UKR Journal of Multidisciplinary Studies (UKRJMS)
Homepage: https://ukrpublisher.com/ukrjms/
Email: submit.ukrpublisher@gmail.com
Volume 2, Issue 6, 2026 ISSN: 3049-432X (Online)

EVALUTION OF TRANSIT SEARCH-BASED CONVOLUTIONAL NEURAL NETWORK FOR LUNG CANCER IDENTIFICATION

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DOI: *https://doi.org/10.5281/zenodo.20539896*

Article History
Original Research Article
Received: 06-04-2026
Accepted: 12-05-2026
Published: 04-06-2026

Citation: Olufunke Kemi Ogunniyi, Folasade Muibat Ismaila, Ogirima Wanta Sanni, Wasiu Oladimeji Ismaila, Olajide Blessing Olajide, Ogunkan Stella Kehinde, and Orukotan Felicia Funmilayo (2026). *Evaluation of Transit Search-Based Convolutional Neural Network for Lung Cancer Identification.* UKR Journal of Multidisciplinary Studies (UKRJMS), 2(6), 34-41.

Abstract

Lung cancer remains one of the leading causes of cancer-related mortality worldwide, largely due to late-stage detection and diagnostic challenges associated with medical imaging. This study focuses on the Transit Search-Based Convolutional Neural Network (TS-CNN) for lung cancer identification using computed tomography (CT) scan images. The proposed model integrates convolutional neural networks with a transit search optimisation mechanism to enhance feature extraction, automate hyperparameter tuning, and improve classification performance. The system is designed within a Computer-Aided Diagnosis (CAD) framework, incorporating preprocessing, segmentation, feature learning, and classification stages. Experimental evaluation demonstrates that the improved TS-CNN model achieves higher accuracy, sensitivity, and specificity compared to conventional CNN models by reducing false positives and enhancing generalisation. The findings suggest that the integration of search-based optimisation techniques into deep learning architectures significantly improves the reliability and efficiency of lung cancer detection systems. This study contributes to the advancement of intelligent diagnostic tools and provides a foundation in optimised deep learning models for medical imaging.

Keywords: *Transit search-based, convolutional neural network, lung cancer identification.*

1.1 Introduction

Convolutional Neural Networks (CNNs) have been a popular choice for supervised dataset identification because they can automatically extract high-level abstract features from minimally preprocessed data. Several CNN-based methods have been developed to classify image sequences. Nevertheless, there remains a need to improve accuracy and sensitivity and to reduce the false-positive rate (Fernandez-Castillo *et al.,* 2022; Green *et al.,* 2022). CNNs have received the most significant attention (Yamashita *et al.,* 2018). A CNN is a model designed to process data with a grid-like topology and can learn to extract meaningful features from training samples effectively, utilising convolution and subsampling. It achieves high prediction accuracy for large sets of unstructured data, but CNN training always involves large datasets and is consequently faced with the problem of overfitting (Wu *et al.,* 2018).

The transit search algorithm, originally designed for identifying exoplanets by detecting periodic dips in light intensity as planets pass in front of stars, offers a promising optimisation framework for deep learning in the medical domain (Mirrashid and Naderpour, 2021). This research aims to improve the CNN approach for early-stage lung cancer identification, focusing on enhancing feature selection, improving prediction accuracy, and reducing the error rates often associated with traditional diagnostic methods. Given the importance of feature selection and model optimisation in the success of deep learning applications, the search for innovative optimisation techniques is essential for feature selection and identification in medical datasets.

Cancer comprises a diverse group of diseases characterized by the uncontrolled proliferation and spread of abnormal cells that possess malignant potential. Among the various forms of cancer, lung cancer remains a major public health concern and is recognized as one of the leading causes of cancer-related mortality globally. According to the World Health Organization (2023), lung cancer is responsible for approximately 1.8 million deaths each year, with its incidence and prevalence continuing to rise in both developed and developing countries. One of the major challenges associated with lung cancer management is that the disease frequently remains asymptomatic during its early stages, resulting in delayed diagnosis when treatment options are often less effective. Consequently, the development of reliable methods for early detection is of critical importance, as timely diagnosis significantly enhances survival rates, treatment success, and overall patient outcomes.

