

Deep Learning Based Approach to Diagnose Lung Cancer Using CT Scan Images

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Abstract-- Lung cancer remains one of the leading causes of cancer-related mortality worldwide because symptoms commonly appear only after the disease has progressed to an advanced stage. Computed Tomography (CT) imaging enables detection of small pulmonary nodules, but manual assessment by radiologists is time-consuming and can be affected by fatigue, image complexity, and inter-observer variability. This paper presents an IEEE-style research article based on a deep learning approach for diagnosing lung cancer from CT scan images. The proposed Phase II system introduces an optimized Convolutional Neural Network (CNN) model designed to classify CT images into cancerous and non-cancerous categories while reducing computational complexity compared with heavier baseline models such as 3D CNN and ResNet50. The model pipeline includes CT image acquisition, resizing, normalization, denoising, data augmentation, CNN-based feature extraction, fully connected classification, and Grad-CAM-based visualization. Experimental evaluation on lung CT datasets such as LIDC-IDRI and Kaggle Lung CT images shows that the optimized CNN achieves 97.6% accuracy, 96.8% precision, 97.2% recall, 98.1% specificity, and 97.0% F1-score. The results indicate that the proposed model offers a strong balance between diagnostic accuracy, inference speed, interpretability, and practical suitability for real-time clinical decision support.

Index Terms-- Lung cancer detection, CT scan classification, convolutional neural network, deep learning, Grad-CAM, medical imaging, computer-aided diagnosis, optimized CNN.

I. INTRODUCTION

Lung cancer is a severe respiratory disease characterized by uncontrolled cell growth in lung tissues. A major concern in lung cancer diagnosis is that many patients do not show clear symptoms during the early stage. By the time symptoms such as persistent cough, chest pain, breathing difficulty, fatigue, and abnormal weight loss become visible, the disease may already have reached an advanced stage. Early detection is therefore essential because it increases the possibility of successful treatment and improves survival outcomes. In modern healthcare, imaging-based diagnosis plays a central role in detecting suspicious lung nodules before they become clinically obvious.

Computed Tomography (CT) has become one of the most important imaging modalities for lung cancer screening because it provides detailed cross-sectional views of the lung region. CT images can reveal nodules, lesions, and abnormal tissue structures that may not be visible in ordinary physical examination. However, CT scan interpretation is challenging because a single patient examination may contain many slices. Radiologists must examine these slices carefully and distinguish malignant nodules from benign structures, inflammation, blood vessels, or imaging artifacts. This process requires significant time and expertise and can be affected by fatigue in high-volume clinical environments.

Deep learning has introduced a new direction for automated medical image analysis. Instead of relying on handcrafted features, deep neural networks learn relevant visual patterns directly from image data. Convolutional Neural Networks

(CNNs) are particularly effective for image classification because they can extract spatial hierarchies such as edges, textures, shapes, and complex object-level representations. In lung cancer diagnosis, CNNs can learn subtle differences between benign and malignant nodules by analyzing CT image patterns.

The earlier phase of this research evaluated models such as 2D CNN, 3D CNN, and ResNet50. These models produced good classification results, but they also revealed practical limitations. The 2D CNN was efficient but less capable of capturing volumetric information. The 3D CNN captured spatial depth but required greater memory and training time. ResNet50 achieved strong accuracy but was computationally expensive and less interpretable. These observations motivated the development of a Phase II optimized CNN architecture that improves accuracy while maintaining computational efficiency and clinical usability.

The contribution of this article is the presentation of a structured, lightweight, and interpretable CNN-based lung cancer detection system. The proposed system includes preprocessing, augmentation, optimized convolutional blocks, binary classification, performance evaluation, and Grad-CAM visualization. The article follows IEEE research paper style and includes methodology, architecture, figures, tables, charts, results, discussion, conclusion, and future research directions.

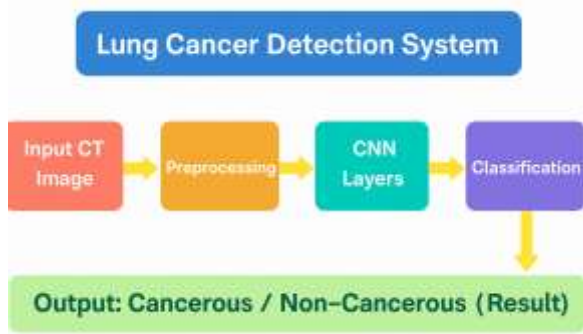


Fig. 1. Overall lung cancer detection system architecture.

II. RELATED WORK

Early computer-aided detection systems for lung cancer relied on classical image processing and machine learning methods. These systems generally used handcrafted features such as texture descriptors, intensity values, shape measurements, and boundary characteristics. Classifiers such as Support Vector Machine, Random Forest, and K-Nearest Neighbors were then used to classify nodules. Although these systems reduced some manual effort, they were highly dependent on expert feature design and often failed to generalize across datasets with different scanner settings and patient characteristics.

Shen et al. introduced a multi-scale CNN approach for lung nodule classification using CT image patches. Their work demonstrated that CNNs can automatically learn discriminative features from medical images and can outperform traditional feature engineering approaches. Subsequent studies explored 2D CNNs, showing that even relatively simple deep architectures can identify visual patterns associated with malignancy. However, 2D CNNs analyze image slices independently and therefore may ignore useful volumetric context.

