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Deep Learning-Based Lung Cancer Detection & Classification

Ms.Sathya[#1], J.Abarna[#2]

Assistant Professor(IT) Student(IT)

Francis Xavier Engineering College, Tirunelveli, India

sathya@francisxavier.ac.in

abarnaj.ug.21.it@francisxavier.ac.in

ABSTRACT:

One of the most common and deadly illnesses in the world, lung cancer requires early and precise detection in order to be effectively treated. In this work, a convolutional neural network (CNN) with transfer learning is used to categorise lung cancer subtypes utilising a deep learning-based methodology. Deep features were extracted from lung cancer histopathology images using the pre-trained Exception model, increasing classification accuracy while lowering computing expenses. Image Data Generator was used to enrich the dataset, and the Adam optimiser and categorical cross-entropy loss were used to train the model. Techniques including dropout layers, early halting, and learning rate reduction were used to avoid overfitting. One of the most common and deadly illnesses in the world, lung cancer requires early and precise detection in order to be effectively treated. In this work, a convolutional neural network (CNN) with transfer learning is used to categorise lung cancer subtypes utilising a deep learning-based methodology. Deep features were extracted from lung cancer histopathology images using the pre-trained Exception model, increasing classification accuracy while lowering computing expenses. Image Data Generator was used to enrich the dataset, and the Adam optimiser and categorical cross-entropy loss were used to train the model. Techniques including dropout layers, early halting, and learning rate reduction were used to avoid overfitting. The disparity in validation performance indicates overfitting, despite the promising training accuracy, underscoring the need for a bigger and more varied dataset. Future work will focus on fine-tuning the pre-trained model by unfreezing selective layers, incorporating additional regularization techniques, and exploring advanced augmentation strategies to improve generalizability. Furthermore, integration with clinical workflows and real-world datasets will be explored to validate the model's applicability in medical diagnostics. The findings of this work demonstrate the potential of deep learning in automating lung cancer diagnosis, establishing a platform for ongoing research in AI-assisted medical imaging. With continuous improvements, this approach could aid radiologists and pathologists in early cancer detection, ultimately improving patient outcomes.

KEYWORDS:

Lung cancer prediction, Lung cancer detection, medical image analysis, Lung tumour classification, Deep learning, machine learning, Transformer network.

I. INTRODUCTION:

Due to late-stage detection and few available treatment options, lung cancer continues to rank among the world's leading causes of cancer-related fatalities, contributing significantly to mortality rates. Early detection of lung cancer subtypes is crucial for improving survival rates, as different types of lung cancer require distinct treatment strategies. Time-consuming and susceptible to human interpretation, traditional diagnostic techniques like biopsy and histological examination may result in inconsistent diagnoses. Deep learning and artificial intelligence (AI) have become effective tools for automated medical image analysis in response to these issues. In this study, we propose a deep learning-based approach to classify lung cancer subtypes using a convolutional neural network (CNN) with transfer learning. By establishing an AI-assisted lung cancer categorization system, this research seeks to contribute to early diagnosis, improved treatment planning, and enhanced patient outcomes. The findings underscore the potential of deep learning in revolutionizing medical diagnostics, reducing diagnostic delays, and assisting pathologists in making more consistent and reliable decisions.This research not only highlights the effectiveness of deep learning in lung cancer classification but also underscores the challenges that must be addressed to ensure real-world applicability. By continuously developing AI-driven diagnostic technologies, the medical community can move closer to achieving faster, more reliable, and cost-effective lung cancer detection, thereby improving patient prognosis and treatment. The diagnosis and treatment of diseases have been completely transformed by the application of artificial intelligence (AI) to the field of medical imaging. AI has shown tremendous promise in automating intricate image-based diagnosis, decreasing human error, and improving radiologists' and pathologists' productivity with the emergence of deep learning models, especially CNNs. Such developments are especially beneficial for lung cancer, one of the most aggressive and deadly cancers. AI-driven diagnostic tools could greatly enhance early detection, which is essential for raising survival rates and administering treatment on time.

II. LITERATURE SURVEY:

1. Chae, K.J.,Jin, G.Y., Ko, S.B., et al. (2020). "Deep Learning for the Classification of Small (≤2 cm) Pulmonary Nodules on CT Imaging: A Preliminary Study." *Academic Radiology*, 27(12), e55–e63.

This study explores the application of deep learning models to classify small pulmonary nodules (≤2 cm) using CT imaging, aiming to improve early detection and diagnosis of lung cancer.

