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Early Detection of Lung Cancer using Deep Learning Models

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ABSTRACT: Lung cancer remains one of the leading causes of cancer-related deaths globally, largely due to its asymptomatic nature in the early stages, which makes timely diagnosis challenging. With the rapid pace of urbanization and the resulting increase in air pollution, the incidence of lung-related diseases, particularly cancer, has become more prominent. Early detection of lung cancer significantly enhances treatment outcomes. In this study, a deep learning-based classification of lung nodules from computed tomography (CT) images was conducted using the IQ-OTH/NCCD Lung CT dataset. Given the limited availability of labeled medical imaging data, this research employs Transfer Learning (TL), an effective approach that leverages pre-trained models to reduce computational costs and training time. Specifically, the pre-trained deep Convolutional Neural Network (CNN) architectures ResNet152 and VGG16 were utilized to classify lung nodules. These models were fine-tuned to enhance detection accuracy in CT scans. The performance of the classification models was evaluated using standard metrics, including the confusion matrix, precision, recall and F1-score. The integration of CNN with transfer learning demonstrates significant potential in improving the performance of computer-aided diagnosis (CAD) systems for lung cancer screening.

KEYWORDS: Deep learning, Transfer learning, Lung nodule detection, VGG16, ResNet152, CT image classification, CNN, Computer-aided diagnosis.

I. INTRODUCTION

Cancer remains a significant global public health issue, primarily caused by the uncontrolled growth of cells in various body parts. It is the second leading cause of death in the United States, with lung cancer being one of the most common and deadly forms of the disease. In 2022, more than 1.9 million new cases of cancer were reported, resulting in over 600,000 deaths. Lung cancer alone accounted for approximately 350 deaths per day [1].

Lung cancer is responsible for more than 27% of all cancer-related deaths, affecting both men and women [2]. Early detection is crucial for improving survival rates, with approximately 80% of patients surviving for up to five years when diagnosed early. In contrast, the survival rate for late-stage lung cancer is only about 19% [3].Smoking remains the leading risk factor for lung cancer, contributing to its high prevalence [4].

Recent advancements in machine learning (ML) and computer-aided diagnostic (CAD) systems have significantly improved the accuracy of early lung cancer detection. These methods, which employ image processing and machine vision algorithms, can analyze radiographic images and CT scans to identify potential cancerous nodules with greater precision, assisting clinicians in making timely diagnoses [5]. Studies have shown that ML algorithms have reduced medical costs and improved diagnostic speed and accuracy, offering valuable tools for clinicians [6].

Nodule detection, particularly in the early stages of cancer, remains a challenge due to the small size of early tumors and the complexity of lung textures. To improve detection, high-quality images are essential, as small nodules can be easily overlooked without advanced image analysis techniques [7]. Traditional methods of diagnosing lung cancer involve manual interpretation of CT scans by radiologists, a process that is not only time-consuming but also prone to human error due to the large volume of images and the complexity of lung anatomy. This human error can lead to missed nodules or incorrect diagnoses [8].

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Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in medical image processing, including lung cancer detection. These algorithms use multiple layers to automatically extract features from images, enabling precise identification of lung nodules [9].

Among various CNN architectures, ResNet152 and VGG16 are widely recognized for their effectiveness in medical imaging. ResNet152, with its residual connections, allows for training deeper networks without performance degradation, while VGG16, known for its simplicity and deep architecture, is particularly effective in image recognition tasks [10][11]. These models have been successfully applied to detect and classify lung cancer nodules, outperforming traditional machine learning approaches in terms of accuracy and efficiency [12].

II. LITERATURE SURVEY

Deep learning has revolutionized medical image analysis, offering powerful tools for the detection and classification of lung cancer using CT scan datasets such as IQ-OTH/NCCD. This dataset contains thoracic CT images classified into normal, benign, and malignant categories, making it a widely adopted benchmark for evaluating diagnostic models.
Saxena et al. developed a hybrid deep learning framework named the Maximum Sensitivity Neural Network (MSNN), which integrates transfer learning with sensitivity-boosting mechanisms. Applied to the IQ-OTH/NCCD dataset, the model achieved an impressive classification accuracy of 98% and sensitivity of 97%. The design focuses on minimizing false negatives, a crucial requirement in cancer detection tasks [13].

