Deep Learning Approaches for Precise Lung Cancer Diagnosis

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Abstract. The leading source of lung cancer serving as a significant health issue among men and women stems from tobacco contact and smoking habits. Medical technology developments since modern times have failed to decrease the substantial mortality from this disease. Early detection of lung cancer relies on successful diagnosis through machine learning technology that has evolved into the best diagnostic method for the disease. The achievement of precise medical diagnosis using different classification systems remains a difficult task due to elusive perfection levels. The poor management of Digital Imaging and Communications in Medicine (DICOM) images creates additional costs in implementation. Medical imaging professionals primarily use CT scanners because this equipment generates clearer images with lower noise levels during the scanning procedure. Deep learning has achieved two main objectives: the detection of nodules and the assessment of abnormal structures and cancer progression in respiratory tissue. The ability to detect conditions has seen major improvements resulting from models utilizing EfficientNet-B0, VGG19 and ResNet-50. The most efficient model for delivering top results is the ResNet-50 model among the available choices.

Keywords: Image preprocessing, Feature extraction & segmentation, VGG19, EfficientNet-B0, ResNet50.

1 Introduction

Lung cancer remains a major contributor to cancer-related deaths worldwide, with a high incidence of new cases and fatalities each year. Due to late-stage diagnoses and restricted access to early screening, it remains a significant health concern despite advances in medical research and treatment. Since prompt intervention significantly improves treatment efficacy and patient outcomes, early detection of lung cancer is crucial for increasing survival rates. Relying on highly qualified radiologists to interpret medical imaging, such CT scans, presents a substantial barrier in the detection of lung cancer. Automated diagnostic technologies are essential for helping medical practitioners achieve accurate and efficient detection in light of the growing number of patients and the scarcity of healthcare personnel. A subfield of machine learning called deep learning has shown great promise in medical imaging analysis, enabling precise and timely disease diagnosis. By identifying intricate patterns in large CT scan datasets, Convolutional Neural Networks (CNNs) in conjunction with cutting-edge designs such as

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VGG19, ResNet50, and EfficientNet-B0 have achieved excellent accuracy in lung cancer detection. The early diagnosis of cancer cells and increased diagnostic precision are made possible by these models' superiority in feature extraction, segmentation, and classification of lung nodules Fig. 2, Fig. 3.

2 Literature Survey

Diagnosis of lung cancer with deep learning (DL) has been reported using various contemporary models, focused on accuracy, computation efficiency, and interpretability.

[1] Kumar et al. combined several deep learning models, such as ResNet-50, ResNet-101, and EfficientNet-B3, to predict lung cancer from DICOM images. Their integrated model achieved better diagnostic accuracy, suggesting the superiority of the hybrid deep models over single models in clinical practice. [2] Raza et al. proposed Lung-EffNet, a variation of the EfficientNet family, for classifying lung nodules as malignant vs benign masses. The proposed model reached a sensitivity of 99%, demonstrating its capability for the early detection and the possibility of being one part of the real-world screening system.

[3] Lakide and Ganesan the effectiveness of ResNet-50 is validated to show that it has the best residual learning ability. Their results demonstrated that ResNet-50 refining feature extraction and classification accuracy is an effective model for precision of lung cancer prediction. [4] Sandag and Kabo performed a comparison between ResNet and EfficientNet, but on lung CT scan classification. Their comparative meta-analysis showed that EfficientNet-B3 had better diagnostic performance across all performance metrics.

[5] Mamun et al. proposed LCDctCNN, a personalized CNN model based on Kaggle datasets of CT scan images. Our frame-work obtained an accuracy of 92%, surpassing the accuracy of ResNet-50, Inception V3, and Xception, and it proved to be robust in distinguishing malignant from benign nodules. [6] Jalali et al. ResBCDU-Net in which a deep network model is developed particularly for lung CT image segmentation. By this approach, they were able to achieve considerable enhancement of the pre-processing phase, which was aimed to provide an accurate diagnosis while minimizing errors in tumor micro boundaries identification stage.

[7] Liu et al. proposed an automatic end-to-end detection system for lung cancer diagnosis. The results showed good capability for detecting and classifying lung nodules, indicating its possibility in real-time screening application. [8] Bonavita et al. combined several convolutional neural networks to evaluate the malignancy of lung nodules in a classification system. Their ensemble strategy strengthened the robustness of the pipelines, and the clinical applicability was further increased for early cancer diagnosis.

[9] Javed et al. submitted a systematic survey on deep learning techniques for lung cancer detection. They also pointed out that the diversity (and volume) of data are essential for enhancing the generalization capacity of a model, and that large numbers of samples (possibly) reduce overfitting. [10] Pathan et al. proposed an efficient CNN architecture specialized for lung cancer detection challenges. Their model was more accurate and computationally efficient and worked well for a trade-off between performance and resource utilization.