2. Chaunzwa, T.L., Hosny, A., Xu, Y., et al. (2021). "Deep Learning Classification of Lung Cancer Histology Using CT Images." *Scientific Reports*, 11, Article 5471.

The authors developed a deep learning model to classify lung cancer histological subtypes directly from CT images, demonstrating the potential of non-invasive diagnostic techniques.

3. Gu, Y., Chi, J., Liu, J., et al. (2021). "A Survey of Computer-Aided Diagnosis of Lung Nodules from CT Scans Using Deep Learning." *Computers in Biology and Medicine*, 137, 104806.

This survey reviews various deep learning approaches for the computer-aided diagnosis of lung nodules from CT scans, highlighting advancements and challenges in the field.

4. Gumma, L.N., Thiruvengatanadhan, R., Kurakula, L., et al. (2022). "A Survey on Convolutional Neural Network (Deep-Learning Technique)-Based Lung Cancer Detection." *SN Computer Science*, 3, Article 66.

The paper provides a comprehensive survey on the use of convolutional neural networks for lung cancer detection, discussing various architectures and their performance metrics.

5. Javed, R., Abbas, T., Khan, A.H., et al. (2024). "Deep Learning for Lungs Cancer Detection: A Review." *Artificial Intelligence Review*, 57, Article 197.

This review discusses the role of deep learning, particularly convolutional neural networks, in automating the diagnosis and classification of lung cancer using various medical imaging modalities.

6. Lanjewar, M.G., Panchbhai, K.G., Charanarur, P. (2023). "Lung Cancer Detection from CT Scans Using Modified Dense Net with Feature Selection Methods and ML Classifiers." *Expert Systems with Applications*, 213, 119961.

The study proposes a modified DenseNet architecture combined with feature selection methods and machine learning classifiers to enhance lung cancer detection from CT scans.

7. Pandit, B.R., Alsadoon, A., Prasad, P.W.C., et al. (2022). "Deep Learning Neural Network for Lung Cancer Classification: Enhanced Optimization Function." *Multimedia Tools and Applications*, 81, 13566–13589.

The authors present an enhanced optimization function for deep learning neural networks to improve the accuracy of lung cancer classification.

8. Said, Y., Alsheikhy, A.A., Shawly, T., Lahza, H. (2023). "Medical Images Segmentation for Lung Cancer Diagnosis Based on Deep Learning Architectures." *Diagnostics*, 13(3), 546.

This research focuses on the segmentation of medical images for lung cancer diagnosis using various deep learning architectures, emphasizing the importance of accurate segmentation in diagnosis.

9. Siddiqui, E.A., Chaurasia, V., Shandilya, M. (2023). "Detection and Classification of Lung Cancer Computed Tomography Images Using a Novel Improved Deep Belief Network with Gabor Filters." Chemometrics and Intelligent Laboratory Systems, *235, 104763.*

The study introduces an improved deep belief network integrated with Gabor filters for the detection and classification of lung cancer from CT images.

10. Wani, N.A., Kumar, R., Bedi, J. (2023). "Deep explainer: An Interpretable Deep Learning-Based Approach for Lung Cancer

Detection Using Explainable Artificial Intelligence." *Computer Methods and* Programs in Biomedicine, *243, 107879.*

The authors propose 'Deep explainer,' an interpretable deep learning approach that utilizes explainable artificial intelligence techniques for lung cancer detection.

III.METHODOLOGY:

1.Data collection and Preprocessing:

Four kinds of histological images—normal, adenocarcinoma, large cell carcinoma, and squamous cell carcinoma—are included in the collection. To guarantee uniformity in input size and quality, these photos are preprocessed after being taken from publically accessible medical databases. To improve model generalization and avoid overfitting, image preparation include downsizing all images to 350 × 350 pixels, rescaling pixel values to a [0,1] range by dividing by 255, and using data augmentation techniques such horizontal flipping.

2 Model Selection and Transfer Learning:

This study uses the Xception model, a CNN architecture pre-trained on the ImageNet dataset, to harness the power of deep learning for lung cancer classification. In order to preserve learnt representations, the weights of the pre-trained convolutional layers—which operate as feature extractors—are initially frozen. After reducing dimensionality with a Global Average Pooling (GAP) layer, a fully linked Dense layer with softmax activation is added for multi-class classification. Without a large dataset, transfer learning enables the model to identify significant patterns in medical images.

