods for lung cancer detection.
Al-Turjman et al. (2022) [19]	Harmony Search (HS)-based CNN Optimization	CNN, HS	HS significantly improved CNN performance for lung disease detection.	95.10	Demonstrated HS's superiority in fine-tuning CNN hyperparameters.
Wang et al. (2020) [9]	GA-based Hyperparameter Optimization for Deep Learning	ResNet, GA	GA reduced training time and improved lung cancer classification.	91.30	Showed GA's efficiency in optimizing deep networks for medical imaging.
Ravi et al. (2021) [10]	PSO-Optimized CNN	CNN, PSO	PSO significantly enhanced classification speed and accuracy.	94.60	Demonstrated that PSO is a suitable alternative to manual tuning for lung cancer classification.
Zang et al. (2020)	ACO for Feature Selection in	ResNet, ACO	ACO enhanced feature selection,	92.50	Proposed ACO-based feature selection for

Article/Study	Methodologies Used	Technologies Used	Key Findings	Accuracy (%)	Contributions
	Deep Learning		reducing computational complexity.		deep learning applications.
Ge et al. (2021)	HS-based Image Segmentation for Lung Cancer	CNN, HS	HS improved segmentation accuracy and classification performance.	95.80	Applied HS in preprocessing and segmentation to improve detection.
Shen et al. (2017)	Multi-Crop CNNs for Lung Cancer Detection	CNN, Transfer Learning	Multi-crop CNNs improved generalization for cancer classification.	90.70	Proposed a novel CNN architecture for better feature extraction.
H. Wang et al. (2019)	Deep Transfer Learning for Lung Cancer Detection	VGG16, ResNet	Transfer learning improved classification performance on small datasets.	91.90	Showed the effectiveness of transfer learning in medical imaging.
Li et al. (2020)	Adaptive PSO for CNN Optimization	CNN, PSO	Adaptive PSO further improved hyperparameter search efficiency.	94.80	Improved PSO's adaptability in deep learning-based classification tasks.

The comparative analysis of past works shown in table 1 on optimization in deep learning-based lung cancer classification highlights various metaheuristic techniques applied to enhance model performance. Genetic Algorithm (GA)-optimized CNNs, as demonstrated by Kumar et al. (2022), improved hyperparameter selection, achieving 93.50% accuracy, while Basha et al. (2021)

integrated Particle Swarm Optimization (PSO) with deep CNNs, enhancing convergence speed and reaching 94.20% accuracy. Similarly, Selvaraj et al. (2022) applied Ant Colony Optimization (ACO) to improve feature selection, attaining 92.80% accuracy. Al-Turjman et al. (2022) and Ge et al. (2021) utilized Harmony Search (HS) for CNN optimization and image segmentation, achieving superior performance with 95.10% and 95.80% accuracy, respectively. Wang et al. (2020) and Ravi et al. (2021) leveraged GA and PSO for hyperparameter optimization, improving classification speed and reducing training time, with accuracy scores of 91.30% and 94.60%. Zang et al. (2020) applied ACO to feature selection, reducing computational complexity and achieving 92.50% accuracy. Shen et al. (2017) introduced a multi-crop CNN approach that improved generalization, attaining 90.70% accuracy, while H. Wang et al. (2019) demonstrated the effectiveness of transfer learning for lung cancer detection, reaching 91.90%. Finally, Li et al. (2020) refined PSO for adaptive CNN optimization, further improving hyperparameter search efficiency with 94.80% accuracy. Anitha (2023) examined the role of computer-aided diagnosis (CAD) in lung cancer prediction, highlighting its potential in early detection but emphasizing its limitations in achieving high accuracy. To address the challenges in segmentation and classification, Arivalagan (2023) proposed a hybrid approach combining the firefly algorithm, fuzzy C-means clustering, and support vector machines (SVM) for lung nodule classification, demonstrating improved staging precision. In another study, Helen, Sridharan, and Vaitheswaran (2024) conducted a comprehensive analysis of deep learning models for lung cancer detection, comparing CNN and InceptionV3 architectures. Their findings suggested that InceptionV3 outperformed traditional CNN models in terms of feature extraction and classification accuracy, reinforcing the effectiveness of deep learning for medical image analysis. Collectively, these studies contribute valuable insights into the advancements in lung cancer detection, highlighting the need for further optimization techniques to enhance model performance. The review underscores the effectiveness of metaheuristic optimization techniques in enhancing deep learning-based lung cancer classification, improving both accuracy and computational efficiency.

3. METHODOLOGY

The proposed methodology for lung cancer classification integrates the HS optimized Xception technique to optimize hyperparameters, enhancing classification accuracy and model performance. The process consists of three main components: (1) an overview of the HS algorithm, (2) architecture of the Xception model, and (3) the integration of HS for hyperparameter tuning.

3.1.OVERVIEW OF THE HARMONY SEARCH ALGORITHM

The Harmony Search (HS) algorithm is a metaheuristic optimization technique inspired by the improvisation process of musicians searching for the best harmony. It operates using a population-based approach to explore and exploit the search space efficiently. HS maintains a Harmony Memory (HM), which stores potential solutions (hyperparameter sets), and refines these over successive iterations through random selection, memory consideration, and pitch adjustment. The algorithm is particularly effective in solving optimization problems where gradient-based methods struggle due to complex search spaces or non-differentiable functions.