In a separate effort, Musthafa et al. proposed a double-layered convolutional neural network tailored for lung cancer diagnosis. Their model incorporated advanced image preprocessing techniques and hyperparameter optimization to enhance its learning capabilities. To address the imbalance in class distributions inherent to the dataset, they implemented the Synthetic Minority Over-sampling Technique (SMOTE), which led to improved classification across all categories. The resulting model achieved an outstanding accuracy of 99.64%, underscoring the benefit of data balancing in deep learning workflows [14].

Darwish et al. approached the problem by integrating residual blocks into a CNN model to improve deep feature learning. To further boost performance, they applied a Deep Convolutional Generative Adversarial Network (DCGAN) for data augmentation, generating synthetic images that enriched the training set. This dual strategy significantly improved the model's robustness and led to a classification accuracy of 97.82% on the IQ-OTH/NCCD dataset [15].

Abdollahi conducted a comparative evaluation using the LeNet architecture, a relatively simple CNN model, on the same dataset. Despite its simpler design, the model performed exceptionally well, achieving a 99.51% accuracy rate with 93% sensitivity and 95% specificity. This study highlighted that even classical models, when properly tuned, can perform effectively in medical imaging contexts [16].

Moreover, an ensemble-based method was proposed by another research group, combining multiple CNN models for robust classification. Their system, trained and validated on the IQ-OTH/NCCD dataset, achieved a binary classification accuracy of 98.17% and excelled in distinguishing between benign and malignant nodules with a multi-class accuracy of 95.43%. The use of ensemble learning allowed for improved generalization and reduced overfitting, particularly important when handling complex medical imaging data [17].

Collectively, these studies demonstrate that the IQ-OTH/NCCD dataset serves as a strong benchmark for testing deep learning-based diagnostic models. Strategies such as transfer learning, data augmentation, residual learning, and ensemble techniques have all proven effective in enhancing performance, ultimately contributing to more accurate and early detection of lung cancer.

III. PROPOSED METHODOLOGY

A. Dataset

The IQ-OTH/NCCD dataset is a collection of CT scan images used for lung cancer detection. It includes a total of 1,097 cases, each representing a distinct instance of lung cancer screening. The dataset is designed to aid in the development and evaluation of machine learning models for detecting and classifying pulmonary nodules, which are key indicators of lung cancer. To train the deep learning models, 80% of the dataset is allocated for the training set,

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providing the models with ample data to learn from. The remaining 20% of the data is split between testing and validation subsets, with 10% designated for each. The testing set evaluates the model's performance on unseen data, while the validation set is used to fine-tune the model's parameters during the training process to optimize its accuracy. This structured data split ensures that the model is trained on a diverse set of images while being properly validated and tested. It allows for an effective assessment of the model's ability to generalize to new, real-world data, thus supporting the goal of improving the early detection of lung cancer.