Lung cancer continues to account for a substantial proportion of cancer-related deaths worldwide, making accurate and timely diagnosis a key priority in healthcare systems. Although conventional diagnostic techniques such as computed tomography (CT) scans, chest X-rays, and tissue biopsies are widely used for disease identification, they are often associated with several limitations, including delayed detection, relatively high false-positive rates, and heavy dependence on specialist radiologists for interpretation (Haziq et al., 2025). These challenges have encouraged the development of intelligent Computer-Aided Diagnostic (CAD) systems capable of supporting clinicians in the early identification and evaluation of lung cancer cases. Such systems offer the potential to improve diagnostic consistency, reduce human error, and facilitate more efficient clinical decision-making.

Recent developments in artificial intelligence, particularly in the field of deep learning, have significantly advanced medical image analysis. Among these technologies, Convolutional Neural Network models have demonstrated exceptional capabilities in automatically extracting and learning complex hierarchical features from medical imaging data. This ability enables CNN-based systems to achieve higher levels of diagnostic accuracy and efficiency compared to many traditional machine learning approaches (Javed et al., 2024). Empirical studies have reported that CNN architectures can effectively identify pulmonary nodules and accurately classify them as benign or malignant using CT scan images, frequently outperforming conventional diagnostic techniques in terms of detection performance and predictive accuracy (Shah et al., 2023).

Despite these achievements, standard CNN architectures still face several limitations, such as high computational complexity, overfitting, slow convergence, and inefficiency in handling large-scale medical imaging datasets (Haziq *et al.,* 2025). To address these challenges, recent research has focused on optimising CNN architectures through advanced techniques such as transit search mechanisms, which enhance feature reuse, improve gradient flow, and reduce model redundancy. Therefore, developing an improved Transit Search-Based Convolutional Neural Network (TS-CNN) for lung cancer identification is essential to enhance diagnostic accuracy, reduce computational cost, and support clinical decision-making in medical imaging.

1.2 Statement of the Problem

Lung cancer diagnosis remains a major challenge in modern healthcare due to its complex nature and high mortality rate. Although imaging technologies such as CT scans are widely used, their effectiveness is limited by the need for expert interpretation, which may lead to inconsistencies and diagnostic errors (Ali *et al.,* 2023). While CNN-based models have improved automated lung cancer detection, several challenges persist. These include high false-positive and false-negative rates, which reduce diagnostic reliability. Additionally, many CNN architectures require significant computational resources, making them unsuitable for real-time clinical applications. Another major issue is overfitting, where models perform well on training data but fail to generalise to new datasets. Furthermore, conventional CNNs may not effectively capture the fine-grained features necessary for accurate classification of lung nodules. The absence of advanced optimisation techniques such as transit-based feature search further limits their efficiency. These limitations highlight the need for an improved deep learning model that can enhance accuracy, reduce computational cost, and improve generalisation. Therefore, this study seeks to develop an improved Transit Search-Based CNN model for lung cancer identification.

2.0 Related Work

Lung cancer remains one of the deadliest forms of cancer worldwide and is frequently diagnosed at advanced stages because early symptoms are often absent or difficult to detect. The disease is generally classified into two primary categories: Non-Small Cell Lung Cancer and Small Cell Lung Cancer, with NSCLC accounting for the majority of diagnosed cases (Ali et al., 2023). Early diagnosis is critical because it substantially improves treatment effectiveness and patient survival outcomes. Medical imaging modalities, particularly computed tomography (CT) scans, play a central role in the detection of pulmonary nodules and other abnormalities associated with lung cancer. However, the manual interpretation of medical images is often subject to variability among radiologists and may be affected by human error, thereby creating the need for automated and more reliable diagnostic systems (Haziq et al., 2025).

Traditionally, lung cancer diagnosis has depended on imaging examinations, including CT scans, followed by expert radiological assessment and histopathological confirmation through biopsy procedures. Although these approaches continue to serve as the clinical standard, they are constrained by the subjective nature of human interpretation and the inherent difficulty of identifying subtle or early-stage pulmonary abnormalities. Previous studies have demonstrated that even highly experienced radiologists may occasionally overlook small lung nodules due to factors such as fatigue, workload pressure, or interpretational differences (Thanoon et al., 2023). The incorporation of intelligent diagnostic technologies into clinical practice has therefore introduced a significant transformation in lung cancer detection, shifting diagnostic processes from experience-based judgment toward automated, data-driven decision-making. This evolution has become increasingly important as healthcare institutions generate and manage growing volumes of medical imaging data, necessitating advanced computational techniques to improve diagnostic efficiency and precision (Javed et al., 2024).