3.Model Compilation and Training:
For effective gradient-based learning, the model is optimized using the Adam optimizer and built using the categorical cross-entropy loss function, which is suitable for multi-class classification problems. Eight batches of augmented data are used to train the model, and early stopping is used to cease training if the loss does not decrease after six epochs. To provide smoother convergence, a Reduce LR On Plateau callback is also employed to reduce the learning rate when performance reaches a plateau.

4.Performance Evaluation:
Throughout the training process, training and validation accuracy are tracked in order to evaluate the model's efficacy. Potential overfitting is indicated by the final model's 93% training accuracy and 65% validation accuracy. The model's learning behavior is examined through the visualization of performance indicators, such as accuracy and loss curves. Unseen test photos are used to further validate predictions and evaluate their relevance in real life.

5. Model fine-tuned and Optimization:
The pre-trained Xception model's selected layers are unfrozen and retrained on the lung cancer dataset in order to fine-tune the model and enhance its generalization. To lessen overfitting, additional regularization strategies are investigated, including dropout layers. To improve model resilience, future research will also use ensemble learning and a bigger, more varied dataset.

6. Deployment and Future Enhancements:
For possible use in clinical settings or incorporation into computer-aided diagnostic (CAD) systems, the trained model is stored in HDF5 format. The model will be tested on actual clinical datasets in the future, and explainable AI (XAI) techniques will be used to increase interpretability. The ultimate objective is to create a lung cancer detection system driven by AI that helps pathologists and radiologists diagnose patients more reliably and accurately, increasing patient outcomes and early detection.

IV. PROPOSED SYSTEM:

1. Data Acquisition and preprocessing:
Lung Tissue images are sourced from publicly available medical databases to ensure diversity and reliability in training data. Each image is categorized into one of four classes: normal, adenocarcinoma, large cell carcinoma, or squamous cell carcinoma, representing different conditions of lung tissue. To ensure consistency and improve model performance, images are resized to 350 × 350 pixels, making them suitable for deep learning models that require uniform input dimensions. The pixel values are

2. Deep learning model selection and architecture:
To achieve high accuracy in lung cancer classification, the system utilizes the Xception model, a powerful deep learning architecture pre-trained on the ImageNet
3.Model selection and Optimisation:

Training and optimization are the next steps. The categorical cross-entropy loss function, which works well for multi-class classification applications, is used to create the model. For effective gradient-based learning, which guarantees quicker convergence, the

dataset. Transfer learning is implemented, allowing the model to leverage previously learned features from large-scale image datasets, significantly reducing the computational requirements for training. The pre-trained convolutional layers serve as feature extractors, capturing important visual patterns in histopathological images. A Global Average Pooling (GAP) layer is introduced to reduce dimensionality while retaining the most significant information. The fully connected layer of the model is customized with a Dense layer and softmax activation function, which classifies the images into the four lung cancer subtypes. This approach enables the system to efficiently extract and classify complex patterns in medical images, enhancing diagnostic accuracy.

Adam optimizer is used. To maximize memory use during training, the dataset is separated into training and validation sets using a batch size of eight. In order to prevent overfitting, the model is trained over 50 epochs, however an early stopping mechanism is included to terminate training if the loss does not improve over six epochs in a row. Furthermore, a Reduce LR On Plateau technique is used to dynamically modify the learning rate, guaranteeing seamless convergence and enhanced generalization. Unfreezing specific layers of the previously trained model and retraining them using the lung cancer dataset is another method of fine-tuning.

4.Model Evaluation and performance analysis:
Following training, the model's efficacy is assessed using a variety of performance criteria. Accuracy, loss, and confusion matrix analysis are the main evaluation measures that shed light on the model's classification abilities. With a validation accuracy of 65% and a training accuracy of 93%, there may be overfitting that needs to be addressed. Model generalization problems are identified and learning trends are analyzed using visualization approaches including loss curves and training-validation accuracy. To evaluate the model's resilience and real-world applicability, additional tests are conducted on unseen photos. To find opportunities for improvement, such as adding more training data or improving preprocessing methods, misclassified examples are thoroughly examined.