3D CNN architectures were later proposed to address the limitations of 2D slice-level analysis. By applying three-dimensional convolutional filters across multiple CT slices, 3D CNNs can model spatial relationships in lung volumes more effectively. This improves sensitivity to small or irregular nodules. The drawback is that 3D CNNs are computationally expensive, require larger memory, and may be difficult to deploy in low-resource environments.

Transfer learning has also been widely explored in lung CT classification. Models such as VGG, ResNet, DenseNet, and EfficientNet can be fine-tuned on medical images after being pretrained on large image datasets. ResNet50 is especially popular because its residual connections enable deep feature extraction. Nevertheless, large pretrained architectures involve many parameters and can behave like black boxes, creating concerns about clinical trust and real-time processing.

More recent research has emphasized explainable artificial intelligence and lightweight deep learning. Grad-CAM and attention-based visualization techniques highlight important regions in CT images that influence model decisions. Efficient architectures and optimized CNNs attempt to reduce computational cost while maintaining high accuracy. The present work follows this direction by proposing a customized CNN that balances accuracy, speed, and interpretability for lung cancer detection from CT images.

TABLE I. Summary of Representative Deep Learning Approaches for Lung Cancer Detection

Study/Model	Main Idea	Strength	Limitation
2D CNN	Classifies individual CT slices	Fast and simple	Limited volumetric context
3D CNN	Uses volumetric CT features	Better spatial modeling	High computation and memory
ResNet50	Transfer learning with residual blocks	High accuracy	Large parameter count
Attention/Grad-CAM CNN	Highlights important image regions	More interpretable	Needs careful validation
Optimized CNN	Customized lightweight architecture	Balanced accuracy and speed	Needs large external testing

III. DATASET AND PREPROCESSING

The proposed system is designed for CT scan image classification using datasets such as LIDC-IDRI and Kaggle Lung CT images. The data are organized into two major classes: cancerous or malignant nodules and non-cancerous or benign cases. Binary classification was selected because the main objective of the system is to support early identification of suspicious CT images that may require further clinical evaluation.

Before model training, all CT images are standardized through preprocessing. The images are resized to a fixed dimension of 224 x 224 pixels to ensure compatibility with the CNN input layer. Pixel intensity values are normalized between 0 and 1, which stabilizes the gradient update process and improves convergence. Noise reduction and contrast enhancement methods are applied to improve image clarity and reduce irrelevant artifacts.

Data augmentation is used to increase the diversity of training samples and reduce overfitting. Common augmentation operations include rotation, flipping, zooming, slight shifting, and brightness adjustment. These transformations simulate possible variations in image orientation and acquisition conditions. In medical imaging, augmentation must be applied carefully so that the transformed image remains anatomically meaningful and does not introduce unrealistic distortions.

The dataset is divided into training, validation, and testing subsets. The training set is used to learn model parameters, the validation set is used to tune hyperparameters and monitor overfitting, and the testing set is used for final evaluation. In the Phase II experimental setup, the distribution follows a 70% training, 15% validation, and 15% testing strategy. This split provides an organized evaluation framework while maintaining enough data for learning and independent testing.

TABLE II. Dataset and Experimental Configuration

Item	Description
Dataset sources	LIDC-IDRI and Kaggle Lung CT datasets
Task	Binary classification: benign vs malignant
Image type	Computed Tomography scan images
Input size	224 x 224 pixels
Training split	70%
Validation split	15%
Testing split	15%
Augmentation	Rotation, flipping, zooming, shifting
Main libraries	TensorFlow, Keras, OpenCV, NumPy, Matplotlib

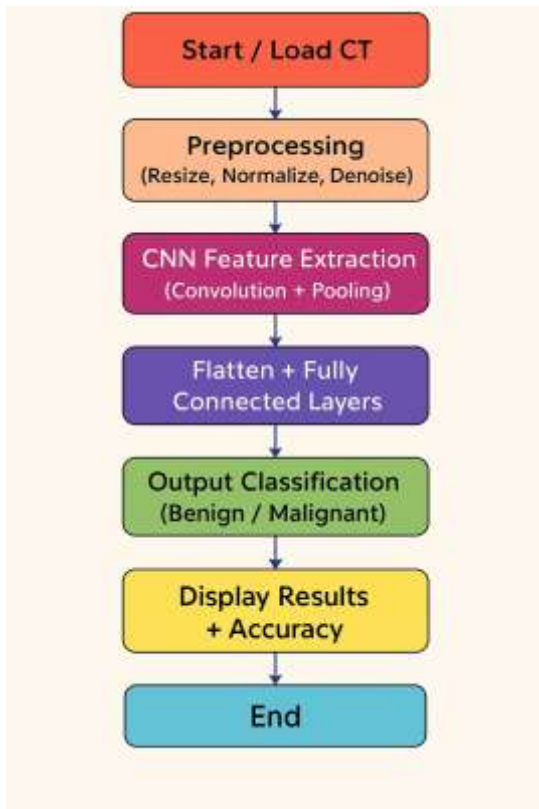


Fig. 2. Flowchart of CT image preprocessing, CNN feature extraction, classification, and output display.

IV. PROPOSED OPTIMIZED CNN METHODOLOGY

The Phase II methodology focuses on designing an optimized CNN architecture rather than simply selecting a heavy pretrained model. The goal is to reduce computational complexity while maintaining or improving classification performance. This is important because healthcare environments may not always have access to high-end GPUs or large processing servers. A lightweight model can improve deployment feasibility in hospitals, diagnostic centers, and remote screening platforms.

