Interpretability in AI for Early Lung Cancer Diagnosis: Fostering Confidence in Healthcare

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Keywords: Explainable AI (XAI), Convolutional Neural Networks (CNN), Medical Imaging, Grad-CAM, ResNet-18, MobileNetv4, Chest X-Ray Analysis.

Abstract: Lung cancer represents a significant cause of death, making early detection essential for better survival rates. Lung nodules, which are small tissue masses in the lungs, can be initial indicators of lung cancer but are often difficult to detect in chest X-rays due to their subtle appearance and potential overlap with normal anatomical features. Analyzing these images manually is both error-prone and inefficient, often leading to discrepancies. This research integrates convolutional neural networks (CNNs), specifically ResNet-18 and MobileNetV4, with explainable AI techniques such as Grad-CAM to overcome these challenges. The ResNet-18 model demonstrates high accuracy in nodule classification, while MobileNetV4 also shows strong performance, highlighting the potential of deep learning in this area. Grad-CAM is used to provide interpretability by visually highlighting the regions of chest X-rays that influence the model's predictions. This transparency is essential for gaining trust from medical professionals, as it addresses the clinical need for accountability and supports more informed diagnostic decisions.

1 INTRODUCTION

Lung cancer is the one of the primary causes of cancer as there is increase in number of deaths related to lung cancer. In majority of cases, lung cancer is detected during critical stages where treatment is very limited. Lung cancer is the leading cause of cancer-related deaths globally, accounting for 1.8 million deaths in 2020 (18% of all cancer-related deaths). Early detection significantly improves outcomes, with localized cases achieving a five-year survival rate of 61.2%. In Malaysia, lung cancer constitutes 10% of all cancer cases but has a notably low five-year survival rate of 9.0% (95% CI: 8.4–9.7).(Sachithanandan et al., 2024) LDCT screening overcomes lung cancer mortality by 20–61%, yet its high cost and limited accessibility hinder widespread adoption .

Timely detection of lung cancer is critically important as it increases the survival rates but the drawback is positive decisions cannot be taken as the results obtained from the X-rays may be sometimes inaccurate or invasive. The machine learning language has created major important opportunities to detect the lung cancer in early stage through medical images and patient data. The implementation of AI in healthcare sector must not only gives accurate data, but it also gives explanation about how it reached to the conclusion. In the recent times with the help of AI and medical imaging has given significant results in terms of detection of lung cancer in its early stage using the assistance of deep learning techniques. It is useful in detecting the features that may be difficult to analyze by the human radiologists. However, it is essential for AI systems to not only provide high accuracy but also offer transparency in their decision-making processes. This clarity is essential in building trust among healthcare professionals, as it ensures that AI-driven conclusions can be understood and confidently integrated into clinical practice.

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Walishetti, S., Khot, S., Marihal, S., Kittur, P., Giraddi, S. and Akkasaligar, P. T.
Interpretability in AI for Early Lung Cancer Diagnosis: Fostering Confidence in Healthcare.
DOI: 10.5220/0013610300004664

In *Proceedings of the 3rd International Conference on Futuristic Technology (INCOFT 2025) - Volume 3*, pages 143-151
ISBN: 978-989-758-763-4

Deep learning methods, especially convolutional neural networks (CNNs), are among the most prominent solutions for early lung cancer detection. These techniques are commonly applied to medical imaging modalities like chest X-rays and CT scans, achieving notable accuracy in identifying lung nodules. Advanced CNN variants, such as ResNet-18, have been particularly effective in analyzing medical images for tumor detection. Some models also incorporate patient-specific data, including medical history and genetic markers, to improve the precision of predictions. Early detection frameworks are designed to pinpoint minute changes in lung tissues that is signify the early stages of cancer, potentially leading to better patient prognosis.

A 2024 study (Divya et al., 2024) underscored the high detection performance of CNN models in categorizing lung cancer cases. However, these systems face significant obstacles, such as their reliance on extensive computational resources and the availability of large, annotated datasets for effective scaling. The challenges in early lung cancer detection with AI include the need for significant computational power, large labeled datasets, and handling data imbalance. Moreover, issues like limited model generalization, interpretability, and ethical concerns related to patient data privacy make it difficult to implement these systems effectively in clinical practice.