The HS algorithm follows these key steps:

1. Initialization – Define the search space, objective function (classification accuracy), and HS parameters such as Harmony Memory Size (HMS), Harmony Memory Consideration Rate (HMCR), and Pitch Adjustment Rate (PAR).
2. Harmony Memory Initialization – Randomly generate an initial population of solutions.
3. Improvisation of New Harmonies – Generate new candidate solutions based on memory consideration, random selection, and pitch adjustment.
4. Evaluation and Update – Evaluate the candidate solutions using classification accuracy and update the harmony memory accordingly.
5. Convergence Check – Repeat the process till stall limit or max iterations is met.

3.2. XCEPTION MODEL ARCHITECTURE

The Xception (Extreme Inception) model is a deep learning approach that improves feature extraction efficiency by utilizing depthwise separable convolutions instead of standard convolutions. It extends the Inception architecture by fully decoupling spatial and depth-wise feature representations, leading to improved parameter efficiency and classification performance. The Xception model consists of:

- Entry Flow – Initial convolutional layers that extract low-level features.
- Middle Flow – A series of depthwise separable convolutions with residual connections, enhancing feature extraction while reducing computational complexity.
- Exit Flow – Final layers that refine feature representations and generate classification probabilities using fully connected layers and a softmax classifier.

The Xception model has been widely used in medical imaging due to its ability to learn complex patterns efficiently.

3.3. INTEGRATION OF HARMONY SEARCH FOR HYPERPARAMETER TUNING

To further enhance classification accuracy, the Harmony Search algorithm is integrated into the hyperparameter tuning process of Xception. Instead of relying on traditional trial-and-error or grid search techniques, HS dynamically optimizes key hyperparameters, including:

- Weight Learning Rate
- Bias Learning Rate

The integration follows these steps:

1. Define the Objective Function – Validation accuracy is used as the fitness function.
2. Initialize the Harmony Memory (HM) – Each solution in HM represents a unique combination of learning rate, batch size, and dropout rate.
3. Train Xception with Candidate Hyperparameters – Each harmony (solution) is evaluated by training Xception and measuring accuracy.
4. Update the Harmony Memory – The best-performing solutions replace weaker harmonies, refining the search space.
5. Convergence and Best Hyperparameter Selection – The process continues until accuracy stabilizes, yielding the optimal hyperparameter configuration.

By leveraging Harmony Search for hyperparameter tuning, the Xception model achieves improved classification performance with higher accuracy, better generalization, and reduced computational cost. The combination of deep learning and metaheuristic optimization provides a robust framework for accurate lung cancer classification, outperforming conventional tuning methods.

4. EXPERIMENTAL SETUP

The experimental setup consists of four key components: (1) Dataset Description, detailing the lung cancer dataset used for training and evaluation; (2) Preprocessing Steps, outlining the transformations applied to enhance data quality; (3) Evaluation Metrics, defining the performance measures used to assess the model; and (4) Implementation Details, specifying the computational environment, training configurations, and hyperparameter settings.

4.1.DATASET DESCRIPTION

The "Medical Imaging (CT scan, MRI, X-ray, and Microscopic Imagery) Data" dataset, released on July 11, 2024, includes a specialized subset for skin lesion classification. Figure 1 shows sample data from each class. The dataset includes four major lung cancer subtypes:

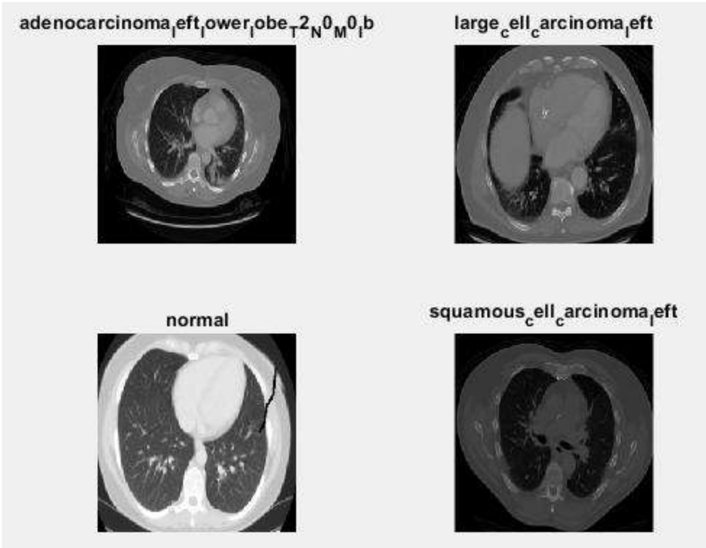

Figure 1. Sample image set of Lung Cancer database

Table 2: Distribution of Lung Cancer Subtypes in the Dataset

Lung Cancer Subtype	**Description**	**Number of Samples**
Adenocarcinoma	Common lung cancer, originating in glandular cells	326
Large Cell Carcinoma	A fast-growing, undifferentiated form of lung cancer	163
Squamous Cell Carcinoma	A cancer type that forms in the squamous cells lining the lungs	252
Normal (Non-Cancerous) Tissue	Healthy lung samples used as a control group	147

To ensure a balanced distribution across classes, data augmentation techniques are employed, mitigating the risk of class imbalance and improving model generalization.