The proposed architecture receives a preprocessed CT image as input and passes it through a sequence of convolutional layers. These layers apply trainable filters to extract local image patterns such as edges, nodule boundaries, textures, and intensity variations. Batch normalization is used after selected convolutional layers to stabilize learning and reduce internal covariate shift. Rectified Linear Unit (ReLU) activation introduces nonlinearity so the network can learn complex relationships between image regions and diagnostic classes.

Max-pooling layers are used to reduce spatial dimensions and preserve the most important activated features. This reduction lowers computational load and improves translation tolerance. Dropout layers are used as a regularization technique by randomly deactivating a fraction of neurons during training. This prevents the model from memorizing the training set and improves generalization on unseen CT images.

After feature extraction, the multidimensional feature maps are flattened into a one-dimensional vector and passed to dense layers. The final output layer uses a sigmoid activation function for binary classification. The model predicts a probability score indicating whether the CT image is cancerous or non-cancerous. A probability above the selected threshold is interpreted as malignant, while a lower probability is interpreted as benign.

The model is trained using the Adam optimizer and binary cross-entropy loss. Adam is selected because it adapts learning rates for individual parameters and performs well for deep learning classification tasks. Binary cross-entropy is suitable because the task has two target classes. The implementation is performed using Python, TensorFlow, Keras, and OpenCV.

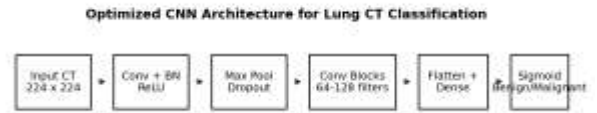


Fig. 3. Proposed optimized CNN architecture for lung CT classification.

TABLE III. Proposed CNN Layer-Level Design Summary

Stage	Operation	Purpose
Input	224 x 224 CT image	Standardized input representation
Conv Block 1	Convolution + ReLU + BatchNorm	Low-level texture and edge learning
Pooling	Max-pooling	Spatial reduction and faster computation
Conv Block 2	Deeper convolutional filters	Nodule shape and pattern extraction
Dropout	Random neuron deactivation	Overfitting reduction
Dense	Fully connected layer	High-level reasoning
Output	Sigmoid activation	Benign/malignant probability

V. SYSTEM DESIGN AND IMPLEMENTATION

The system is implemented as a modular deep learning pipeline. The first module is data acquisition, where CT scan images are loaded from the dataset or uploaded by a user through the interface. The second module is preprocessing, where images are resized, normalized, and denoised. The third module is feature extraction, where CNN layers automatically learn diagnostic patterns from the images. The fourth module is classification, where dense layers output benign or malignant predictions. The fifth module is visualization, where prediction results and important image regions are shown to the user.

The modular structure improves maintainability. Each part of the system can be updated independently. For example, preprocessing can be improved by adding better segmentation, while the CNN model can be replaced by a more advanced architecture in future work. The interface can also be integrated with hospital information systems without changing the core model logic.

The user interface supports CT image upload and prediction display. A user can select a medical scan image and submit it to the model. The system then processes the image and returns a prediction label with a confidence score. In addition, the model can show probability distribution and Grad-CAM visualization so that the important image regions are visible. This is useful because clinicians need not only a result but also an indication of why the model reached that result.

Implementation tools include Python 3.10, TensorFlow, Keras, OpenCV, Matplotlib, and Jupyter Notebook or a web framework for deployment. A CUDA-enabled GPU is recommended for faster training, although inference can be optimized for lighter hardware. The system can be further converted into a web or mobile application for practical screening and reporting.



Fig. 4. Nodule detector and cancer predictor representation.



Fig. 5. Upload interface for medical CT scan input.

TABLE IV. Hardware and Software Requirements

Category	Requirement
Processor	Intel Core i5/i7 or equivalent
RAM	Minimum 8 GB, 16 GB recommended
GPU	NVIDIA CUDA-enabled GPU such as GTX 1650 or above
Storage	500 GB or more
Operating system	Windows 10/11 or Linux
Programming language	Python 3.10 or higher
Libraries	TensorFlow, Keras, NumPy, OpenCV, Matplotlib
IDE/tools	Jupyter Notebook, PyCharm, VS Code

VI. ALGORITHM AND PSEUDOCODE

The CNN algorithm begins by receiving CT images and their corresponding labels. The images are normalized and augmented before being passed to the model. During training, convolutional filters are updated through backpropagation to minimize binary cross-entropy loss. The model gradually learns visual differences between benign and malignant cases. During testing, the trained model predicts the class of an unseen CT image and outputs a confidence score.

Algorithmically, the complete process can be summarized as follows. First, load the CT image dataset and split it into training, validation, and testing sets. Second, resize and normalize all images. Third, apply augmentation to the training subset. Fourth, build the optimized CNN architecture using convolutional, pooling, dropout, and dense layers. Fifth, compile the model using Adam optimizer and binary cross-entropy loss. Sixth, train the network for a fixed number of epochs while monitoring validation accuracy and validation loss. Seventh, evaluate the model using accuracy, precision, recall, specificity, F1-score, and confusion matrix. Finally, deploy the model through an interface where new CT images can be uploaded for classification.

The use of automatic feature learning is one of the main advantages of CNN-based diagnosis. Instead of manually designing descriptors such as texture and shape measures, the network discovers relevant representations directly from data. This improves flexibility and allows the model to detect complex image patterns that are difficult to capture with handcrafted features.