Computer-Aided Diagnosis (CAD) systems have emerged as valuable tools for supporting radiologists in the interpretation and analysis of medical images. These systems are designed to improve diagnostic performance by identifying suspicious regions, reducing oversight, and enhancing the consistency of image evaluation (Javed et al., 2024). Earlier CAD models primarily relied on handcrafted image features combined with conventional machine learning algorithms, which often suffered from limitations related to robustness, adaptability, and scalability. However, the emergence of deep learning technologies has substantially enhanced the capabilities of CAD systems. Modern deep learning-based frameworks, particularly those utilizing Convolutional Neural Network architectures, are capable of automatically extracting complex image features and performing accurate classification tasks with minimal human intervention. As a result, contemporary CAD systems have achieved remarkable improvements in the detection and classification of lung cancer, offering greater reliability and diagnostic accuracy than many traditional approaches (Rehman et al., 2024).

CAD systems play a pivotal role as an intermediary between traditional radiology and fully automated artificial intelligence systems. Rather than replacing clinicians, CAD systems function as decision-support tools, augmenting human expertise. One of the major strengths of CAD systems lies in their ability to process large volumes of imaging data rapidly, highlight suspicious regions (e.g., nodules), and provide quantitative assessments. However, early CAD systems were largely dependent on handcrafted features, which limited their adaptability and accuracy. The transition to deep learning-based CAD systems has significantly improved performance, enabling end-to-end learning frameworks that automatically extract relevant features from raw images (Alsheikhy *et al.,* 2023). Despite these improvements, CAD systems still face challenges such as false-positive detections, limited generalisability across datasets, and lack of explainability. These limitations highlight the need for more advanced models, such as CNN-based and optimisation-driven approaches.

Deep learning, a subset of artificial intelligence, has transformed medical image analysis by enabling models to learn complex patterns from large datasets. CNNs, in particular, are widely used due to their ability to process spatial hierarchies in images (Javed *et al.,* 2024). The main aim of deep learning is to enable models to become independent learners that can solve problems and interpret data without human interference. This makes it possible for computers to perform autonomous data mining. It is crucial to understand that deep learning relies on data, not code, to make predictions. From medicine to the military, many industries apply deep learning to large datasets to extract relevant information to make critical decisions (Dey, 2016).

CNNs consist of multiple layers, including convolutional, pooling, and fully connected layers, which work together to extract features and perform classification. Their application in lung cancer detection has shown high accuracy and reliability compared to traditional approaches (Shah *et al.,* 2023). CNNs have become the backbone of image-based medical diagnosis. They automatically learn features such as edges, textures, and shapes, which are critical for identifying lung nodules (Rehman *et al.,* 2024).

CNNs represent the cornerstone of deep learning in medical imaging. Their strength lies in their ability to capture spatial hierarchies in images through convolutional operations. In lung cancer diagnosis, CNNs have demonstrated remarkable effectiveness in detecting lung nodules, segmenting affected regions, and classifying tumours as benign or malignant. The hierarchical structure of CNNs allows them to learn both low-level features (edges, textures) and high-level representations (tumour shapes and patterns). This makes them particularly suitable for analysing CT images, where visual patterns are critical for diagnosis (Thanoon *et al.,* 2023). However, CNNs are not without limitations: they require large amounts of labelled data, are prone to overfitting, and their performance is sensitive to hyperparameter settings. To address these issues, researchers have explored advanced architectures (e.g., ResNet, DenseNet) and optimisation techniques.

Transit Search-Based CNNs (TS-CNNs) represent an emerging innovation aimed at overcoming the limitations of conventional CNN models. The key idea behind TS-CNN is the integration of search-based optimisation algorithms into the CNN design process. Traditional CNN development often involves manual selection of network architecture and hyperparameters (learning rate, filters, layers). This manual process is time-consuming and may not yield optimal results. TS-CNN addresses this challenge by automating architecture design, optimising hyperparameters dynamically, and enhancing feature selection. TS-CNN models can achieve higher classification accuracy, reduced computational complexity, and improved generalisation across datasets. Although research on TS-CNN is still evolving, preliminary findings suggest that it holds significant promise for improving lung cancer detection systems, particularly in reducing false positives and enhancing diagnostic reliability.