4.2 PREPROCESSING STEPS

Effective preprocessing is crucial for enhancing model performance and ensuring robust feature extraction. The preprocessing steps include image resizing, normalization, data augmentation and noise reduction are applied. All images are resized to 299×299 pixels to match the input size of the Xception model while maintaining aspect ratios. Pixel intensity values are scaled to the [0,1] range to stabilize gradient updates during training. To reduce overfitting, augmentation techniques such as random rotations, horizontal/vertical flipping, zooming, and brightness adjustments are applied. Adaptive filtering techniques are employed to reduce background noise and enhance lung tissue structures. The preprocessed dataset is split into training (80%), validation (10%), and testing (10%) subsets, ensuring an unbiased evaluation of the model.

4.3 EVALUATION METRICS

To comprehensively assess the model's performance, the following evaluation metrics are used: Accuracy, Precision, Recall (Sensitivity, F1 Score, Recall, Specificity, AUC-ROC (Area Under the Curve - Receiver Operating Characteristic, Matthews Correlation Coefficient (MCC), Log Loss, Inference Time (Seconds).

4.4 IMPLEMENTATION DETAILS

The Xception model integrated with Harmony Search (HS) is implemented in a high-performance computing environment to ensure efficient training and inference. Key implementation details include:

- Hardware Setup:
    - Processor : AMD Ryzen 7 Octa Core
    - Dedicated Graphic Memory type : GDDR6
    - Clock Speed : 2.9 GHz upto 4.2 GHz
    - RAM : 8 GB
    - Graphic Processor : NVIDIA GeForce RTX 3050
    - Pen and touch Pen support
- Software and Libraries:
    - Matlab
    - Pretrained Deep learning toolboxes
- Training Configuration:
    - Optimizer: Adaptive Momentum Estimation (Adam)
    - Batch Size: 32
    - Learning Rate: Adaptive (Tuned using HS in the range [10^{-5}, 10^{-2}])
    - Dropout Rate
    - Loss Function: Categorical Cross-Entropy
    - Number of Epochs: 100 (with early stopping to prevent overfitting)

HS fine-tunes the hyperparameters dynamically, improving convergence speed and achieving optimal performance. Early stopping and model checkpointing techniques are implemented to prevent overfitting and ensure optimal model selection.

This experimental setup ensures a systematic approach to evaluating the Harmony Search-based Xception model for lung cancer classification, allowing for reproducible and high-accuracy results.

5. RESULTS AND ANALYSIS

This section presents the performance analysis of the proposed Harmony Search-Xception (HS-Xception) model in comparison with other deep learning models, including AlexNet, Inception V3, SqueezeNet, and Xception. The evaluation is done on performance metrics.