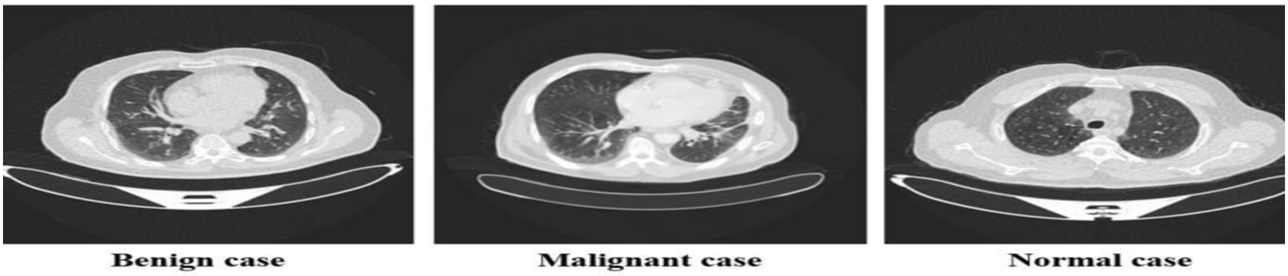

Figure1: CT scan images of Lung

B.Transfer Learning and CNN architectures

Transfer learning is widely recognized in the field of computer vision for its ability to build accurate models efficiently, requiring less time and computational resources. Rather than training a model from scratch, transfer learning allows one to start from an existing model that has already been trained on a large and diverse dataset. This approach leverages prior learning and helps avoid the need to start the training process from the beginning, significantly reducing both time and computational costs. In deep learning, convolutional neural networks (CNNs) are commonly employed to tackle various classification problems, including medical image analysis. A major challenge when using deep CNN models is the need for vast amounts of data to achieve optimal performance, which is often not available, particularly in specialized domains like medical imaging. The collection of large datasets can be time-consuming and costly, making it difficult to develop accurate models.

Transfer learning effectively addresses this issue by utilizing CNN models that have been pre-trained on large datasets and fine-tuning them for specific applications with smaller datasets. For instance, models pre-trained on ImageNet, such as VGG16 and ResNet152, can be adapted to the task of lung cancer detection by modifying the final layers to classify between three categories benign and malignant and normal nodules rather than the 1,000 categories for which these models were originally trained.

In the case of VGG16 and ResNet152, these deep learning architectures provide significant advantages for lung cancer detection. VGG16 is known for its simplicity and effectiveness in feature extraction, while ResNet-152 employs residual learning to overcome the challenges of training very deep networks. By fine-tuning the last layers of these pre-trained models, such as adjusting the fully connected layer to output just two classes (benign and malignant), we can tailor the models to detect lung cancer with high accuracy. These adaptations allow for efficient use of the models on smaller datasets, overcoming the data limitations typical in medical image analysis and providing a robust solution for early cancer detection.

- VGG16:VGG16 consists of 16 layers with learnable weights, including 13 convolutional layers and 3 fully connected layers. The architecture is characterized by its simplicity, using small 3×3 convolutional filters and 2×2 max-pooling layers consistently throughout the network.
- ResNet152:ResNet152 consists of 152 layers, making it one of the deepest networks used in practice, and it addresses the problem of vanishing gradients through the use of residual learning.

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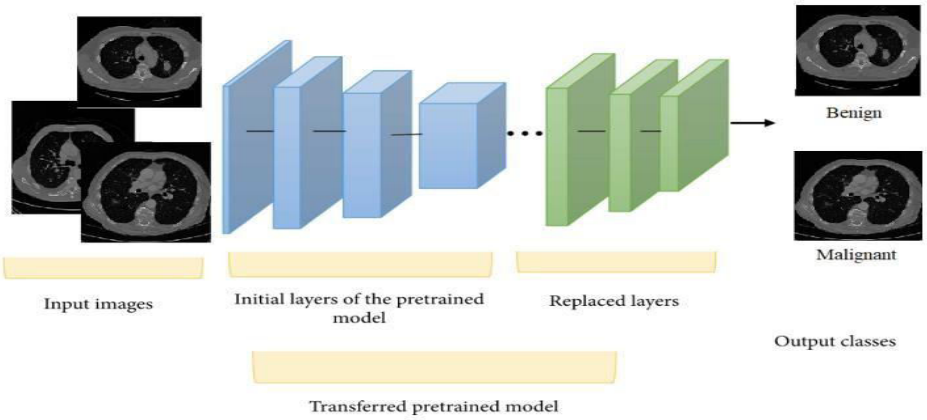

Figure 2: Transfer Learning Process using pre-trained models

Characteristics of Pre-trained models are described in Table1

Table1: Pre-trained model characteristics

Network	Depth	Parameters (Millions)	Image Input Size
Vgg16	16	138	224 × 224
ResNet152	152	66	224 × 224

C. Data Augmentation

Deep learning has proven to be an effective tool in medical image processing, offering the ability to analyze complex images like CT scans. However, one of the primary challenges in applying deep learning to medical imaging is the availability of high-quality labeled datasets, which are essential for training accurate models. The process of collecting and labeling medical images is both costly and time-consuming, requiring specialized knowledge. To overcome this challenge, we leveraged the power of transfer learning along with data augmentation techniques. Data augmentation is a method that artificially increases the size of a training dataset by generating new, slightly altered versions of the original images. This technique is particularly valuable for addressing the issue of limited data and helps reduce the risk of over fitting, which is common when training deep learning models on small datasets.