The present paper focuses on developing an accurate AI model for early lung cancer detection, integrating explainable AI techniques to ensure transparency. The model aims to improve clinical decision-making by providing interpretable insights for healthcare professionals, boosting patient confidence. The model's effectiveness is assessed in practical scenarios to ensure its dependability and efficiency in clinical settings, enhancing early detection and treatment outcomes.

The structure of this paper is as follows. Section 2 presents a concise overview of recent research in the field. Section 3 outlines the problem statement, background information, and the proposed methodology. Section 4 details the implementation process, followed by the outcomes and an analysis of the results. Lastly, Section 5 wraps up the paper.

2 LITERATURE SURVEY

Advancements in imaging technologies and machine learning have revolutionized lung cancer detection. The survey delves into a variety of innovative methodologies proposed by researchers for early detection, classification, and diagnosis of lung cancer. It highlights the strengths of these computational models while addressing the challenges faced in achieving widespread clinical application.

(Praveena et al., 2022) MobileNet V2: Efficient Lung Cancer Detection Models for Mobile Devices are discussed. It is an used on a small dataset efficiently. But to ensure clinical reliability, diverse datasets need to be evaluated for it. (Elnakib et al., 2020) reported that CNN models using architectures like AlexNet demonstrate high accuracy in early detection but require significant computational resources, limiting their real-world application. (Wulan et al., 2021) reported that probabilistic neural networks demonstrate notable accuracy using X-rays but may experience misclassifications due to poor-quality images.

(Ingle et al., 2021) reported that AdaBoost-based models demonstrate strong accuracy in predicting lung cancer types, but their performance can be impacted by dataset imbalances. (Maalem et al., 2022) Hybrid models (CNN + Faster R-CNN) outperform traditional methods but demand high computational resources, hindering use in under-resourced settings.(Mukherjee and Bohra, 2020) CNN models minimize human intervention for CT scan-based lung cancer detection, but hardware requirements hinder real-time applications. (Thallam et al., 2020) Combining SVM, random forest, and ANN outperforms single models, but handling noisy data remains a limitation.

(Aharonu and Kumar, 2023) stated that CAD systems using neural networks demonstrate high accuracy, but challenges remain with noisy (Thaseen et al., 2022) Artificial neural networks (ANN) combined with segmentation and noise reduction show high early detection accuracy.(Prasad et al., 2023) reported that EfficientNet B3 models effectively classify lung cancer on CT scans, but broader generalization to varied datasets remains necessary. (Ravi et al., 2023) AlexNet combined with SVM achieves high sensitivity but requires large annotated datasets for general applicability. (Kalaivani et al., 2020) reported that CNNs for image processing exhibit strong accuracy in lung cancer detection, demonstrating significant potential for clinical use.

In conclusion, the majority of the studies are concerned with the determinant value, a few have explored explainable artificial intelligence approaches. There is a deficiency in determining specific nodule regions, which is imperative in gaining the confidence of the medical practitioners. The aim of this research is to close these gaps through the use of Grad-CAM and other techniques that not only provide predictions but also expose the inner workings of the model. It increases the trust in lung nodule detection.

3 PROPOSED METHODOLOGY

Lung cancer is the one of the deadliest disease, where early detection is vital for improving survival rates. Chest X-rays are widely used for screening, but manual analysis is complex, often leading to diagnostic inaccuracies. Deep learning models, such as ResNet-18 and MobileNetV4, show promise for detecting nodule but face trust issues due to their lack of transparency. Explainable AI technique, such as Grad-CAM, overcomes the issue by creating visual representation into the model predictions. Grad-CAM highlights the region in X-ray, improving interpretability, fostering trust among the medical professionals.

Since lung cancer is a major cause of death, early detection is crucial in today's world. The primary method for detecting lung cancer is X-ray imaging; however, it is often insufficient for identifying tumors because cancerous tissues are very minute in the early stages and difficult to detect. The goal of this study is to create a model that enhances early lung cancer detection using deep learning technique and Grad-CAM, which highlights the exact location of nodule, thereby increasing the confidence of the medical community. The objectives of this study are as follows:

- To develop deep learning AI model for early lung cancer detection
- To implement the explainable AI techniques to identify minute cancerous tissues in early stage