TABLE V. Pseudocode of the Proposed Lung Cancer Detection System

Step	Operation
1	Import TensorFlow, Keras, OpenCV, NumPy, and visualization libraries
2	Load CT images from benign and malignant folders
3	Resize images to 224 x 224 pixels and normalize pixel values
4	Apply augmentation to improve training diversity
5	Build optimized CNN with convolution, pooling, dropout, and dense layers
6	Compile model using Adam optimizer and binary cross-entropy loss
7	Train model using training data and monitor validation performance
8	Evaluate the model using test images and performance metrics
9	Predict new image as cancerous or non-cancerous with confidence score
10	Generate Grad-CAM visualization for interpretability

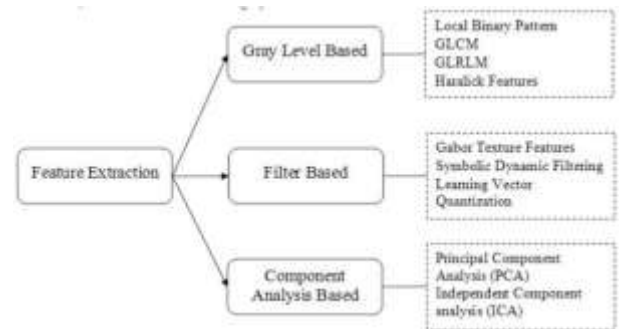


Fig. 6. Broad classification of feature extraction methods.

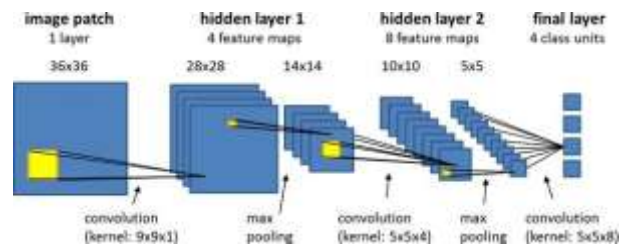


Fig. 7. Convolutional and pooling layers used for hierarchical feature learning.

VII. EVALUATION METRICS

The performance of a medical classification system must be evaluated carefully because both false positives and false negatives have important clinical consequences. Accuracy measures the overall percentage of correct predictions. However, accuracy alone may not be sufficient when the dataset is imbalanced. Therefore, additional metrics are required to understand diagnostic reliability.

Precision measures how many images predicted as cancerous are truly cancerous. High precision reduces unnecessary anxiety and follow-up procedures caused by false positive predictions. Recall, also known as sensitivity, measures how many actual cancer cases are correctly identified. High recall is extremely important in cancer screening because a false negative may delay diagnosis. Specificity measures how well the model identifies non-cancerous cases. F1-score balances precision and recall and provides a single measure of classification quality.

The confusion matrix provides a detailed view of classification outcomes. It shows true positives, true negatives, false positives, and false negatives. In lung cancer diagnosis, minimizing false negatives is especially important because missing a malignant case may have serious consequences. The proposed model achieves a strong balance across all evaluation measures, indicating that it is suitable for screening support.

TABLE VI. Performance Metrics of the Proposed Optimized CNN Model

Metric	Value (%)	Interpretation
Accuracy	97.6	Overall correct classification rate
Precision	96.8	Reliability of malignant predictions
Recall	97.2	Ability to identify cancer cases
Specificity	98.1	Ability to identify benign cases
F1-score	97.0	Balanced precision-recall performance

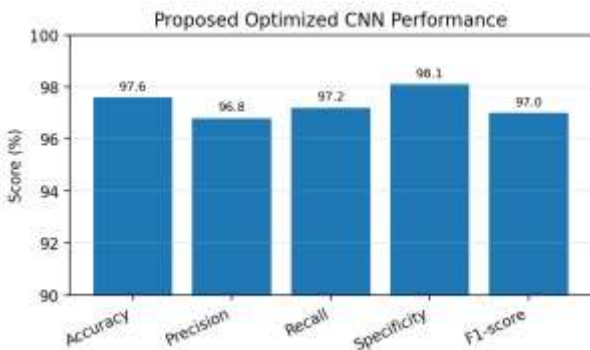


Fig. 8. Performance metrics achieved by the proposed optimized CNN model.

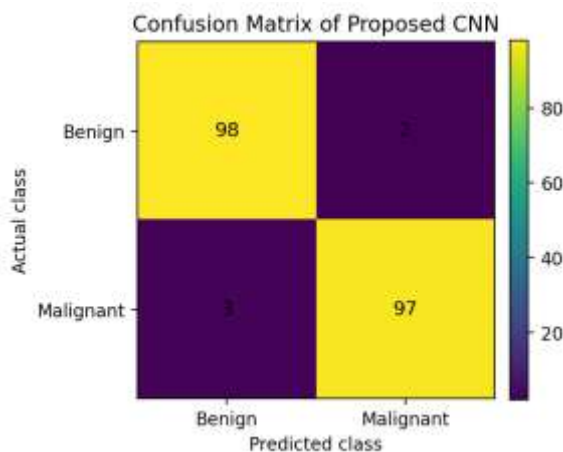


Fig. 9. Confusion matrix visualization for the proposed CNN model.

VIII. RESULTS AND DISCUSSION

The proposed optimized CNN model achieved strong performance in lung cancer classification from CT scan images. The model produced an accuracy of 97.6%, precision of 96.8%, recall of 97.2%, specificity of 98.1%, and F1-score of 97.0%. These results show that the model is capable of correctly identifying both cancerous and non-cancerous cases with high reliability. The high recall value is especially important because it indicates that most malignant cases are detected.