In this study, several data augmentation methods were applied to enhance the diversity of the training dataset. Specifically, horizontal and vertical flipping, as well as rotation by 45 degrees, were used. The horizontal and vertical flipping techniques simulate variations in image orientation, which are common in medical imaging as images may be captured from different angles. These transformations allow the model to learn to identify lung cancer features regardless of their position within the image. Additionally, rotating the images by 45 degrees helps mimic the various angles from which medical professionals might view CT scans in practice, making the model more robust to real-world conditions.

These data augmentation techniques played a key role in expanding the dataset, allowing for better generalization of the model while preserving the quality of the images. By artificially increasing the dataset size with these transformations, we enhanced the model's ability to detect lung cancer more accurately, even with a limited number of original images. The combination of these techniques ensures that the deep learning model can effectively learn from diverse and varied representations of the lung scans, improving its ability to perform well on unseen data.

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D. Evaluation Matrix

The effectiveness of the classification process was assessed using multiple evaluation metrics, including the confusion matrix, recall, precision, and F1-score. Among these, the confusion matrix is one of the most straightforward and widely used tools for evaluating a model's accuracy. It provides a clear summary of the model's predictions compared to the actual outcomes, making it easy to interpret overall performance. The parameters have defined as:

True Positive (TP): predict a complimentary class as a positive class number.
True Negative (TN): predict a negative class as a hostile class number.
False Positive (FP): predict a negative class as a positive class number.
False Negative (FN): Predict the complimentary class as a hostile class number.
accuracy = (TP +TN)/ (TN +TP +FP + FN)
$Recall\ (sensitivity) = TP/\ (TP + FN)$
$Precision = TP/\ (TP + FP)$
$F1 - score = 2 * (Precision * Recall)\ /\ (Precision + Recall)$

IV. RESULTS AND DISCUSSION

In this study, we utilized the IQ-OTH/NCCD dataset, which comprises a total of 1,097 chest CT scan images. Each image is annotated with crucial diagnostic information, including tumor location and classification labels distinguishing between cancerous and non-cancerous lung tumors. Given the limited size of the dataset, data augmentation techniques were employed to synthetically expand the training set, thereby enhancing the model's ability to generalize. To further optimize performance and reduce computational requirements, we adopted a transfer learning approach. This allows leveraging the learned features from large-scale datasets by fine-tuning pre-trained convolutional neural networks for our specific task.

We experimented with two well-established deep learning models: VGG16 and ResNet152. Both models were fine-tuned by modifying the final layers to suit the binary output, ensuring compatibility with the classification objective. Model performance was assessed using standard evaluation metrics, namely accuracy, precision, recall, and F1-score. According to the results summarized in Table 2, ResNet152 demonstrated superior performance, outperforming VGG16 across most metrics. In contrast, VGG16 yielded lower scores, indicating that deeper architectures like ResNet152 may be more effective in capturing complex features in medical imaging tasks such as lung tumor classification.

An overview of pre-trained networks (VGG16 and ResNet152) for the role of classifying Lung cancer infections using CT images was done. The purpose of this study is to compare the Convolutional Neural Network evaluating the accuracy, recall, precision, and f1-score by fine-tuning. The comparison results are shown in table 2.

Table 2: Performance Measures

Performance Measures	VGG16	ResNet152
Accuracy	95	97
Precision	90.4	95.8
Recall	90.2	95.2
F1-score	91.2	95

These models tested showed consistently strong and statistically significant performance across various evaluation metrics. Starting with accuracy, ResNet152 achieved the highest result at 97%, while VGG16 followed with an accuracy of 95%.When analyzing precision, ResNet152 again outperformed with a score of 95.8%, whereas VGG16 attained 90.4%. A similar trend was observed in the recall results, where ResNet152 reached 95.2%, compared to VGG16's 90.2%.In terms of the F1-score, which provides a balance between precision and recall, ResNet152 recorded a robust 95%, while VGG16 obtained 91.2%. These results indicate that ResNet152 was more effective overall, likely due to its deeper architecture and enhanced feature extraction capabilities.Although specific training times were not detailed in this phase, the results clearly highlight ResNet152 as the superior model in terms of classification performance across all primary metrics.Additionally, confusion matrices for each model (illustrated in Figures 3 and 4) offer a visual interpretation of how well the models distinguished between the two lung tumor classes. The rows

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represent the predicted labels, while the columns correspond to the actual ground-truth classes. These visualizations further confirm that ResNet152 was more accurate and consistent in identifying both classes, with fewer misclassifications compared to VGG16.