[11] Thanoon et al. reviewed current deep-learning-based CT screening methods with emphasis on issues regarding false positives and lack of sensitivity. However, their survey raised important design aspects to enhance models, when they are deployed in clinical settings. [12] Noman et al. introduced the novel ensemble-based transfer learning model with explainable AI: LungCT-NET. This method not only increased diagnostic performance, but also increased interpretability, thus making AI prediction more transparent to radiologists. [13] Haziq et al. created improved Convolutional Sequential models (better accuracy than current CNN models) A further benefit of their research was to emphasize enhanced clinical utility, ensuring improved integration of DL models into clinical diagnostic scenarios

3 Methodology

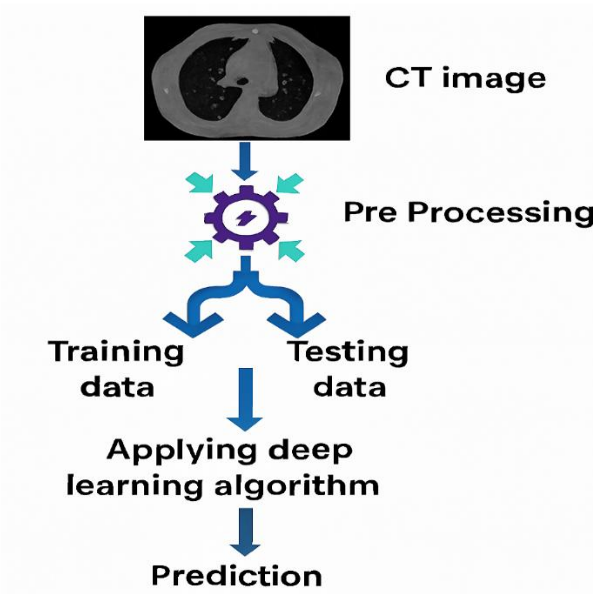

Fig.1. Process Flow.

Using data from publicly available databases this work reports on the application of deep learning algorithms to the identification of lung cancer. As for preprocessing which we report on normalization, scaling and augmentation which we include for the better quality of images and which we put in to also improve feature extraction and model performance. We see the use of convolutional neural networks and also other feature extraction methods put forth for very accurate diagnosis between benign and malignant lung nodules. To improve model generalization and also for the models' adaptation to real-world clinical settings, we also report on transfer learning and fine-tuning techniques. Fig 1 shows the process flow.

3.1 Data Collection and Preprocessing

The dataset used included images from the database which we annotated. We put in effort to include large enough sets of underrepresented groups to improve our class balance. Also, we normalized the pictures for consistency and resized them to 48 x 48 pixels. We did a train-test split of 70–30 which is stratified, and also did one-hot encoding of labels.

3.2 Enhancement and Splitting

As reported in ref deep learning models perform better when used in conjunction with image preprocessing. For example, in the case of lung nodule images, edge sharpening and contrast adjustment improve the images, which in turn we use for more in-depth processing to determine if the nodules are cancerous. In this work, we focus on the issue of differentiating between malignant and benign nodules. Also, we use additional datasets for training and evaluation of the model's performance, helping to determine generalizability.

3.3 Feature Extraction

Finding pertinent features in processed photos requires feature extraction. Advanced methods such as radiomics provide important insights by analyzing the provided data. To accurately distinguish between cancerous and non-cancerous nodules, important features are automatically extracted using the deep learning models. By improving feature extraction, superfluous data is eliminated and key elements of medical images are highlighted, optimizing classification performance.

3.4 Prediction

This model is trained in such a way that it can differentiate between cancerous and non-cancerous nodules once important features have been extracted. While performance metrics are used to evaluate performance, loss functions are used to upgrade deep learning architecture. The efficacy of the trained model is then confirmed by testing it on unobserved data. The system is kept extremely dependable for the identification of lung cancer by analyzing the final results and making the required modifications to improve accuracy even more.

3.5 Models

3.5.1 Vgg19

VGG19 is known for its powerful feature extraction capabilities, and it is a deep learning CNN model with 19 layers. It efficiently finds patterns in lung CT scans to spot anomalies using tiny 3×3 convolution filters. This project improved the accuracy of early-stage lung cancer detection by using it as a feature extractor through transfer learning.

3.5.2 Resnet50

The deep convolutional neural network ResNet50 handles the vanishing gradient issue properly so deep architectures can achieve successful training. The residual or skip connections enable the model to detect sophisticated patterns together with essential features thus optimizing its performance in medical image examinations. Medical practitioners employed ResNet50 for lung CT analysis to develop improved malignant nodule detection capabilities through hierarchical feature learning methods.

The deep structure of the network led to both improved diagnostic precision and fewer wrong positive and negative results. The early diagnosis system used ResNet50 effectively as an appropriate method to distinguish between benign and malignant lung tissue types.

3.5.3 EfficientNet B0

EfficientNet-B0 reaches high accuracy levels and efficient computing power because it applies compound scaling to optimize network dimensions. Its superior performance together with reduced parameter counts makes EfficientNet-B0 optimal for real-time applications. The research utilized lung CT scans to train EfficientNet-B0 along with information about identifying benign or malignant nodules. Through its effective scaling the model surpassed other models while needing reduced processing requirements.