5. Deployment and future Enhancement:

The model is saved in HDF5 format for possible use in computer-aided diagnostic (CAD) systems after it has been trained and assessed. By being incorporated into hospital procedures, the technology can help pathologists and radiologists diagnose lung cancer more quickly. Future improvements include using explainable AI (XAI) techniques to improve interpretability, incorporating ensemble learning techniques to improve classification performance, and growing the dataset to increase variety. To guarantee accuracy and dependability in practical applications, the model will also be validated using clinically certified datasets. Early identification, quicker treatment decisions, and better patient outcomes could all be made possible by an AI-driven technology, which has the potential to transform lung cancer diagnostics through constant system improvement.

V. EXPERIMENTAL ANALYSIS:

1.Dataset distribution and characteristics:
Four classes of histopathological images—normal, adenocarcinoma, large cell carcinoma, and squamous cell carcinoma—make up the dataset used to train and evaluate the model. To enhance generalization, the photos are preprocessed by scaling them to 350 × 350 pixels, normalizing pixel values, and using data augmentation techniques. To guarantee a fair representation of every class, the dataset is divided into training, validation, and test sets. In order to avoid biased predictions, augmentation or weighting procedures are used to resolve any class imbalance in the dataset, which is a critical factor in model learning.

2.Model performance Evaluation:
Key performance indicators, including as loss values, validation accuracy, and training accuracy, are used to assess the model. Potential overfitting is indicated by the final training accuracy of 93% and the validation accuracy of 65%. To make sure the model generalizes adequately to unknown data, the loss curve is examined for underfitting or overfitting. The model's ability to categorize new lung cancer images outside of the training data is also evaluated by looking at performance on the test dataset.

3.Model Training and convergence analysis:
The preprocessed photos are sent into the Xception based deep learning model during the training phase. The Adam optimizer with categorical cross-entropy loss for multi-class classification is used to train the model. With a batch size of eight, the training is carried out over 50 epochs. When the validation loss does not decrease for six consecutive epochs, training is stopped as part of an early stopping strategy to avoid overfitting. Furthermore, when performance reaches a plateau, a learning rate reduction approach is used to dynamically modify the learning rate. Real-time accuracy and loss curves are used to track the training process, which aids in comprehending how the model learns.

4.Confusion matrix and classification:
A confusion matrix is created in order to obtain a better understanding of the model's categorization capabilities. Each class's true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) are detailed in this matrix. For every subtype of lung cancer,

the classification report contains important evaluation metrics like precision, recall, and F1-score. While a high recall score implies that the model accurately detects the majority of cancer cases, a high accuracy score denotes fewer false positives. By enhancing data preparation, adjusting hyperparameters, or broadening dataset diversity, misclassification analysis aids in model refinement.

5. Comparative analysis with existing models:

The suggested system is compared to current lung cancer categorization models in order to evaluate its efficacy. Accuracy, training duration, model complexity, and computing efficiency are used to compare performance. When compared to deep learning-based methods, traditional machine learning techniques like Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) usually produce poorer accuracy. The strengths and shortcomings of the Xception model in this particular application are also better understood by comparisons with other CNN designs, such as VGG16, ResNet50, and InceptionV3. The outcomes show that the suggested model maintains effective feature extraction while providing competitive accuracy.

6.Limitations and future enhancements:

The model shows some overfitting even if it achieves excellent training accuracy, as evidenced by the performance gap between training and validation accuracy. The small dataset size and differences in the quality of histopathology images are two potential causes. Future improvements to strengthen the model's resilience will involve

gathering a bigger and more varied dataset, applying ensemble learning strategies, and incorporating explainable AI (XAI) methodologies for improved interpretability. Furthermore, improving hyperparameter tuning and data augmentation techniques will be investigated to improve generalization and practical application.

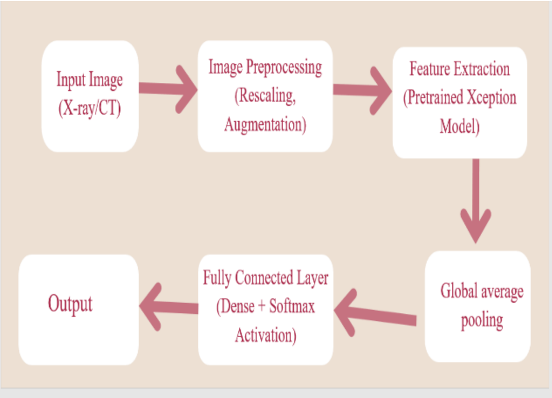
7.Result and Discussion:

Important metrics like accuracy, loss, precision, recall, and F1-score were used to assess the effectiveness of the suggested lung cancer classification model. A certain amount of overfitting was evident in the model's 93% training accuracy and 65% validation accuracy. The model did a good job of identifying cases of normal and adenocarcinoma, but it had trouble telling the difference between large cell carcinoma and squamous cell carcinoma, which resulted in misclassifications, according to the confusion matrix.