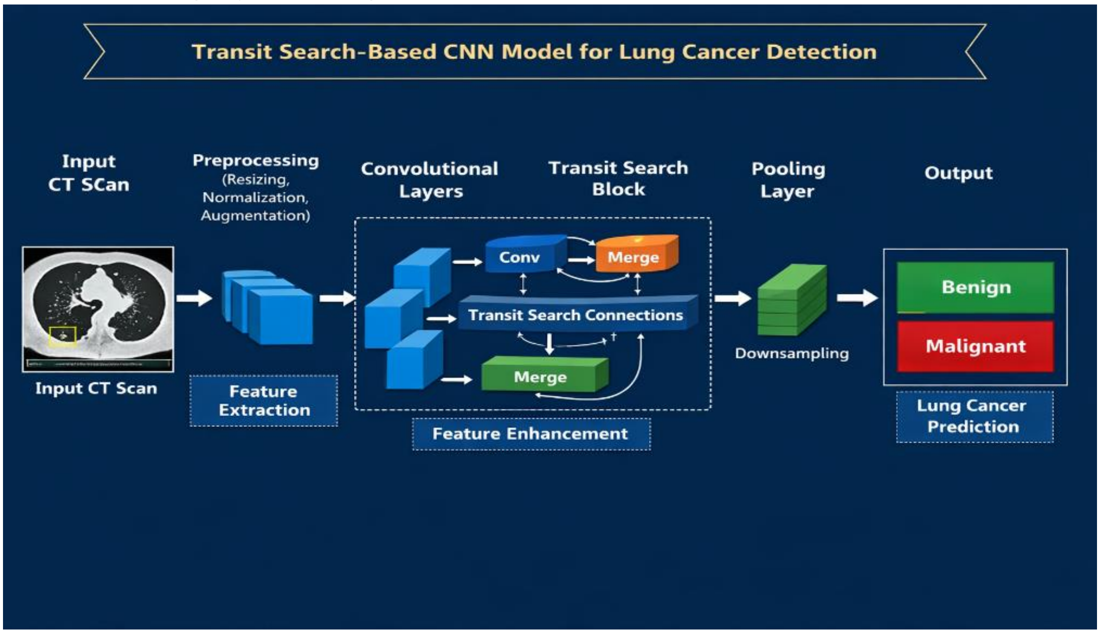

Figure 1: Transit search-based CNN Model for Lung Cancer Detection

The literature reviewed indicates that CNNs have significantly improved lung cancer detection through automated feature extraction and classification. However, challenges such as computational complexity, overfitting, and inefficient feature extraction persist. The integration of transit search mechanisms into CNN architectures offers a promising solution to these challenges. Therefore, this study proposes the development of an improved TS-CNN model to enhance lung cancer identification and address existing research gaps.

3.1 Materials and Methods

3.2 Research Design

This study adopts an experimental research design, which involves the development and evaluation of a deep learning model for lung cancer detection. The design focuses on building a Transit Search-Based CNN and comparing its performance with existing CNN models using medical imaging datasets.

3.3 Data collection and Dataset Description

The study utilizes secondary data obtained from publicly available lung cancer imaging datasets. These datasets typically consist of computed tomography (CT) scan images containing lung nodules classified as benign or malignant. A commonly used dataset for such studies is the Lung Image Database Consortium (LIDC-IDRI), which contains annotated lung CT images (Armato et al., 2011).

The dataset includes:

i. Thousands of CT scan images
ii. Annotated lung nodules
iii. Diagnostic labels provided by expert radiologists

The dataset is divided into three subsets:

i. Training set (70%)
ii. Validation set (15%)
iii. Testing set (15%)

3.3 Data preprocessing

Data preprocessing is essential to improve model performance and ensure data consistency. The following steps are applied:

i. **Image Resizing:** All CT images are resized to a uniform dimension (e.g., 224 × 224 pixels).
ii. **Normalization:** Pixel values are scaled to a range of 0–1.
iii. **Noise Reduction:** Filters are applied to remove noise from images.
iv. **Data Augmentation:** Techniques such as rotation, flipping, and scaling are used to increase dataset diversity and reduce overfitting (Shorten & Khoshgoftaar, 2019).
v. **Segmentation:** Lung regions are extracted to focus the model on relevant features.