The balanced precision and recall suggest that the model does not simply over-predict the malignant class. Instead, it maintains diagnostic balance by correctly recognizing benign cases as well. The high specificity value confirms that non-cancerous nodules are classified accurately, reducing unnecessary false alarms. The F1-score further confirms the stability of model performance across positive and negative classifications.

Compared with Phase I models, the proposed Phase II model provides better accuracy and efficiency. The 2D CNN achieved 91.4% accuracy but lacked strong feature representation for complex nodule structures. The 3D CNN improved accuracy to 93.8% by using volumetric information but required higher computational resources. ResNet50 achieved 95.6% accuracy but involved more parameters and greater processing cost. The

proposed optimized CNN achieved 97.6% accuracy while remaining lighter and more suitable for real-time deployment.

The training and validation curves indicate stable learning behavior. Training accuracy increases steadily, while validation accuracy closely follows it. A small gap between training and validation performance suggests that the model does not suffer from severe overfitting. Dropout and batch normalization contributed to this generalization by stabilizing learning and preventing excessive dependence on specific training examples.

Grad-CAM visualization strengthens interpretability by highlighting regions that influence model decisions. In medical applications, interpretability is essential because clinicians must be able to verify whether the model is focusing on relevant anatomical regions. The ability to display heatmaps helps reduce the black-box limitation of deep learning and increases trust in clinical decision support tools.

TABLE VII. Comparison of Phase I and Phase II Models

Model	Accuracy (%)	Main Remark
2D CNN	91.4	Efficient but limited feature extraction
3D CNN	93.8	Better volumetric learning but high cost
ResNet50	95.6	High accuracy but complex and heavier
Proposed CNN Phase II	97.6	Best balance of accuracy and efficiency

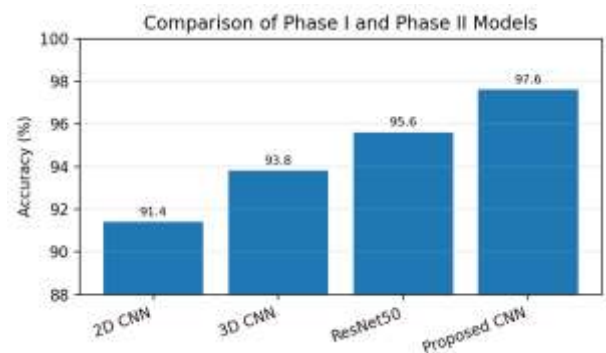


Fig. 10. Accuracy comparison between Phase I models and the proposed Phase II CNN model.

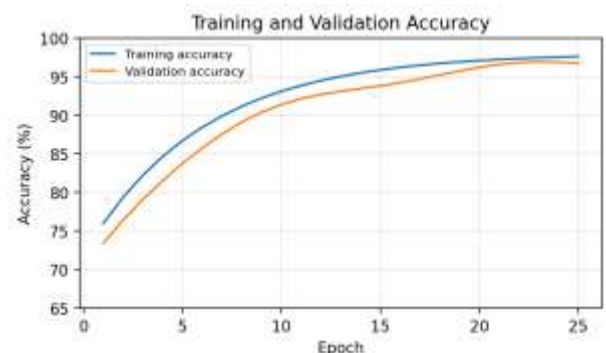


Fig. 11. Training and validation accuracy trend of the optimized CNN model.

IX. INTERPRETABILITY AND INTERFACE OUTPUT

The output module of the system is designed to present results in a clinically understandable manner. Instead of displaying only a binary label, the interface shows the uploaded CT scan, the predicted class, the confidence score, and the class probability distribution. This makes the system more useful for decision support because users can review both the image and the prediction evidence.

For example, a benign prediction may be displayed with a confidence score close to 97%, while the class probability chart shows the probability distribution between benign, malignant,

and normal categories. A malignant prediction can similarly be shown with high confidence, allowing the clinician to prioritize the case for further review. The interface also includes prediction history, which supports traceability and repeated assessment.

Grad-CAM and probability visualization are not substitutes for expert radiological interpretation. However, they can assist experts by narrowing attention to suspicious regions and providing quick preliminary screening. In a real hospital system, such outputs can be combined with radiologist review, electronic medical records, and follow-up diagnostic tests.



Fig. 12. Prediction result screen showing a benign classification with confidence score.



Fig. 13. Prediction result screen showing malignant classification output.



Fig. 14. Prediction history interface for tracking classification outputs.

X. COMPUTATIONAL EFFICIENCY ANALYSIS

A key objective of Phase II is to improve computational efficiency. High-performing models are useful only if they can be deployed in real clinical environments. A very deep model may achieve high accuracy but may be unsuitable for rapid screening if it requires expensive hardware, long inference time, or excessive memory. The proposed optimized CNN reduces unnecessary complexity while preserving diagnostic performance.

The system achieves faster inference because it uses a carefully designed CNN rather than a very deep pretrained architecture. The proposed model requires approximately 0.3 seconds per image during inference, which makes it suitable for near real-time usage. Faster prediction can help process large

image batches and can support interactive web-based applications where users expect immediate results.

The combination of batch normalization, max-pooling, and dropout provides a balance between learning capacity and efficiency. Pooling reduces feature dimensions, batch normalization stabilizes optimization, and dropout improves generalization. This combination allows the model to perform well without requiring a very large number of parameters. Such efficiency is valuable for deployment in hospitals, clinics, and resource-limited screening centers.