The system is proposed for automated lung cancer classification. Figure 1 shows the block diagram of the proposed methodology. The X-ray images, sourced from the JSRT dataset, which includes chest X-ray images, their associated diagnoses, and the location of lung nodules, are uploaded by the user through the interface and then undergo the required transformations to prepare them for future processing. The JSRT created this dataset to offer a standardized dataset for the creation and assessment of CAD systems for identifying lung cancer. This dataset includes 154 nodule images and their corresponding locations, and 93 no nodule images. The original images were in .IMG format with a resolution of 2048×2048 pixels, encoded with 16-bit unassigned numbers. These images were converted to .png usable format using "Image J" (Schneider, 2012). Preprocessing includes resizing the given input X-ray images to 224×224 pixels and normalizing the pixel values. By standardizing the input, the model ensures consistency of the images and provides accurate results across the system. The data augmentation module addresses the challenge of the limited dataset size by expanding the original dataset of 247 X-ray images to a total of 10,000 samples. This module applies various augmentation techniques, such as geometric transformations like flipping, rotation, and cropping. The augmentation process introduces diversity into the dataset, enhancing the model's ability to generalize and reducing the risk of overfitting. The module ensures that the dataset is well-balanced between the two classes (nodule present and nodule absent), enabling the models to learn effectively from both categories.

The training module is the important system, where the two advanced deep learning models like ResNet-18 and MobileNetV4 are trained, The training features differentiate the chest X-rays into nodule present and nodule absent categories.

ResNet-18 is a deep convolutional neural network renowned for its strong effectiveness in image classification. It utilizes residual learning with skip connections, which help train deeper networks by alleviating the vanishing gradient issue. In this study, a modified ResNet-18 model features an architecture with multiple convolutional layers, batch normalization, and ReLU activation functions, enhancing feature extraction and learning capabilities. To tackle class imbalance in the dataset, a weighted Cross-entropy loss function is used, ensuring balanced learning from both classes. This method harnesses the strengths of ResNet-18's architecture and adapts it for effective lung nodule detection.

MobileNetV4 is a lightweight and efficient neural network architecture specifically designed for resource-constrained environments, providing a faster alternative to larger, more complex models. A custom MobileNetV4 inspired model developed, incorporating a simpler architecture composed of convolutional layers, max-pooling, and dropout to reduce overfitting. To address the issue of class imbalance in the dataset, a weighted Cross-entropy loss

Table 1: Comparative Analysis of Diagnostic Models for Chest X-ray Imaging.

Methodology	**Dataset Description**	**Year**	**Performance Parameter**	**Limitation**	**Gap Identified**
DenseNet-121 (Wedisinghe and Fernando, 2024)	Dataset has 247 images of frontal chest X-ray.	2024	Training accuracy: 85%, Validation accuracy: 73%.	Early detection issues, lack of diversified datasets, and technical challenges in AI integration.	Challenges in public education, AI adoption, and follow-up processes.
Combined AI-assisted chest radiography and LDCT (Sachithanandan et al., 2024)	Dataset of 16,551 X-rays; 389 indeterminate pulmonary nodules (IPNs) detected (2.35% yield).	2024	Sensitivity: 96%, Specificity: 100%, High diagnostic accuracy: 96%.	Mixed attitudes towards AI, technical integration issues, poor follow-up on detected nodules.	Research on public education, follow-up strategies, and AI adoption needed.
CNN Model (Jose et al., 2024)	Dataset of 6034 balanced images (cancerous and non-cancerous cases).	2024	Accuracy: 96.4%, Sensitivity: 83.3%, Specificity: 91.7%, AUC: High ROC performance.	Overfitting risks; reliance on augmentation techniques like rotations and flips.	Limited clinical validation and interpretability issues.
CNN for Lung Cancer Classification (Divya et al., 2024)	Dataset of 16,000 images covering adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal cases.	2024	Accuracy: 90%.	High data requirements; overreliance on X-rays limits generalizability.	Need for transfer learning techniques and healthcare integration.
Ante-hoc Concept Bottleneck Model (Rafferty et al., 2024)	Dataset of 2374 chest X-rays from the public MIMIC-CXR database.	2024	Accuracy: 97.1%, AUC: 0.9495.	Small dataset limits generalizability.	Validation on larger datasets needed.
CNN and ResNet-50 (Sekhar et al., 2024)	Kaggle dataset: 120,561,416 CT images (benign, malignant, normal).	2024	CNN: 95% accuracy, ResNet-50: 96%.	Limited to two architectures; requires broader experimentation.	Results lack generalization across datasets.

function is utilized, ensuring the model effectively learned from two classes. This approach maintained the efficiency of the MobileNetV4 design while tailoring it to the specific requirements of the lung nodule detection.