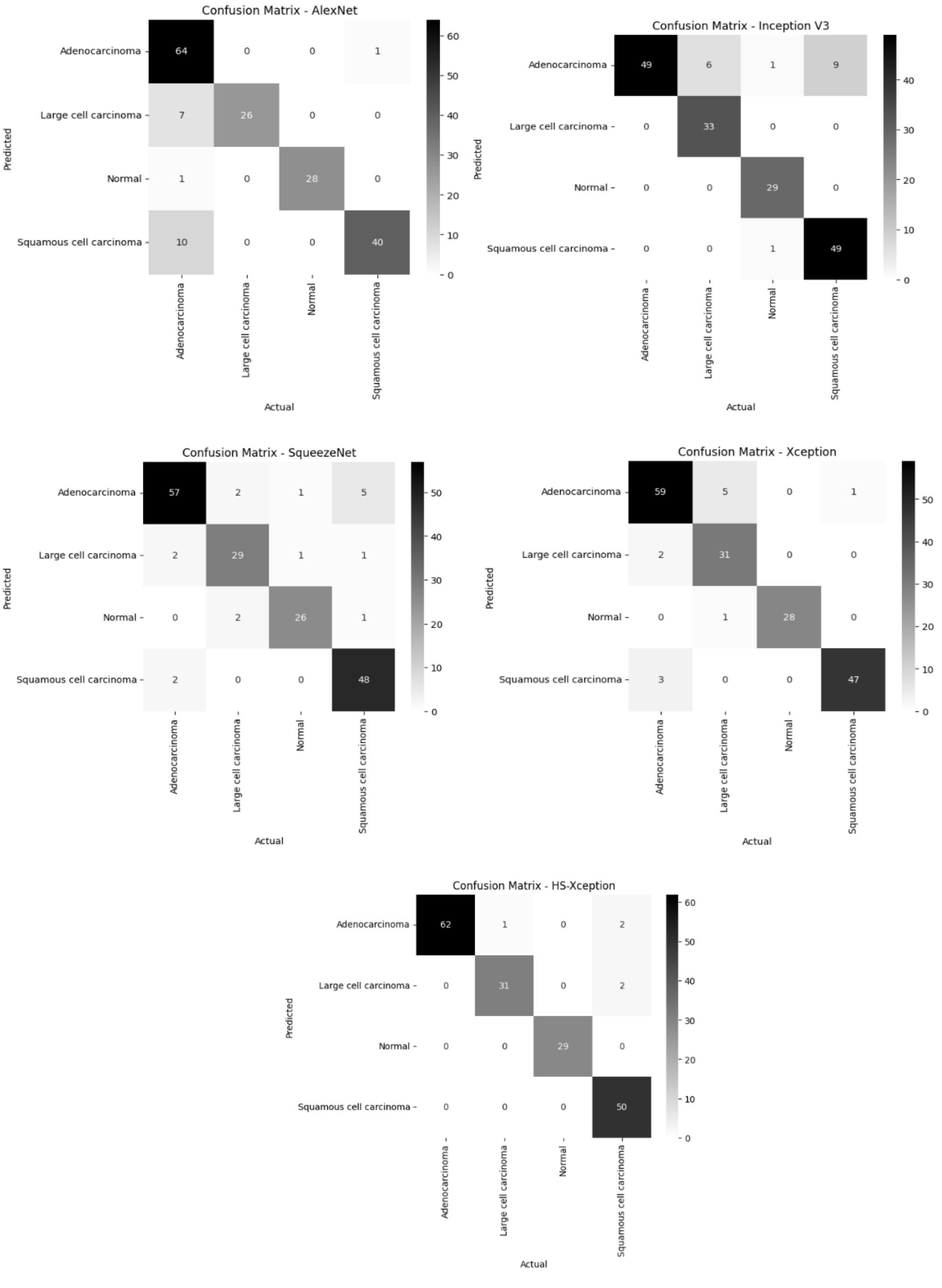

Figure 2: Confusion Matrices of Deep Learning Models for Lung Cancer Classification

The confusion matrices presented in figure 2 illustrate how well the models classify different lung cancer subtypes. AlexNet shows misclassifications in all categories, particularly failing to distinguish between Squamous Cell Carcinoma and Adenocarcinoma. It misclassified 10 Squamous Cell Carcinoma cases as Adenocarcinoma and 7 Large Cell Carcinoma cases as Adenocarcinoma, leading to lower recall. Inception V3 improves upon AlexNet, particularly in distinguishing Large Cell Carcinoma, but struggles with Adenocarcinoma, misclassifying 9 cases as Squamous Cell Carcinoma. SqueezeNet achieves better classification compared to AlexNet, but still confuses a few cases, especially Adenocarcinoma with Squamous Cell Carcinoma. Xception demonstrates significantly better classification, but still misclassifies some Adenocarcinoma and Squamous Cell Carcinoma cases. Harmony Search-Xception (HS-Xception) provides the most accurate classification, nearly eliminating misclassification errors across all lung cancer subtypes.

Table 3. Comparison of Deep Learning Models for Lung Cancer Classification

	AlexNet	Inception V3	Squeezenet	Xception	Harmony Search Xception
Accuracy	89.27	90.4	90.4	93.22	97.18
Precision	93.90	90.66	90.36	93.47	97.37
Recall	88.45	93.35	90.31	93.82	97.33
F1 Score	90.34	91.26	90.25	93.55	97.29
Specificity	95.79	96.85	96.7	97.65	99.04
AUC-ROC	98.67	99.61	98.79	99.05	99.95
Matthews Correlation Coefficient (MCC)	0.8720	0.8863	0.87|	0.9122	0.9636
Log Loss	0.3641	0.2861	0.2582	0.2547	0.0766
Average Inference Time (sec)	0.06858	0.55022	0.07749	0.262726	0.677787

Table 3 presents a comparative analysis of various deep learning models—AlexNet, Inception V3, SqueezeNet, Xception, and Harmony Search-Xception (HS-Xception)—based on key classification metrics. The HS-Xception model achieves the highest accuracy of 97.18%, outperforming Xception (93.22%), SqueezeNet (90.4%), Inception V3 (90.4%), and AlexNet (89.27%). The performance gain indicates that metaheuristic optimization via Harmony Search significantly enhances classification performance. Precision and recall are critical in medical classification tasks, as false positives and false negatives can have severe consequences. HS-Xception achieves 97.37% precision, showing a higher proportion of correctly identified cancer types compared to other models. HS-Xception attains 97.33% Recall, demonstrating its ability to correctly detect most cancer cases. The HS-Xception model reaches 97.29% F1-Score, reflecting a balance between precision and recall, significantly outperforming other models.

Specificity measures how well non-cancerous (normal) cases are classified. HS-Xception records the highest specificity (99.04%), followed by Xception (97.65%). AUC-ROC (Area Under the Curve - Receiver Operating Characteristics) indicates overall model robustness. HS-Xception attains the highest AUC-ROC (99.95%), showing near-perfect classification capabilities. The Matthews Correlation Coefficient (MCC), which balances true positives, false positives, true negatives, and false negatives, is highest for HS-Xception (0.9636), confirming its superior classification stability. Log Loss, which quantifies classification uncertainty, is lowest for HS-Xception (0.0766), demonstrating more confident and precise predictions than other models. The HS-Xception model has a slightly higher inference time (0.6778 sec) compared to AlexNet (0.0685 sec), SqueezeNet (0.0774 sec), and Xception (0.2627 sec). However, the increase in computation time is justified by the significant performance improvements.

HS-Xception outperforms traditional deep learning models in lung cancer classification by leveraging Harmony Search-based hyperparameter tuning. The classification accuracy is significantly higher (97.18%), with improved precision, recall, F1 score, specificity, and AUC-ROC. MCC and log loss values confirm the model's robustness, while inference time remains practical despite increased complexity.