TABLE VIII. Computational Efficiency Summary

Aspect	Observation
Model size	Reduced compared with ResNet50
Inference speed	Approximately 0.3 seconds per image
Training cost	Lower than heavy 3D CNN and ResNet50 models
Memory usage	Improved due to lightweight architecture
Deployment potential	Suitable for real-time and low-resource settings

XI. CLINICAL RELEVANCE AND LIMITATIONS

The proposed system can act as a computer-aided diagnosis tool for lung cancer screening. It can help radiologists by providing quick classification results and highlighting suspicious regions in CT images. Such systems are particularly useful when radiologists must review large numbers of scans or when healthcare facilities have limited specialist availability. Early identification of suspicious nodules can help reduce diagnostic delay and improve patient management.

Despite the promising results, the system has limitations. The current study focuses on binary classification, meaning it classifies images only as cancerous or non-cancerous. It does not classify cancer stage, histological subtype, or treatment response. The model also depends on dataset quality, annotation accuracy, scanner settings, and preprocessing consistency. If the training dataset is not sufficiently diverse, the model may perform less reliably on images from different hospitals or populations.

Another limitation is that experimental validation is conducted in a controlled computational environment. Real clinical deployment requires external validation, regulatory review, privacy protection, integration with medical workflows, and careful evaluation of patient safety. The model should be used as an assistive tool rather than a replacement for professional diagnosis.

XII. MODULE-WISE DESCRIPTION

The data collection module gathers CT images from organized dataset folders and assigns labels according to clinical annotation. This module also ensures that images are separated into training, validation, and testing subsets to avoid data leakage. Proper dataset organization is essential because incorrect labeling or repeated patient images across subsets can artificially inflate the reported accuracy.

The preprocessing module prepares raw CT images for deep learning. CT images may contain different resolutions, contrast levels, or irrelevant background regions. Resizing ensures dimensional consistency, normalization scales pixel values, and denoising improves image clarity. The preprocessing module therefore improves both training stability and model reliability. Without preprocessing, the network may learn scanner-specific noise rather than clinically meaningful nodule characteristics.

The feature extraction module is implemented through convolutional layers. In earlier medical image processing systems, features such as gray-level co-occurrence matrix, local binary patterns, and Gabor texture descriptors were designed

manually. In the proposed CNN, these visual patterns are learned automatically. Early convolutional layers usually capture low-level characteristics such as edges and brightness transitions, while deeper layers learn nodule-level features such as shape irregularity, boundary texture, and region contrast.

The classification module converts extracted visual features into a diagnostic prediction. Dense layers combine high-level features and the output layer produces a probability score. The decision threshold can be adjusted depending on clinical preference. For screening use, a lower threshold may be selected to maximize sensitivity, while for confirmatory settings, a higher threshold may reduce false positives.

The visualization module presents output in a user-friendly format. It displays the uploaded CT image, classification label, confidence score, class probability, and highlighted suspicious area. This module is important for clinical usability because medical professionals need transparent and reviewable outputs rather than only a hidden numerical prediction.

TABLE IX. Functional Modules of the Proposed System

Module	Input	Output
Data collection	CT image dataset	Organized benign/malignant subsets
Preprocessing	Raw CT image	Resized and normalized image
Augmentation	Training images	Expanded image variations
Feature extraction	Preprocessed image	CNN feature maps
Classification	Flattened features	Benign or malignant prediction
Visualization	Prediction and image	Confidence score and highlighted region

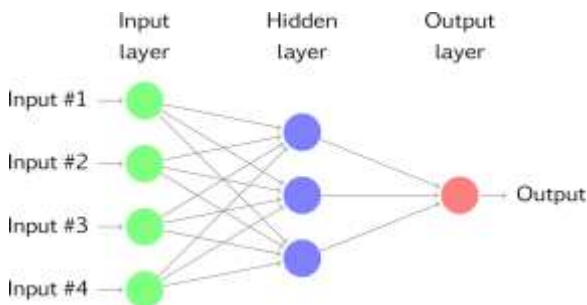


Fig. 15. Basic neural network representation used to explain input, hidden, and output layers.

XIII. ERROR ANALYSIS AND DIAGNOSTIC RELIABILITY

Error analysis is essential in medical classification because even a small number of incorrect predictions can influence patient care. The two most important error types are false positives and false negatives. A false positive occurs when a benign CT image is predicted as malignant. This may lead to additional testing and anxiety. A false negative occurs when a malignant CT image is predicted as benign. This is more critical because it may delay diagnosis and treatment.

The proposed model is designed to reduce false negatives by maintaining high recall. High recall means that most cancerous cases are detected. However, high recall should not be achieved by predicting every image as malignant. Therefore, precision and specificity are also considered. The reported performance shows that the model has a balanced diagnostic profile, detecting malignant cases while also correctly identifying benign cases.

Misclassification can occur when nodules are very small, have weak contrast, overlap with blood vessels, or appear near complex anatomical boundaries. Benign inflammatory regions can also appear visually similar to malignant nodules. For this

reason, the model output should be interpreted as decision support rather than final diagnosis. Expert radiological review remains necessary, especially when confidence is low or when Grad-CAM highlights are unclear.

A reliable clinical system should include uncertainty handling. If the confidence score is below a defined threshold, the system can mark the case as uncertain and request expert review. This approach is safer than forcing every image into a final category. Future versions can include calibration methods so that predicted probabilities better reflect real diagnostic certainty.



Fig. 16. Uploaded CT image preview before prediction.