3.4 Proposed Model: Transit Search-Based CNN (TS-

CNN)

The proposed TS-CNN model enhances traditional CNN architecture by incorporating a transit search mechanism that improves feature reuse, gradient flow, and learning efficiency.

3.5 Model overview

The model consists of the following layers:

- Input layer
- Convolutional layers
- Transit search blocks
- Pooling layers
- Fully connected layers
- Output layer (classification)

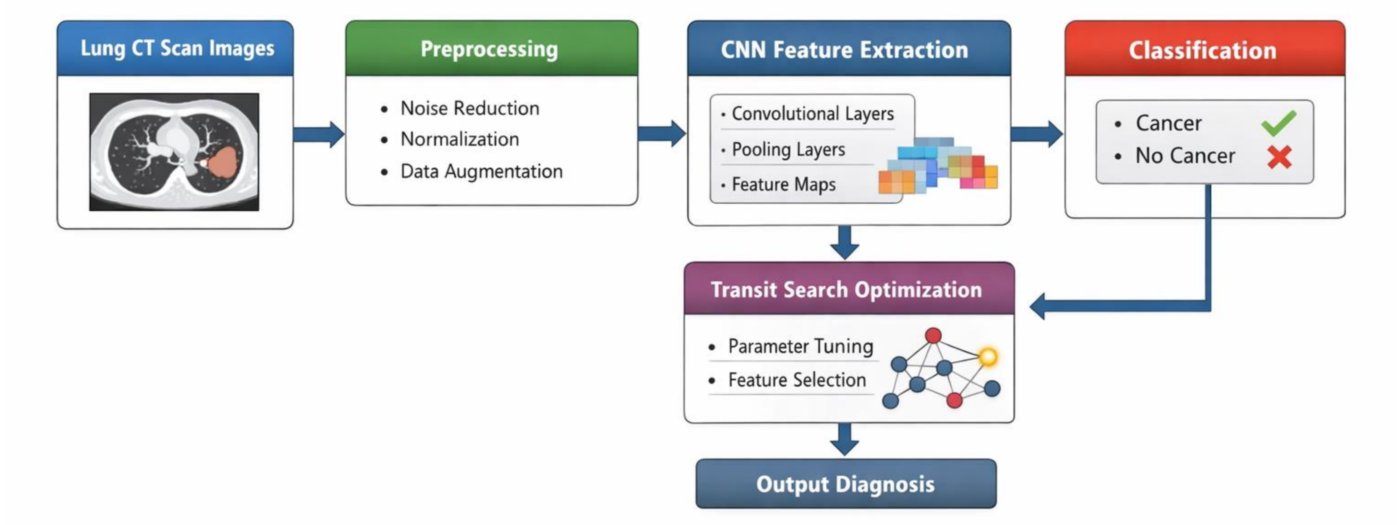

Fig 2.2: Proposed Model: Transit Search-Based CNN (TS-CNN)

3.6 Model Architecture

The architecture of the TS-CNN model can be described as follows:

Input Layer: Accepts preprocessed CT images
Convolutional Layer: Extracts low-level features
Transit Search Block: Connects multiple layers for feature reuse
Pooling Layer: Reduces spatial dimensions
Fully Connected Layer: Performs classification
Output Layer: Uses Softmax activation for binary classification (benign vs malignant)