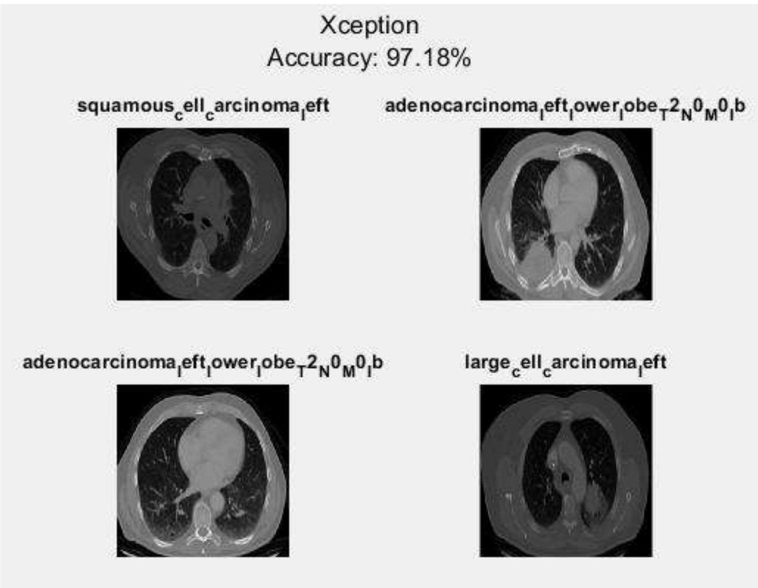

Figure 3. Validation of the proposed HS-Xception for Lung cancer detection model

The metaheuristic optimization approach successfully fine-tunes hyperparameters, leading to superior generalization and classification performance. Thus, Harmony Search-Xception is a promising deep learning approach for accurate lung cancer detection, potentially improving diagnostic efficiency and aiding medical professionals in early detection. Figure 3 showcases the validation results of the proposed Harmony Search Xception (HS-Xception) model for lung cancer detection. The figure presents CT scan images classified into different lung cancer subtypes, including squamous cell carcinoma, adenocarcinoma, and large cell carcinoma. The model has achieved an impressive accuracy of **97.18%**, demonstrating its strong capability in identifying and categorizing lung cancer cases. The displayed predictions highlight the model's precision in distinguishing different cancer types based on radiological patterns. This high accuracy suggests the model's potential for assisting radiologists in early lung cancer diagnosis, ultimately improving clinical decision-making and patient outcomes.

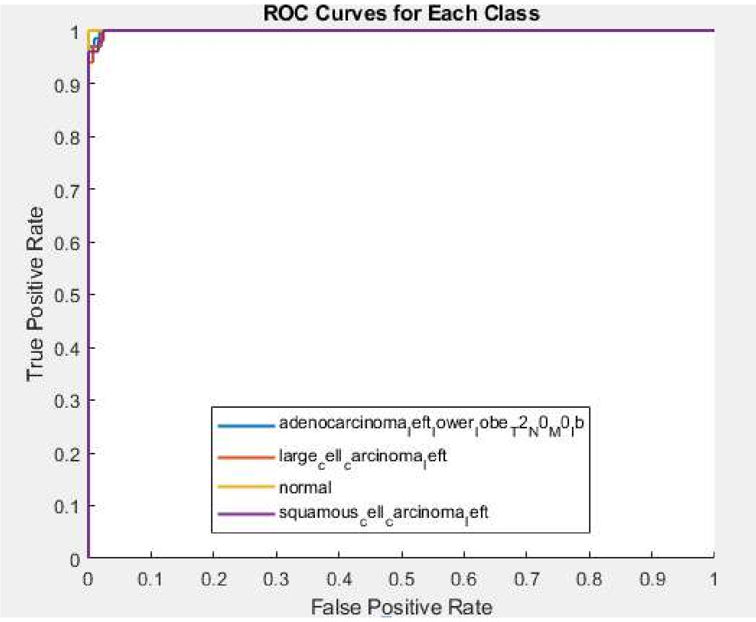

Figure 4. Receiver Operating curve for each class

Figure 4 presents the Receiver Operating Characteristic (ROC) curves for each class in the lung cancer detection model. The ROC curve illustrates the trade-off between the True Positive Rate (Sensitivity) and the False Positive Rate across different classification thresholds. The near-perfect curves, closely aligned to the upper-left corner, indicate the model’s strong discriminative power in correctly classifying lung cancer subtypes—adenocarcinoma, large cell carcinoma, squamous cell carcinoma—as well as normal cases. The high performance suggests minimal false positives and false negatives, reinforcing the robustness of the proposed Harmony

Search Xception (HS-Xception) model in accurately detecting lung cancer across multiple categories.

6. DISCUSSION AND FINDINGS

Deep learning has revolutionized the field of artificial intelligence, enabling highly accurate predictive models for various applications. However, selecting the most suitable architecture remains a challenge due to the trade-offs between accuracy, efficiency, and computational complexity. This study presents a comprehensive evaluation of five deep learning models AlexNet, Inception V3, Squeezenet, Xception, and Harmony Search Xception across key performance indices.