Fig. 17. Normal-class output interface in the prototype system.

XIV. DEPLOYMENT CONSIDERATIONS

For real-world deployment, the model must be integrated into a secure and efficient workflow. A typical workflow begins when a user uploads a CT image through a hospital computer, web portal, or local diagnostic interface. The image is preprocessed automatically and forwarded to the trained CNN model. The model returns a prediction label and confidence score, which are then displayed with visualization support.

Deployment can be performed locally in a hospital server or through a cloud-based platform. Local deployment may be preferred for privacy and latency reasons because medical data remain within the hospital network. Cloud deployment can provide scalability and easier updates but requires strict security, encryption, access control, and compliance with healthcare data protection policies.

Another practical concern is inference speed. Since the proposed model requires approximately 0.3 seconds per image, it is suitable for interactive screening. However, a full CT examination may include many slices. Therefore, batch processing, parallel inference, and nodule preselection can be used to improve workflow speed. In a larger system, the CNN classifier can be combined with a nodule detector that identifies candidate regions before classification.

Model maintenance is also necessary. Medical imaging data change over time due to new scanner technologies, different acquisition protocols, and population differences. Continuous

validation and periodic retraining with approved data can help preserve performance. Version control should be used so that clinicians know which model version produced a specific prediction.

TABLE X. Deployment Requirements for Clinical Integration

Requirement	Reason
Secure upload	Protects sensitive medical images
Fast inference	Supports real-time clinical workflow
Result history	Improves traceability and review
Visualization	Assists radiologist interpretation
Model versioning	Supports audit and reproducibility
External validation	Confirms generalization before clinical use

XV. ETHICAL AND SAFETY CONSIDERATIONS

Artificial intelligence in healthcare must be developed and used responsibly. A lung cancer detection model can support early diagnosis, but it should not replace professional medical judgment. The system should clearly communicate that predictions are assistive and must be reviewed by qualified clinicians. This is important because a model may fail on unusual cases, poor-quality images, or populations not represented in the training data.

Patient privacy is another important issue. CT images are sensitive medical records and must be handled securely. Dataset storage, model training, and web deployment should use proper access control and encryption. If data from multiple hospitals are used, privacy-preserving approaches such as federated learning may be considered so that models can learn from distributed data without directly sharing patient records.

Bias and fairness must also be evaluated. If the training dataset does not include diverse patient populations, scanners, and clinical conditions, performance may vary across groups. External testing on independent datasets is therefore necessary before clinical deployment. Reporting should include not only overall accuracy but also subgroup performance, failure cases, and confidence calibration.

Finally, explainability is critical for clinician trust. Grad-CAM visualizations can help users verify whether the model focuses on relevant nodule regions. However, explanation maps should be interpreted carefully because they are supportive visual tools rather than definitive proof of clinical reasoning. The safest deployment strategy is to combine AI prediction, visualization, and expert review within a transparent diagnostic workflow.

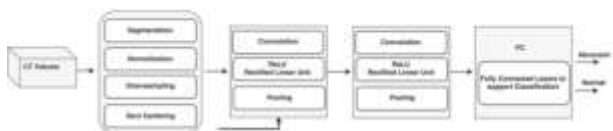


Fig. 18. Illustration of 3D convolutional layer architecture for volumetric medical imaging.

XVI. VALIDATION PROTOCOL AND REPRODUCIBILITY

A reproducible validation protocol is necessary for any deep learning system intended for medical use. In this study, the dataset is divided into training, validation, and testing subsets, and the testing subset is kept separate until final evaluation. This prevents the model from indirectly learning information from test images during hyperparameter tuning. Patient-level splitting is preferred whenever patient identifiers are available, because slice-level splitting may place similar images from the same patient in both training and testing sets.

To ensure fair comparison, the same preprocessing steps should be applied to all models. This includes resizing, normalization, denoising, and augmentation strategy. Augmentation should be applied only to the training data and not to validation or test images. Applying augmentation to test images can distort the real evaluation scenario and may produce misleading results. The validation set is used to monitor training behavior and select model checkpoints, while the test set provides final unbiased performance.

Reproducibility also requires recording software versions, random seeds, batch size, number of epochs, optimizer settings, and hardware environment. Deep learning results can vary if initialization, data shuffling, or GPU operations differ between experiments. Therefore, experiment logs and model checkpoints should be saved. The final system should include a record of the trained model version so that predictions can be traced and audited later.

For clinical acceptability, internal validation should be followed by external validation. Internal validation shows that the model performs well on the available dataset. External validation tests the model on images collected from other hospitals, scanners, or patient populations. This step is critical because medical images vary depending on scanning protocol, reconstruction algorithm, slice thickness, patient anatomy, and disease presentation.

TABLE XI. Recommended Validation Protocol

Stage	Purpose	Important Control
Training	Learn CNN parameters	Use only training images and augmentation
Validation	Tune architecture and monitor overfitting	Do not report as final test performance
Testing	Measure final performance	Keep unseen until final evaluation
External validation	Assess real-world generalization	Use independent hospital or dataset
Clinical review	Confirm decision-support usefulness	Radiologist-in-the-loop assessment

XVII. MATHEMATICAL FORMULATION OF EVALUATION METRICS

The confusion matrix is the basis for most evaluation metrics in binary lung cancer classification. True positive means a malignant case is correctly predicted as malignant. True negative means a benign case is correctly predicted as benign. False positive means a benign case is incorrectly predicted as malignant, while false negative means a malignant case is missed. These four values provide a detailed view of diagnostic behavior.