The explainability module enhances the system transparency by using Grad-CAM. Grad-CAM generates heatmaps that takes input X-ray images, by highlighting the region which is the most influenced the models predictions. These visual feedback allows the medical professionals to check whether the model is focusing on clinically relevant areas such as the nodule, are present in the lung rather than irrelevant features.

The first step involves calculating the gradients of the target class score (x_c) concerning the feature maps (B_m) in the final convolutional layer. The important feature map weights are calculated using Equation(1):

$$\alpha_m^c = \frac{1}{N}\sum_a\sum_b \frac{\partial x_c}{\partial B_{m,ab}} \quad (1)$$

Here:

- α_m^c represents Importance weight of the m-th feature map.
- N represents the overall count of pixels in the feature map.
- $\frac{\partial x_c}{\partial B_{m,ab}}$ is the gradient of the target score in relation to the activation $B_{m,ab}$.

Further class activation map (CAM)is generated through a weighted combination of feature maps, as described in Equation(2):

$$L_{\text{CAM}}^{ab} = \text{ReLU}\left(\sum_m \alpha_m^c B_{m,ab}\right) \quad (2)$$

The ReLU activation ensures that only positive sample contributions to the target class are

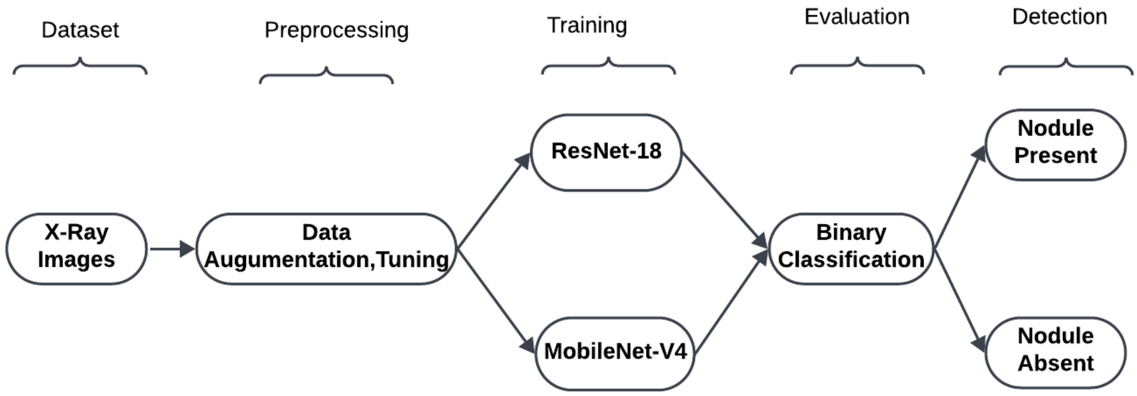

Figure 1: Proposed methodology for lung nodule detection

retained, effectively highlighting regions in the input X-ray image that play a significant role in the model's predictions. By focusing on these regions, the model generates heatmaps that provide interpretable visual feedback.

4 RESULTS AND DISCUSSIONS

The execution is performed in Python, ensuring seamless integration with the PyTorch framework. The dataset is trained on Google Colab's GPU environment, utilizing a high-performance NVIDIA GPU to accelerate training, particularly for large datasets and using data augmentation tasks. The training employed using PyTorch with mixed-precision, enabled through torch.cuda.amp to enhance computational efficiency and reduce memory consumption.

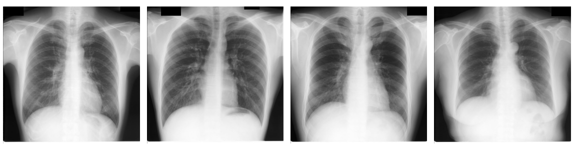

Figure 2: Example Chest X-ray Image Illustrating a without Nodule

The study introduces a lung nodule detection system utilizing chest X-ray images, developed with Python and the PyTorch framework. The JSRT dataset, comprising 247 chest X-ray images (157 with

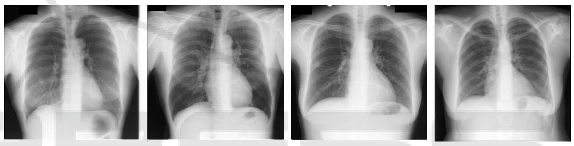

Figure 3: Example Chest X-ray Image Illustrating a Nodule

nodules and 93 without nodules), serves as the foundation. Each image has a resolution of 2048x2048 pixels. The preprocessing phase involves resizing the images to 224x224 pixels and normalizing pixel values to meet the specifications of pre-trained models. To improve the model's robustness and generalization, augmentation methods such as horizontal and vertical flips and random rotations up to 15 degrees are employed. Figure 2 and Figure 3 illustrate examples of images with and without nodules.