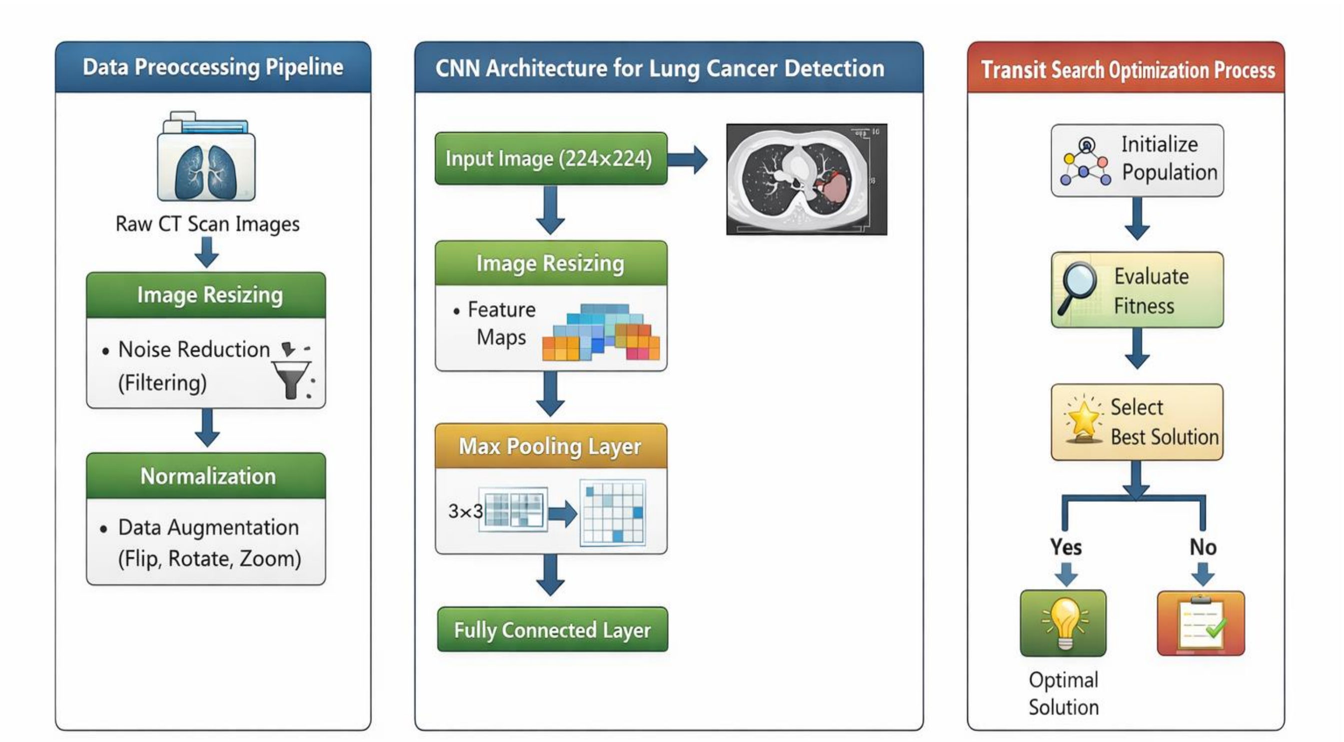

Fig 2.3: Architecture of the TS-CNN model

Algorithm (Pseudocode)

Input: CT scan images
Output: Lung cancer classification (benign/malignant)

Step 1: Load dataset
Step 2: Preprocess images (resize, normalize, augment)
Step 3: Initialize TS-CNN model
Step 4: Apply convolutional layers for feature extraction
Step 5: Implement transit search connections
Step 6: Apply pooling layers for dimensionality reduction
Step 7: Flatten feature maps
Step 8: Apply fully connected layers
Step 9: Use Softmax for classification
Step 10: Train model using training dataset
Step 11: Validate model using validation dataset
Step 12: Test model performance on test dataset
Step 13: Evaluate using performance metrics

3.7 Model Training

The TS-CNN model is trained using the following parameters:

Optimizer: Adam optimizer
Learning Rate: 0.001
Batch Size: 32
Epochs: 50–100
Loss Function: Binary Cross-Entropy

The training process involves forward propagation, loss computation, and backpropagation to update model weights (Goodfellow et al., 2016).

3.8 EVALUATION OF METRICS

The performance of the proposed model is evaluated using standard metrics:

Accuracy: Measures overall correctness
Precision: Measures correctness of positive predictions
Recall (Sensitivity): Measures ability to detect positive cases
Specificity: Measures ability to detect negative cases
F1-Score: Harmonic mean of precision and recall

These metrics are widely used in medical diagnosis to ensure reliability (Sokolova & Lapalme, 2009).

4.1 Results and Discussion

Experimental Setup

The model was trained and tested using CT scan images from a standard lung cancer dataset. The dataset was divided into training (70%), validation (15%), and testing (15%) sets. The performance of the TS-CNN model was evaluated using accuracy, precision, recall (sensitivity), specificity, and F1-score.