8.Conclusion and Future work:

The experimental study offers a thorough evaluation of the performance of the suggested system, emphasizing both its advantages and disadvantages. The model's promise as an AI-driven lung cancer diagnosis tool is demonstrated by its high training accuracy and respectable classification performance on validation data. Future research will concentrate on resolving current issues and further refining the system for clinical implementation and practical use.

VI. ARCHITECTURE DIAGRAM:



Input layer:

Uses 350 by 350 pixel resized histological lung cancer photos as input. Pixel values are scaled between 0 and 1 to normalize images.

Preprocessing and Data augmentation:

Enhances model generalization by applying augmentation methods such as rescaling and horizontal flipping using Image Data Generator.

Feature Extraction using pretrained model(xception):

As a feature extractor, the Xception model which was pre-trained on ImageNet is employed. To take advantage of its learnt features, the model is in non-trainable mode.

Global average pooling layer:

Enhances computing performance and lowers the dimensionality of feature maps.

Fully connected (dense) layer:

Four types of cancer are classified using a dense layer with Soft max activation: normal, adenocarcinoma, large cell carcinoma, and squamous cell carcinoma.

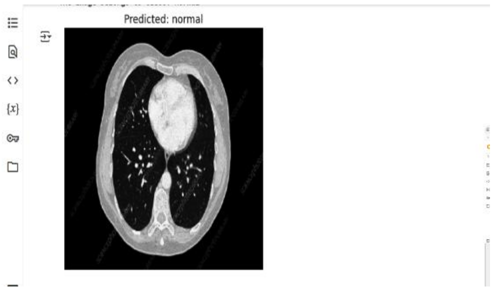
Output layer:

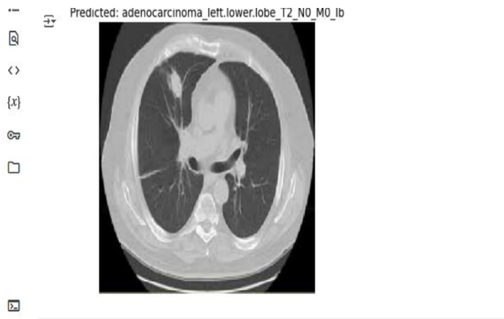
Creates a probability distribution among four classes, where the anticipated cancer kind is determined by the class with the highest likelihood.

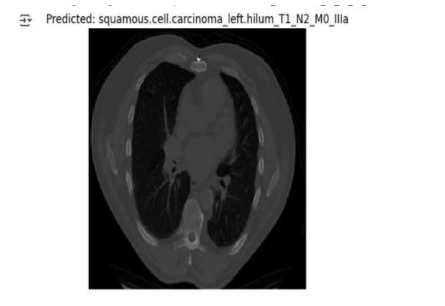
Training and Evaluation:

The Adam optimizer with categorical cross-entropy loss is used to train the model. Learning Rate Reduction and Early Stopping are used to track performance .For training and validation performance, accuracy and loss curves are examined.

VII. OUTPUT:







1. Normal

Lungs appear healthy with no signs of cancerous growth. No abnormalities or suspicious lesions detected in the scan. Represents the baseline for comparison with cancerous cases.

2. Adenocarcinoma

A common type of lung cancer originating in glandular cells. Usually found in the outer lung areas and linked to non-smokers as well. It spreads slowly but can metastasize if not detected early.

3. Large Cell Carcinoma

An aggressive, fast-growing type of non-small cell lung cancer. It can appear in different parts of the lung and lacks distinct cell features.
More challenging to treat due to rapid spread and late detection.

4. Squamous Cell Carcinoma

Develops in the flat cells lining the airways of the lungs. Strongly associated with smoking and exposure to harmful substances.
It often leads to obstruction in the bronchi, causing breathing issues.

VIII. FUTURE SCOPE:

1.Improved Model generalization:
Making sure that models generalize successfully across a variety of demographics, imaging modalities, and equipment changes is one of the major issues in deep learning-based lung cancer classification. Future studies should concentrate on enlarging training datasets by adding pictures from various imaging facilities, hospitals, and geographical areas. By doing this, biases will be lessened and the model will be better able to adjust to real-world situations. To improve the model's performance on unseen data, domain adaptation strategies like data augmentation and transfer learning can also be investigated.