ResNet-18:

The ResNet-18 model is pretrained on the ImageNet, is replaced by modifying its final fully connected layer to accommodate binary segmentation. Training is done with learning rate of 0.01 using SGD of momentum(0.9) and weight decay of(1e-4). A focal loss function is utilized to handle class imbalance with parameters alpha=0.25 and beta=2.0. The model trained with the help of augmented dataset including 10,000 X-ray images. The model is trained for 50 epochs. The Figure 4 shows training accuracy achieved is 90.84% and the validation accuracy is 90.36%. The results demonstrates that the data augmentation has a positive impact on the model performance. Figure 5 shows the training and validation loss for ResNet-18, with both decreasing sharply in the initial epochs and stabilizing thereafter. The close alignment of the curves indicates effective learning with minimal overfitting. Figure 6 presents the confusion matrix, where the model correctly classifies 25 nodule absent images as nodule absent and 25 nodule present images as nodule present, with only 2 false positives and 1 false negative. This indicates high classification accuracy with minimal errors.

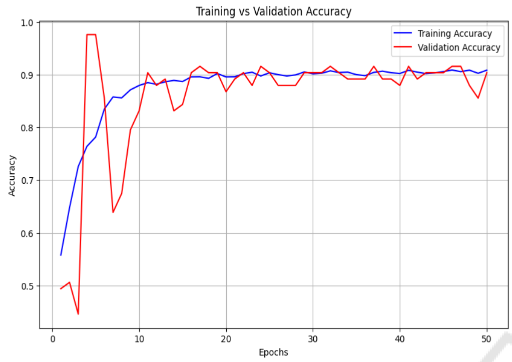

Figure 4: Training vs. Validation Accuracy for ResNet-18

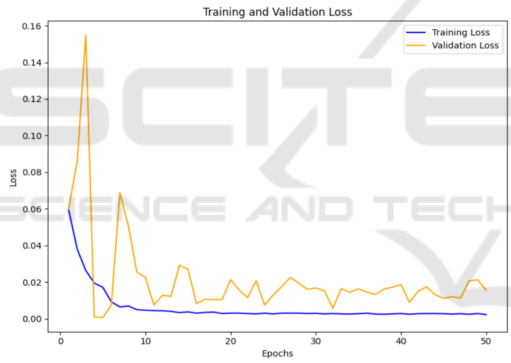

Figure 5: Training vs. Validation Loss for ResNet-18

The Figure 7 shows the ROC curve for the ResNet-18. The curve moves steeply upward, which indicates great performance in separating positive and negative classes. The score for AUC (area under the curve) is 0.94, is quite high, indicating that the model has good classification ability.

MobileNetV4: The MobileNetV4 offers the advantage of faster inference or lower computational cost. Linear SGD with 0.001 and momentum of 0.9 is employed for training with a batch size of 8 and StepLR is a learning rate scheduler that decreases the learning rate by a factor of 0.1 after every 5 epochs. Loss function is Cross-entropy loss with balanced class weights, and training is carried on for 50 epochs. Figure 8 shows training accuracy is 75% and validation accuracy is 74%. Figure 9 shows a steady de-