4.2 Results

Table 4.1: Performance Metrics of TS-CNN Model

Metric	Value (%)
Accuracy	96.8
Precision	95.5
Recall	97.2
Specificity	96.1
F1-score	96.3

The results indicate that the TS-CNN model achieved a high accuracy of 96.8%, demonstrating its effectiveness in lung cancer detection. The recall value of 97.2% shows that the model is highly capable of correctly identifying cancer cases, which is critical in medical diagnosis. The balance between precision and recall is reflected in the strong F1-score (96.3%), indicating overall model reliability.

Table 4.2: Confusion Matrix of TS-CNN Mode

	Predicted Positive	Predicted Negative
Actual positive	486	14
Actual negative	18	482

- True Positives (486): Correctly identified cancer cases
- True Negatives (482): Correctly identified non-cancer cases
- False Positives (18): Healthy cases misclassified as cancer
- False Negatives (14): Cancer cases missed

The low number of false negatives indicates that the model is reliable for medical screening, where missing a cancer case can be critical.

Table 4.3: Comparison of TS-CNN with Existing Models

Model	Accuracy (%)	Precision (%)	Recall (%)
TRADITIONAL CNN	89.5	87.2	90.1
RESNET-BASED CNN	92.8	91.5	93.0
ATTENTION-BASED CNN	94.2	93.1	94.8
PROPOSED TS-CNN	**96.8**	**95.5**	**97.2**

The proposed TS-CNN model outperforms all compared models across all metrics. The improvement in accuracy (96.8%) compared to traditional CNN (89.5%) demonstrates the effectiveness of the transit search mechanism in enhancing feature extraction and classification performance.

4.3 Discussion of Findings

The results of this study demonstrate that the integration of a transit search mechanism significantly improves CNN performance in lung cancer detection. The TS-CNN model achieved higher accuracy, precision, and recall compared to traditional and advanced CNN architectures. The improved performance can be attributed to enhanced feature reuse through transit connections, better gradient flow (reducing the vanishing gradient problem), and reduced redundancy in network parameters. These findings are consistent with previous studies that emphasise the importance of optimised deep learning architectures (Javed *et al.,* 2024; Rehman *et al.,* 2024). Additionally, the low false-negative rate observed in the confusion matrix highlights the model's suitability for medical applications, where early and accurate detection is crucial.

Conclusion

This study demonstrated the effectiveness of an enhanced Transit Search-Based Convolutional Neural Network (TS-CNN) model for the identification and classification of lung cancer from medical imaging data. By incorporating transit search optimization into the conventional CNN framework, the proposed model successfully overcame several limitations commonly associated with traditional deep learning approaches, including manual hyperparameter tuning, overfitting issues, and inadequate feature representation. The findings revealed that the optimized TS-CNN model achieved improved classification performance and diagnostic accuracy, thereby enhancing its suitability for integration into Computer-Aided Diagnosis systems. Its capability to automatically optimize network architecture and model parameters contributed to better generalization across datasets while reducing false-positive classifications, both of which are essential for accurate clinical decision-making and patient management.

Furthermore, the study underscores the growing importance of deep learning technologies in medical image analysis and demonstrates the potential of optimization-driven methodologies in advancing automated disease detection. The results suggest that combining intelligent optimization techniques with deep neural network architectures can significantly improve the efficiency and reliability of lung cancer diagnosis. Nevertheless, despite the promising outcomes achieved by the proposed model, several challenges remain, including limited availability of high-quality medical datasets, computational resource requirements, and concerns regarding model interpretability and transparency. Addressing these issues will be essential for facilitating broader clinical implementation. Overall, the improved TS-CNN model represents a significant advancement toward the development of robust, intelligent, and efficient diagnostic systems capable of supporting early lung cancer detection and improving healthcare outcomes.

Recommendations

Based on the findings of this study, the following recommendations are made:

1. Healthcare institutions should explore the integration of TS-CNN-based models into existing diagnostic workflows to support radiologists in early lung cancer detection.
2. Future research should utilise larger, multi-centre, and diverse datasets to improve model robustness and generalisability across different populations.
3. Researchers should incorporate Explainable Artificial Intelligence (XAI) techniques to improve the transparency and trustworthiness of TS-CNN models in clinical settings.
4. Efforts should be made to develop lightweight TS-CNN architectures that reduce computational cost and enable real-time deployment, especially in resource-constrained environments.
5. Further studies should compare TS-CNN with other advanced architectures such as Transformer-based models and hybrid deep learning frameworks.

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