2.Explainable AI for trustworthy information:
Deep learning models are frequently referred to as "black boxes" because of their inability to be interpreted, which restricts their use in crucial applications such as medical diagnosis. In order to offer transparency and insights into model decisions, future developments should concentrate on incorporating Explainable AI (XAI) approaches. By emphasizing significant aspects in medical pictures, visualization technologies like Grad-CAM and SHAP (Shapley Additive explanations) might assist physicians in comprehending why a model predicts a particular diagnosis. Furthermore, combining deep learning with rule-based AI can provide a decision-making process that is easier to understand. Enhancing patient outcomes and fostering trust among medical practitioners can be achieved by making sure AI models offer confidence scores and justifications for their forecasts.

3.Real-time and Edge AI Implementation :
Early detection and treatment planning can be greatly improved by implementing lung cancer classification models in real-time applications. The application of traditional deep learning models in clinical contexts is limited by their high computing requirements. Future studies should investigate lightweight AI architectures that are tailored for real-time operation on edge devices, including smartphones, embedded systems, and cloud-integrated medical equipment, in order to get around this. It is now feasible to create real-time deep learning models that may be used in remote clinics and hospitals because to developments in AI hardware accelerators such as Tensor Processing Units (TPUs) and Graphics Processing Units (GPUs). This will enable prompt and precise diagnosis of lung cancer, especially in environments with limited resources.

4.Multi- modal Learning for Enhanced diagnosis:
Lung cancer diagnosis can be improved by combining multiple data sources, such as radiological images (CT scans, MRIs), histopathology slides, genomic data, and clinical records. Future deep learning systems should adopt multi-modal learning approaches to integrate these diverse data types, leading to a more comprehensive and accurate diagnosis. This approach will enable AI models to understand complex disease patterns by leveraging multiple input channels rather than relying solely on image-based features.

5.Personalized Recommendations:
Beyond diagnosis, AI-powered lung cancer models can help with treatment planning and tailored therapy suggestions. Deep learning models can forecast which treatment choices (such as surgery, chemotherapy, radiation therapy, and immunotherapy) are best for a given patient by examining patient-specific data, including tumor features, genetic profiles, and prior treatment responses. In order to enable AI models to continuously learn from new medical cases and modify therapy suggestions appropriately, future research should investigate reinforcement learning techniques. Additionally, doctors may make data-driven decisions that are specific to each patient's situation by integrating AI with electronic health records (EHRs), which can improve treatment outcomes and minimize negative effects.

6.Integration with blockchain for secure data management:
Beyond diagnosis, AI-powered lung cancer models can help with treatment planning and tailored therapy suggestions. Deep learning models can forecast which treatment choices (such as surgery, chemotherapy, radiation therapy, and immunotherapy) are best for a given patient by examining patient-specific data, including tumor features, genetic profiles, and prior treatment responses. In order to enable AI models to continuously learn from new medical cases and modify therapy suggestions appropriately, future research should investigate reinforcement learning techniques. Additionally, doctors may make data-driven decisions that are specific to each patient's situation by integrating AI with electronic health records (EHRs), which can improve treatment outcomes and minimize negative effects.

IX. CONCLUSION:

A revolutionary development in medical diagnostics, the incorporation of deep learning into lung cancer detection and classification allows for quicker and more precise evaluations of malignant tumors. AI-driven models have shown great promise in differentiating between various forms of lung cancer, especially those that use convolutional neural networks (CNNs) and pre-trained architectures like Xception. These developments are

essential for early identification, which has a direct effect on survival rates and treatment results. AI improves the consistency and dependability of diagnoses while also lessening the workload for radiologists and pathologists by automating the classification process. Before deep learning models can be completely incorporated into clinical procedures, a number of issues still need to be resolved. Model generalization—making sure AI systems function effectively across various patient demographics, imaging technologies, and medical conditions—is one of the main issues. Large-scale, multi-center datasets must be accessible, and reliable data augmentation and domain adaption strategies must be used. Furthermore, explain ability is still a crucial concern because deep learning models are sometimes "black boxes." AI systems must offer interpretable information, like heatmaps and confidence scores, that make it evident why predictions are made if they are to win over medical practitioners.

X. REFERENCE:

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