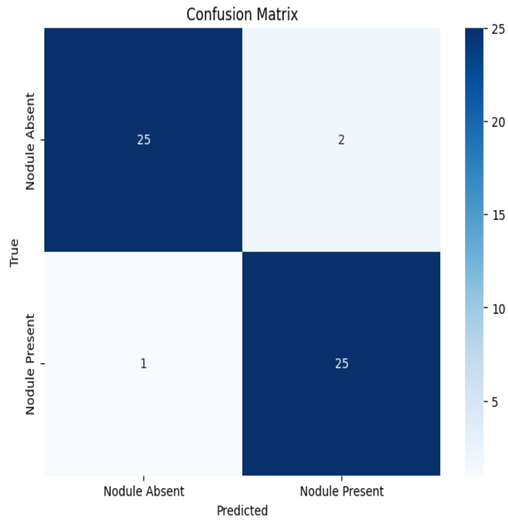

Figure 6: Confusion Matrix for ResNet-18

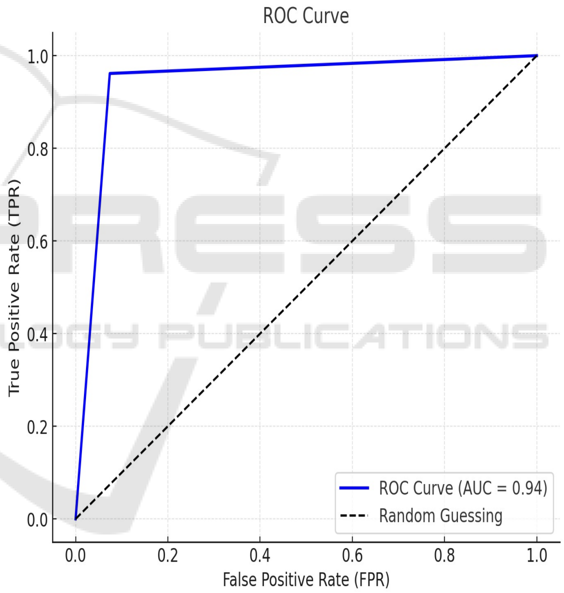

Figure 7: ROC Curve for ResNet-18

cline in training and validation loss, stabilizing after 20 epochs, indicating effective convergence and minimal overfitting. Figure 10 presents the confusion matrix, where the model correctly classifies 22 nodule absent images as nodule absent and 20 nodule present images as nodule present, with only a few misclassifications, demonstrating its reliability in lung nodule detection.

The Figure 11 shows ROC curve representing the true positive rate (TPR) versus false positive rate (FPR) using their respective range of thresholds. This graph shows an AUC value of 0.78, meaning that the model is better than a random classifier. The curve

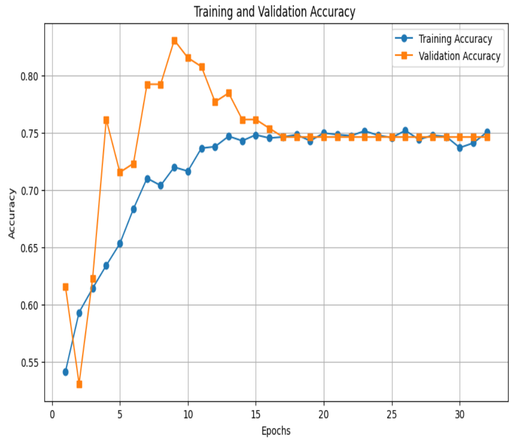

Figure 8: Training vs. Validation Accuracy for MobileNetV4

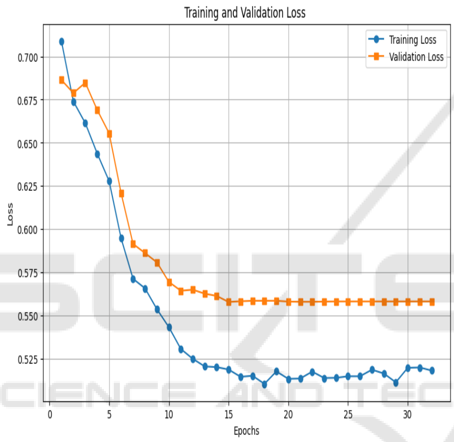

Figure 9: Training vs. Validation Loss for MobileNetV4

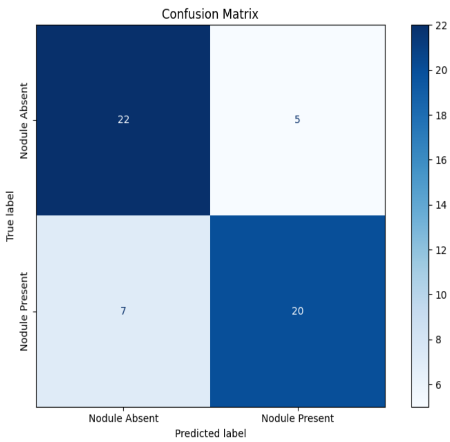

Figure 10: Confusion Matrix for MobileNetV4

indicates that the model has generally good performance, though not perfect in terms of distinguishing true positives and false positives across all thresholds.