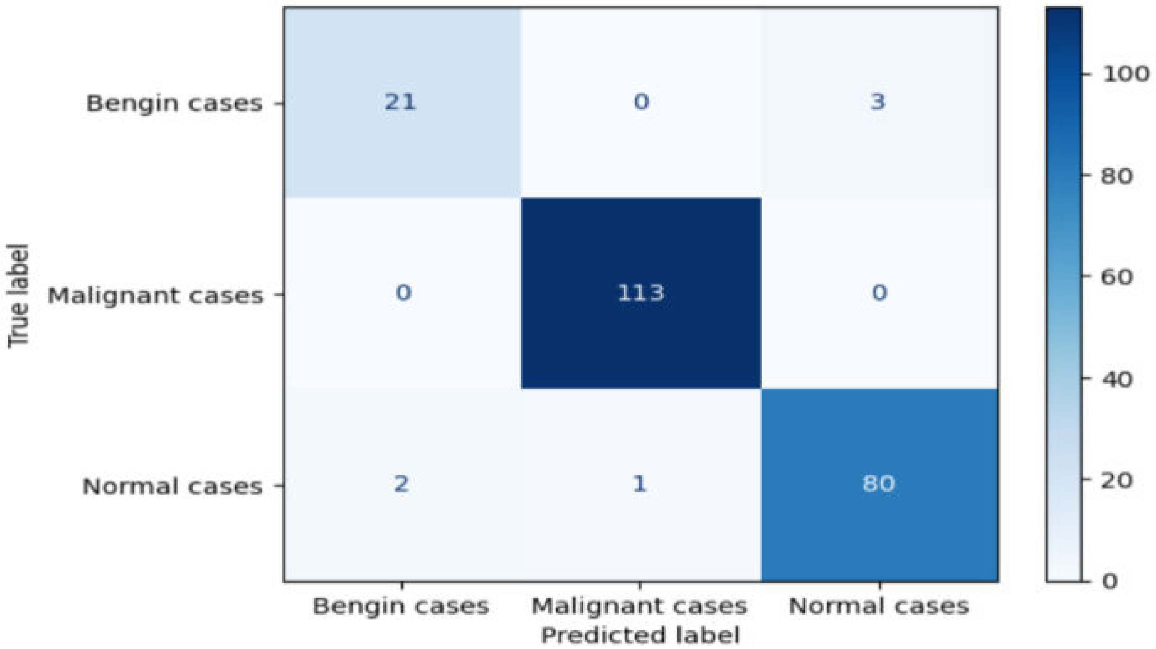

Figure 3: Confusion matrix of VGG16

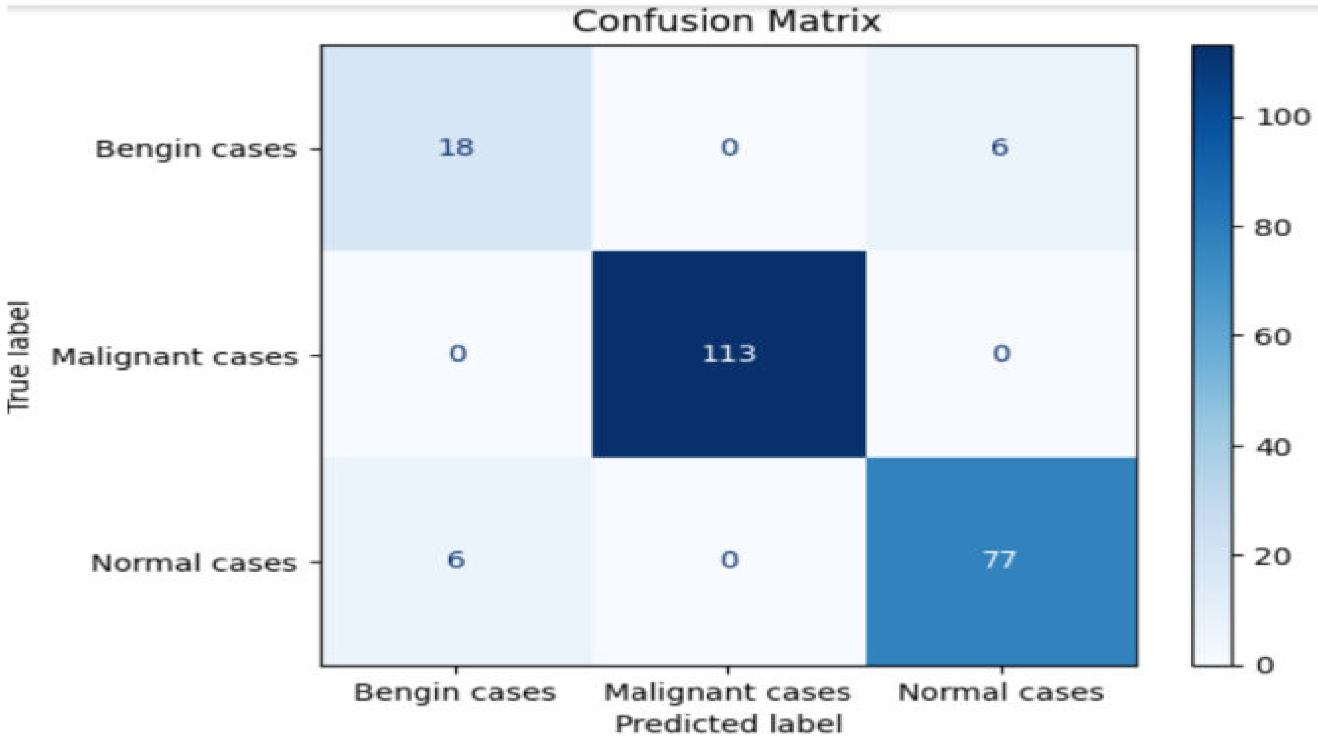