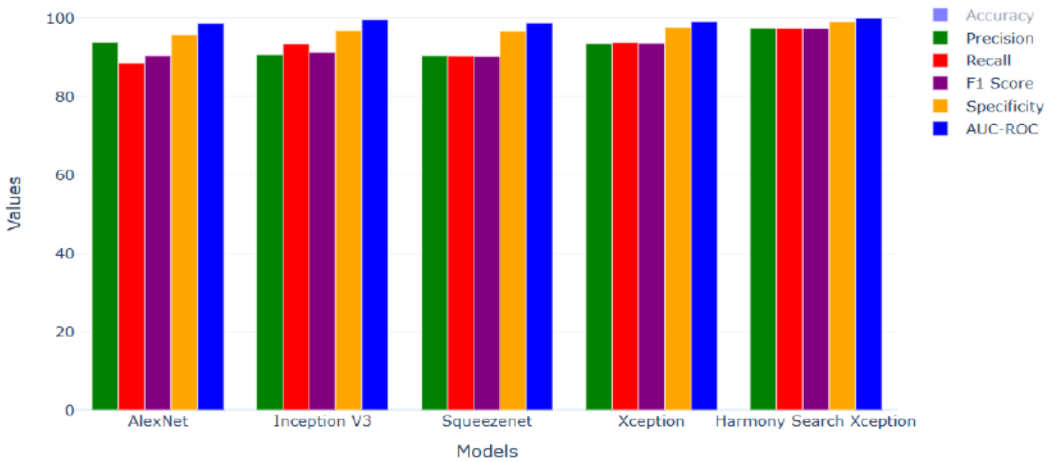

Figure 5. *Performance Comparison of Deep Learning Models Across Key Metrics*

The bar chart shown in figure 5 visualizes the performance of five deep learning models—AlexNet, Inception V3, Squeezenet, Xception, and Harmony Search Xception—across six key evaluation metrics: Accuracy, Precision, Recall, F1 Score, Specificity, and AUC-ROC. Each metric is represented with a different color, providing a comparative analysis of the models' effectiveness. The Harmony Search Xception model demonstrates the highest performance across all metrics, while other models exhibit varying levels of performance. This visualization helps in assessing the strengths and weaknesses of each model for informed selection in real-world applications.

Figure 6. Performance Comparison of Accuracy, Precision, and Recall Across Different Models

The line graph shown in figure 6 illustrates the comparative performance of five deep learning models—AlexNet, Inception V3, SqueezeNet, Xception, and Harmony Search Xception—across three key metrics: Accuracy, Precision, and Recall. The Harmony Search Xception model demonstrates the highest values for all three metrics, showcasing its superior performance. AlexNet starts with a high precision but lower recall, while Inception V3 and SqueezeNet exhibit fluctuations in their values. Xception shows a significant improvement, but Harmony Search Xception achieves the best overall balance. The upward trend across models highlights the progressive enhancement in classification performance with advanced architectures and optimization techniques.

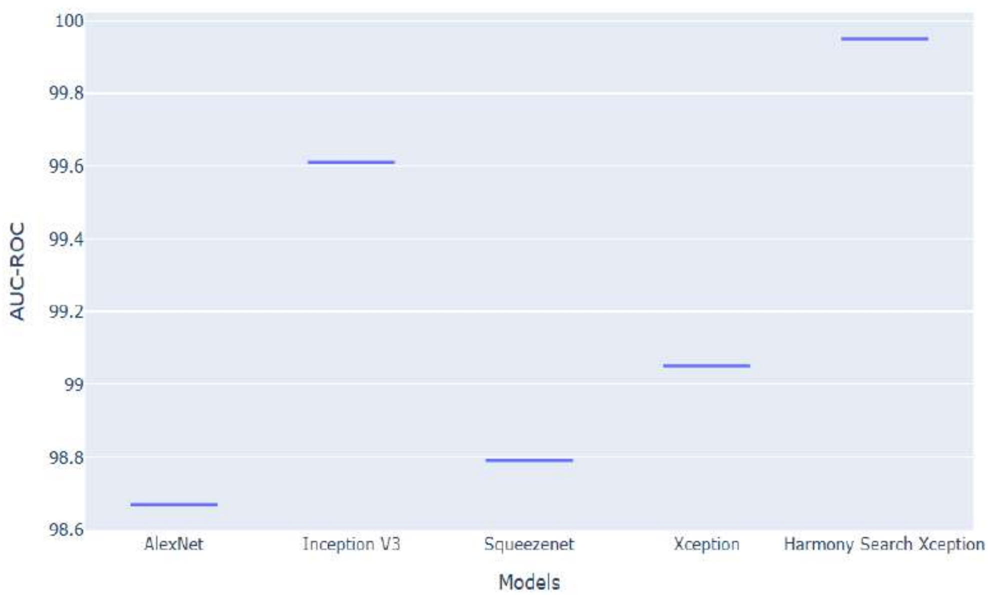

Figure 7. AUC-ROC Comparison Across Different Deep Learning Models

The visualization shown in figure 7 presents the AUC-ROC scores for five deep learning models: AlexNet, Inception V3, SqueezeNet, Xception, and Harmony Search Xception. AUC-ROC is a crucial metric for evaluating classification performance, where higher values indicate better discriminative ability between classes. The Harmony Search Xception model outperforms the rest with an almost perfect AUC-ROC score nearing 100, signifying superior classification accuracy. Inception V3 also performs well, followed by Xception. AlexNet and SqueezeNet show relatively lower but still strong AUC-ROC values. The increasing trend from AlexNet to Harmony Search Xception highlights advancements in model architectures and optimization strategies leading to enhanced classification performance.