The Table 2 shows the comparison of the performance between models. From Table 2, it is observed that ResNet-18 provides high accuracy and reliability for detecting lung cancer nodules. As shown in Table 2, ResNet-18 outperforms MobileNetV4 in terms of accuracy. Moreover, both models surpass the performance of the existing paper (Wedisinghe and Fernando, 2024), where DenseNet21 attained a training accuracy of 85% and a validation accuracy of 73%. The narrow gap between training and validation accuracies presented in this paper highlights the model's ability to generalize effectively from the augmented dataset.

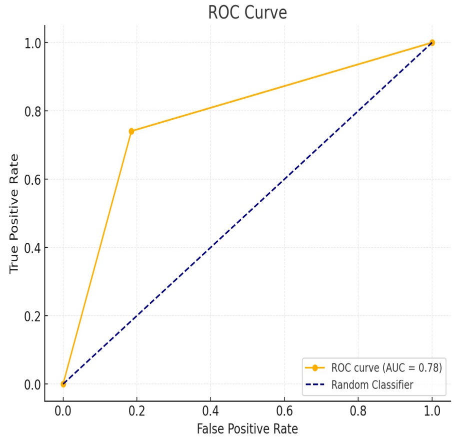

Figure 11: ROC Curve for MobileNetV4

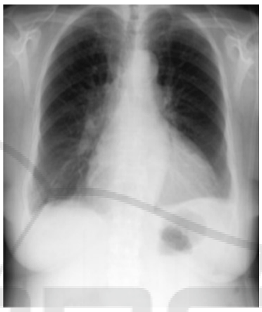

Figure 12: Lung Nodule Detection (a)

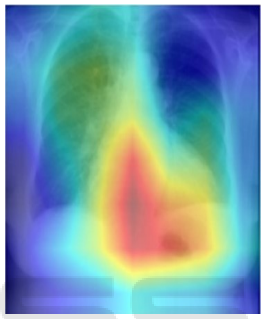

Figure 13: Grad-CAM (b)

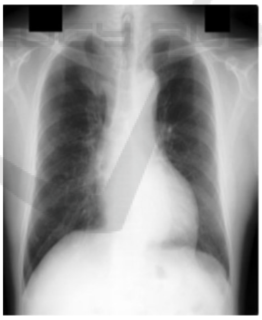

Figure 14: Lung Nodule Detection(c)

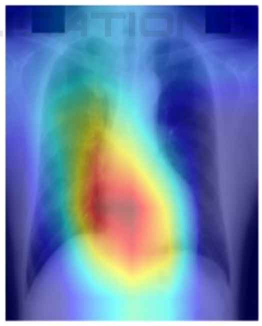

Figure 15: Grad-CAM (d)

Further, Grad-CAM is applied to both ResNet-18 and MobileNetV4 to assess interpretability. Grad-CAM is a technique that visualizes the important areas of an input image that have the greatest influence on the model's decision. By generating heatmaps, Grad-CAM highlights areas in the image with high attention (represented in red), indicating regions likely associated with lung cancer nodules, while blue areas represent less relevant regions. This allows for a better understanding of the model's behavior, making it more interpretable. Figure 13 and Figure 15 illustrate the application of Grad-CAM on chest X-rays to highlight the regions contributing most to the prediction of lung cancer by ResNet-18 and MobileNetV4 models. Both models successfully identify clinically significant regions, as shown by the dark areas in the heatmap. This interpretability helps medical professionals understand the model's predictions and aligns its focus with relevant clinical features, enabling reliable and transparent diagnosis.

Table 2: Performance Comparison of ResNet-18, MobileNet-V4 and DenseNet-121 Classifiers.

Name of Classifier	**ResNet-18**	**MobileNet-V4**	**DenseNet-121 (Wedisinghe and Fernando, 2024)**
Training Accuracy	90.84%	75%	85%
Validation Accuracy	90.36%	74%	73%
Precision	94.41%	77.93%	-
Recall	94.34%	77.78%	-
F1 Score	94.34%	77.75%	-

5 CONCLUSIONS

This paper introduces lung nodule detection in chest X-ray images.The problem is approached using deep learning models such as ResNet-18 and MobileNetV4 trained on an augmented dataset of 10,000 images. ResNet-18 attained a validation accuracy of 90.36% while MobileNetV4 gained 74%. The ResNet-18 model outperformed MobileNetV4 in accuracy, making it more appropriate for accurate lung nodule detection. The use of Grad-CAM for model explainability assures that the systems outcomes are transparent. Future work will focus on increasing the dataset refining models for real-time use, and integrating the system into clinical environments.

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