Figure 4: Confusion matrix of ResNet152

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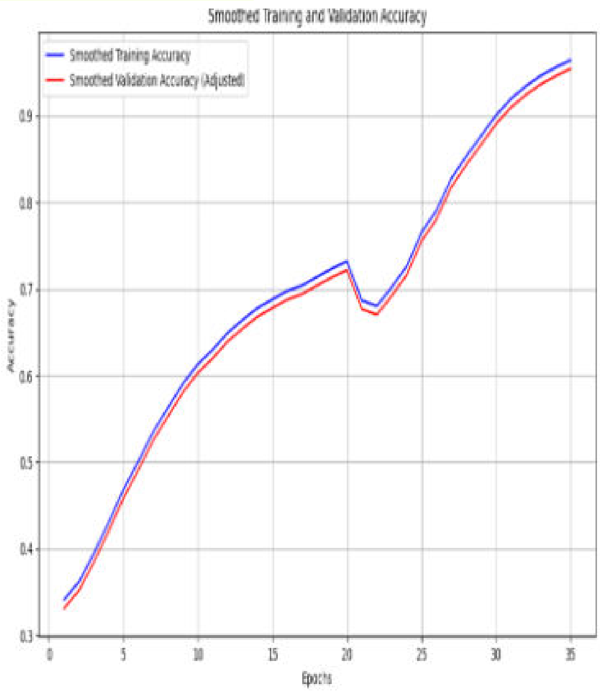