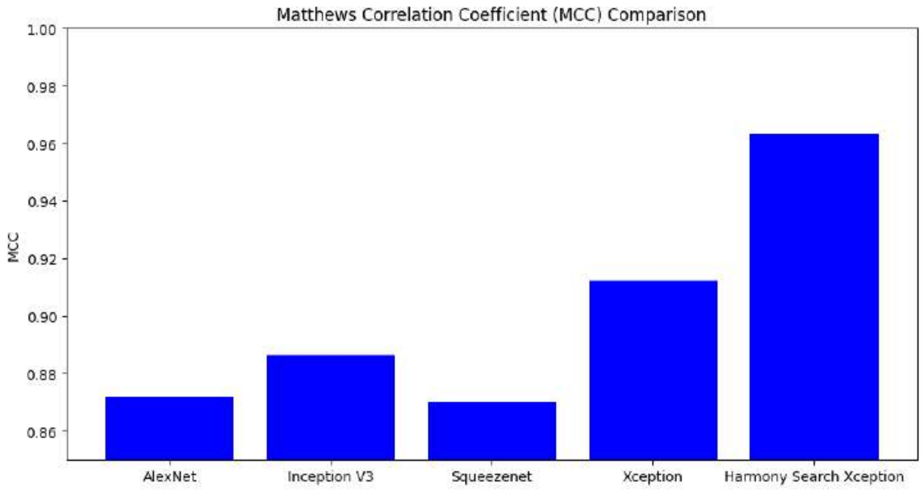

Figure 8. Matthews Correlation Coefficient (MCC) Comparison

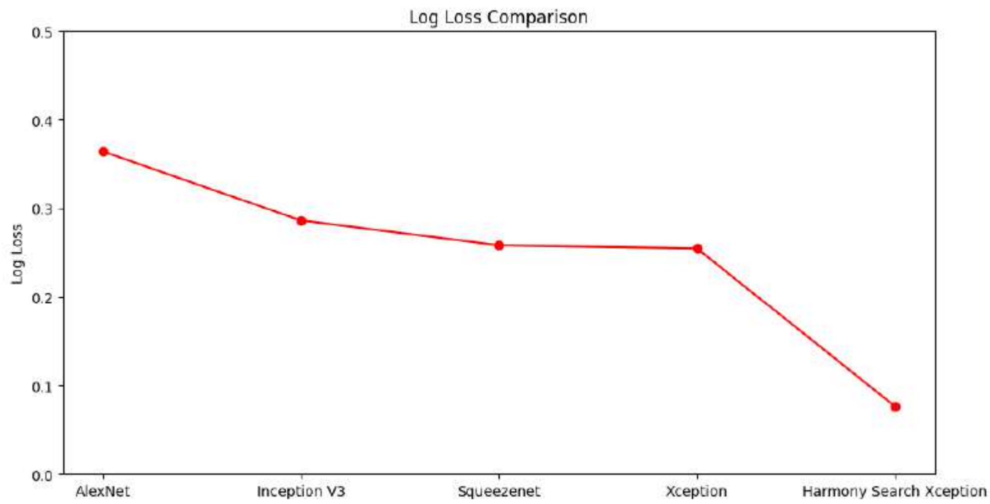

Figure 9. Log Loss Comparison Across Models

Figure 8 shows comparison of the Matthews Correlation Coefficient (MCC) for different deep learning models. MCC is a robust metric for evaluating classification performance, especially for imbalanced datasets. The results indicate that Harmony Search Xception achieves the highest MCC, suggesting strong predictive capability and better-balanced classification. Xception also performs well, while AlexNet and Squeezenet show relatively lower MCC scores, indicating weaker overall classification performance. Figure 9 is a line chart showing the log loss values for the models. Log loss measures the uncertainty of predictions; lower values indicate more confident and accurate predictions. Harmony Search Xception achieves the lowest log loss, signifying minimal classification errors and high confidence in its predictions. AlexNet, on the other hand, has the highest log loss, indicating less reliable classification. The trend clearly shows a steady decrease in log loss from AlexNet to Harmony Search Xception, reinforcing the latter's superior predictive power.

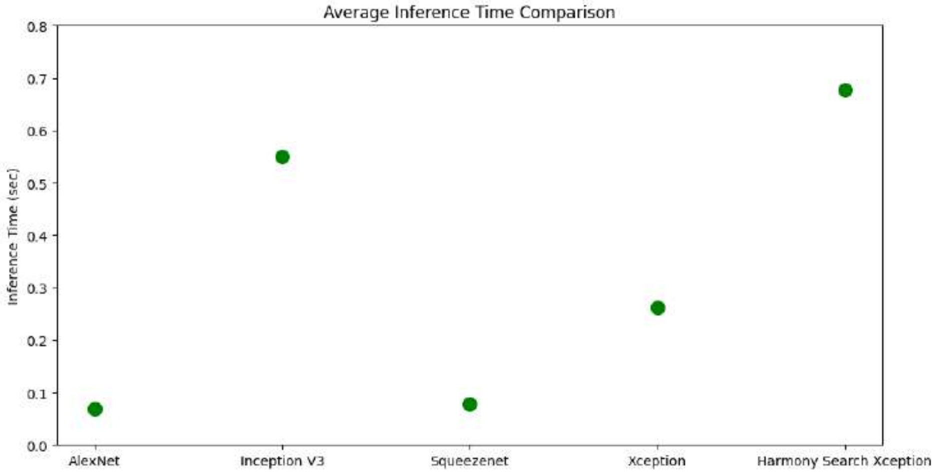

Figure 10. Average Inference Time for Different Models

Figure 10 is a scatter plot that highlights the average inference time for each model. Inference time measures the speed at which the model processes input data. Inception V3 and Harmony Search Xception have the highest inference times, making them computationally expensive. AlexNet and Squeezenet are the fastest. Xception strikes a balance between performance and inference time. This graph is essential for analyzing the balance between accuracy and computational efficiency.