Accuracy is calculated as the ratio of correct predictions to total predictions. Precision is the ratio of true positives to all predicted positives. Recall or sensitivity is the ratio of true positives to all actual positives. Specificity is the ratio of true negatives to all actual negatives. F1-score is the harmonic mean of precision and recall. These metrics are used together because a single metric cannot fully represent diagnostic quality.

In lung cancer screening, recall is especially important because missing a cancer case can delay treatment. However, precision and specificity are also necessary because a high number of false positives can burden healthcare systems and cause unnecessary patient anxiety. The proposed model achieves high values across all these metrics, which indicates that it is balanced rather than optimized for only one type of prediction.

The Receiver Operating Characteristic (ROC) curve provides another perspective by comparing true positive rate against false positive rate at different decision thresholds. A curve closer to the top-left corner indicates better discrimination between benign and malignant classes. Although the final system uses a selected threshold for binary output, ROC analysis helps evaluate the model across different clinical risk preferences.

TABLE XII. Metric Formulas Used in Model Evaluation

Metric	Formula	Clinical Meaning
Accuracy	$(TP + TN) / (TP + TN + FP + FN)$	Overall correctness
Precision	$TP / (TP + FP)$	Reliability of cancer-positive predictions
Recall	$TP / (TP + FN)$	Ability to detect cancer cases
Specificity	$TN / (TN + FP)$	Ability to reject non-cancer cases
F1-score	$2 \times \text{Precision} \times \text{Recall} / (\text{Precision} + \text{Recall})$	Balance between precision and recall

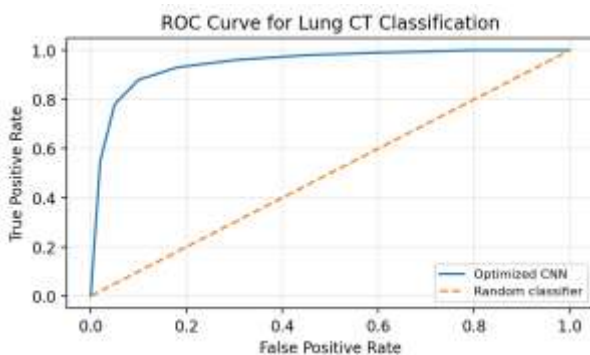


Fig. 19. ROC curve illustrating threshold-based discrimination of the optimized CNN model.

XVIII. PRACTICAL SCREENING WORKFLOW

In a practical screening workflow, the proposed CNN system can be used as a first-level decision-support tool. After CT imaging is completed, relevant slices or candidate nodule regions can be forwarded to the model. The model processes the image, predicts whether it is benign or malignant, and generates a confidence score. Cases with high malignant probability can be prioritized for radiologist review, while benign cases can still be reviewed according to routine clinical policy.

The system can also support telemedicine and remote diagnostic centers. In areas where radiologists are not immediately available, uploaded CT images can be analyzed automatically to support early triage. This does not replace specialist consultation, but it can help identify urgent cases more quickly. Such a workflow may improve access to early screening support in resource-constrained settings.

For hospital use, the system should be connected to image archives or clinical portals using standardized data handling. It should store prediction results, timestamp, model version, and user review outcome. Over time, clinician feedback can be used to improve the model. For example, incorrectly classified cases can be collected, reviewed, and included in future retraining under proper ethical approval.

The best use of the proposed system is therefore a human-AI collaboration. The CNN provides speed, consistency, and quantitative prediction. The clinician provides medical judgment, contextual understanding, and final decision-making. This collaborative workflow can improve diagnostic efficiency while preserving patient safety.



Fig. 20. Probability display supporting clinical review of class confidence.

XIX. CONCLUSION

This paper presented an IEEE-style research article on a deep learning-based approach to diagnose lung cancer using CT scan images. The proposed Phase II system introduced an optimized CNN architecture to improve lung cancer classification while reducing computational complexity. The system includes CT image acquisition, preprocessing, augmentation, CNN feature extraction, binary classification, result visualization, and interpretability support using Grad-CAM.

The experimental results show that the proposed optimized CNN achieved 97.6% accuracy, 96.8% precision, 97.2% recall, 98.1% specificity, and 97.0% F1-score. These results indicate that the model can effectively classify CT images into cancerous and non-cancerous categories. Compared with Phase I models such as 2D CNN, 3D CNN, and ResNet50, the optimized CNN achieved better accuracy while maintaining efficiency and real-time potential.

The study demonstrates that a carefully designed CNN can provide a strong balance between accuracy, interpretability, and deployment feasibility. The inclusion of visualization and confidence output improves user trust and supports clinical review. Overall, the proposed system has strong potential as a computer-aided diagnosis tool for early lung cancer detection.

XX. FUTURE WORK

Future work can extend the system from binary classification to multi-class diagnosis, including different lung cancer stages or subtypes. This would provide more detailed clinical support beyond benign and malignant classification. Another direction is the integration of multimodal data, such as CT images, PET scans, X-rays, patient age, smoking history, symptoms, and laboratory results. Combining image and clinical data may improve personalized diagnosis.

Advanced models such as CNN-Transformer hybrids, attention-enhanced CNNs, and 3D lightweight networks can also be explored. External validation using datasets from multiple hospitals is necessary to test real-world generalization. Finally, the system can be developed into a secure web or mobile application integrated with hospital workflows, enabling radiologists to upload scans, review prediction confidence, and view Grad-CAM heatmaps in real time.

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