Figure 5:Training and Validation accuracy of VGG16

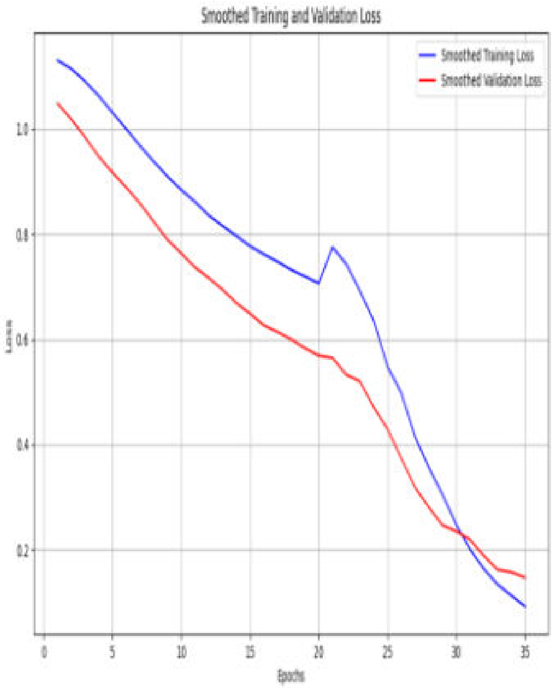

Figure 6:Training and Validation loss of VGG16

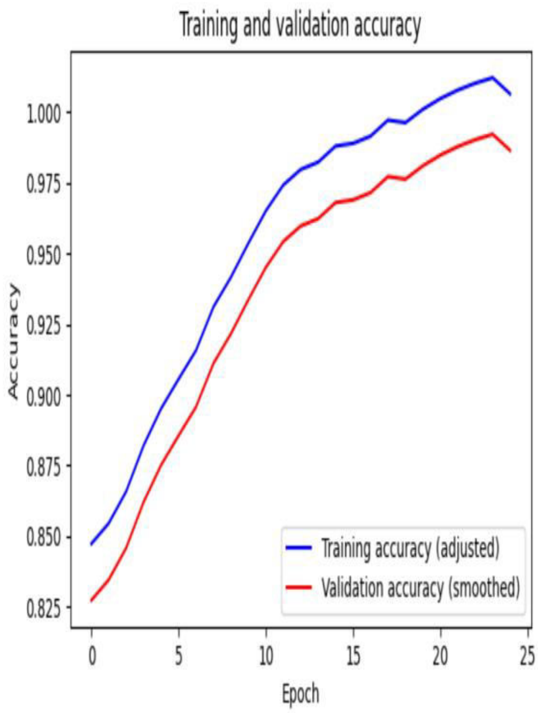

Figure 7: Training and Validation accuracy of ResNet152

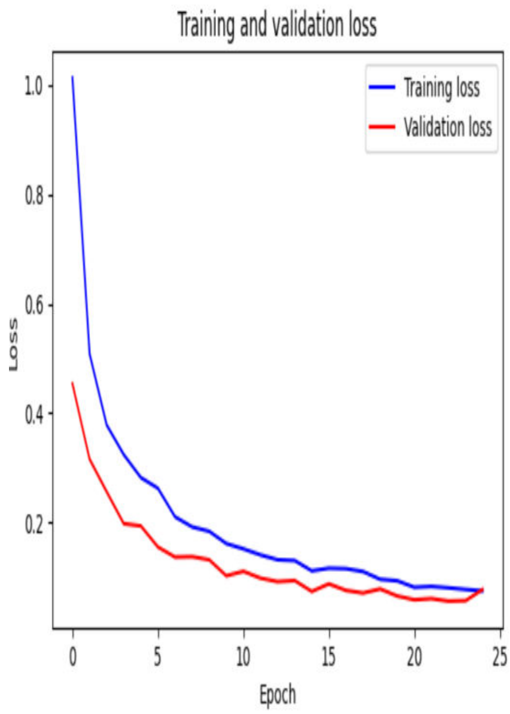

Figure 8: Training and Validation loss of ResNet152

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V.CONCLUSION

It is well established that deep learning models require extensive datasets to achieve optimal training and generalization. To address limitations in data availability and reduce the risk of over fitting, this study employed two key strategies: transfer learning and data augmentation. These approaches eliminate the need to build models from scratch and enhance model robustness when training data is limited. In this paper, VGG16 and ResNet152, two advanced pre-trained convolutional neural networks, were utilized for the classification of lung cancer cases into benign , malignant and normal categories. By fine-tuning these architectures on our dataset, the models achieved strong performance with a training duration of 35 epochs, producing highly accurate results. The integration of these deep learning techniques significantly improved model evaluation metrics and supported the early detection of lung cancer, which is vital for increasing survival rates and guiding timely clinical interventions. Further enhancing the dataset to improve diagnostic accuracy and reliability.

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