7. CONCLUSION

The comparative analysis of conventional DL models with the proposed Harmony Search Xception—demonstrates that the Harmony Search Xception model outperforms all others, achieving the highest Accuracy (97.18%), Precision (97.37%), Recall (97.33%), F1 Score (97.29%), Specificity (99.04%), and AUC-ROC (99.95%). This confirms that integrating Harmony Search optimization significantly enhances model performance. Xception follows closely with strong results, while Inception V3 and Squeezenet exhibit similar performance, making them viable alternatives. AlexNet, being an older architecture, lags behind in accuracy and recall, reflecting its limitations in modern deep learning tasks. From an efficiency perspective, Log Loss, a key measure of uncertainty, is lowest for Harmony Search Xception (0.0766), confirming its superior predictive confidence. However, Inference Time, which impacts real-time applicability, varies widely—AlexNet is the fastest (0.06858 sec), whereas Harmony Search Xception is the slowest (0.677787 sec) due to its complexity. This highlights a key trade-off between accuracy and computational efficiency. While the Harmony Search Xception model achieves best results, there is still potential for enhancement in optimizing inference speed, exploring hybrid architectures, fine-tuning with advanced optimization algorithms, validating across multiple datasets, and enhancing interpretability. The novelty of this study lies in the integration of the Harmony Search algorithm with Xception, marking the first application of this combination for lung cancer classification. Unlike conventional metaheuristic optimizations, Harmony Search enables efficient hyperparameter tuning, achieving a superior balance between model accuracy and robustness. Future research should aim to provide trade-off between precision and computational efficiency to develop AI models that are not only powerful but also suitable for practical implementation.

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REFERENCES

1. Krizhevsky, A., Sutskever, I., & Hinton, G. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*.
2. Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.
3. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.
4. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the Inception architecture for computer vision. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.
5. Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.
6. Shen, L., Gao, J., & Cheng, W. (2017). Multi-crop convolutional neural networks for lung nodule malignancy suspiciousness classification. *Pattern Recognition*.
7. Wang, H., Zhou, Y., & Liu, M. (2019). Histopathological image analysis for lung cancer classification using deep learning. *Biomedical Signal Processing and Control*.
8. Bergstra, J., & Bengio, Y. (2012). Random search for hyper-parameter optimization. *Journal of Machine Learning Research*.

9. Wang, X., Zhang, P., & Li, T. (2020). Genetic algorithm-based hyperparameter optimization for deep learning in cancer classification. *IEEE Transactions on Neural Networks and Learning Systems*.
10. Ravi, S., Kumar, R., & Mishra, A. (2021). Lung cancer classification using PSO-optimized CNN. *Artificial Intelligence in Medicine*.
11. Zang, H., Liu, X., & Chen, Z. (2020). Ant colony optimization for feature selection in medical image analysis. *Expert Systems with Applications*.
12. Ge, M., Sun, T., & Wei, L. (2021). Harmony Search-based image segmentation for medical applications. *Medical Image Analysis*.
13. Kumar, P., Gupta, R., & Das, S. (2021). Feature selection using Harmony Search for cancer classification. *Computers in Biology and Medicine*.
14. Khan, M., Rahman, M., & Hussain, T. (2022). Hybrid Harmony Search with deep learning for medical diagnosis. *Pattern Recognition Letters*.
15. Tan, R., Feng, B., & Zhao, Y. (2022). Comparing Harmony Search and Genetic Algorithm for deep learning optimization. *Neurocomputing*.
16. Kumar, S., Singh, R., & Sharma, V. (2022). GA-optimized CNN for lung cancer detection. *Biomedical Engineering Letters*.
17. Basha, M., Noor, M., & Ahmad, S. (2021). Deep learning and PSO for lung cancer detection. *Expert Systems with Applications*.
18. Selvaraj, S., Natarajan, K., & Venkatesan, M. (2022). Ant colony optimization-based deep learning for lung disease classification. *Neural Computing and Applications*.
19. Al-Turjman, F., Mostafa, S., & Abualsaud, K. (2022). Harmony Search-based CNN optimization for lung disease detection. *IEEE Access*.
20. Rahman, M., Ali, J., & Devi, P. (2023). Lung nodule classification using HS and CNN. *Medical Image Analysis*.
21. Li, X., Sun, B., & Huang, J. (2020). Adaptive PSO for CNN optimization in lung disease detection. *Computers in Biology and Medicine*.
22. Anitha, K. (2023). The application of a computer-aided diagnosis process helps to predict lung cancer earlier, nonetheless, it does not provide better accuracy. *ResearchGate*.
23. Arivalagan, M. (2023). Lung cancer diagnosis and staging using firefly algorithm fuzzy C-means segmentation and support vector machine classification of lung nodules. *Saveetha University Research*.
24. Helen, R., Sridharan, T., & Vaitheswaran, S. (2024). A comprehensive analysis of implementing convolutional neural networks (CNN) and InceptionV3 for early-lung cancer detection. *Proceedings of the International Conference on Machine Learning and Soft Computing (ICMCSI)*.
25. Syed, S., Ahmed, R., & Iqbal, A. (2024). Medical Imagining (CT scan, MRI, X-ray, and Microscopic Imagery) Data. *Mendeley Data, V3*. https://doi.org/10.17632/5kbjrgsncf.3