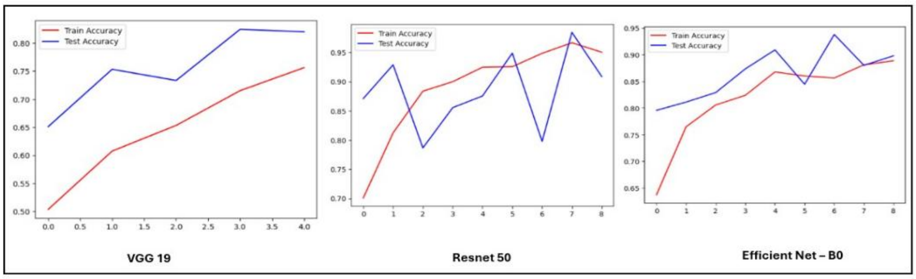

Fig.2. Performance Curve for Training and Testing Accuracy.

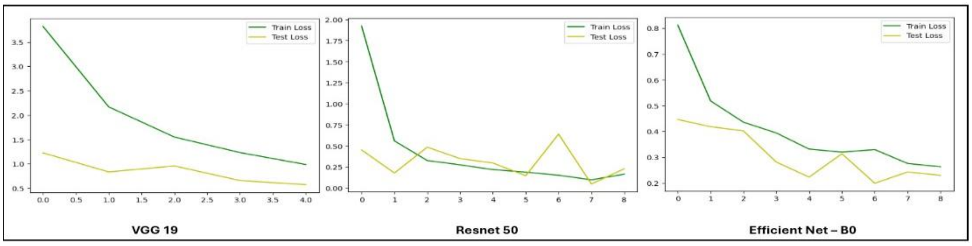

Fig.3. Performance Curve for Training and Testing Loss.

4 Result

The research conducted by ResNet-50 and VGG19 and EfficientNet shows that EfficientNet-B0 exhibits exceptional potential in medical image classification. The deep architecture and numerous convolutional layers in VGG19 make it suitable for tumor detection when processing data with maximum efficiency for complex spatial information. The combination of trained deeper networks and variant ResNet50 results in better feature recognition through its solution for the vanishing gradient problem specifically. A compromise exists in EfficientNet-B0 between its design element that maintains high accuracy and computational efficiency. The system integrates CNN-based feature extraction with data augmentation technology since these models enhance generalization capability and decrease class imbalance issues.

ResNet-50 is one of the most successful of these models, outperforming the others in the categorization of lung cancer and obtaining the best accuracy Fig. 4, Table 1. It is in the top for medical imaging, which it does so by virtue of its ability to extract deep hierarchical features while preserving computing efficiency. Also, it has a robust architecture that improves diagnostic accuracy and reduces false positives, thus enabling early and precise lung cancer diagnosis. To see to the clinical relevance of these models going forward, research should report on improvements in computational efficiency, use of diverse datasets, and in fine-tuning these models.

Table 1. Table of Findings

Model	Disease	Precision	Recall	F1 Score
Vgg19	Adenocarcinoma	0.89	0.87	0.88
	Large cell carcinoma	0.90	0.86	0.88
	Normal	0.93	1.00	0.96
Resnet50	Adenocarcinoma	1.00	0.73	0.84
	Large cell carcinoma	0.79	1.00	0.88
	Normal	1.00	0.99	1.00
EfficientNet B0	Adenocarcinoma	0.78	0.97	0.86
	Large cell carcinoma	0.99	0.73	0.84
	Normal	0.97	1.00	0.99

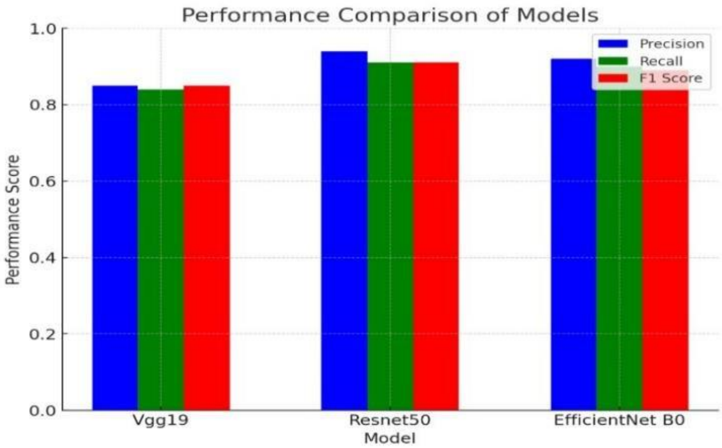

Fig 4. Performance graph.

5 Conclusion

Our project reports on our study of Deep Learning applications in Lung Cancer, which we found to be a very large field of play for this technology mainly in the area of early cancer identification. We developed a model which does better by use of EfficientNet-B0, VGG19, and ResNet-50 as base models. We used CNN to do the classification of pulmonary nodules from CT scans, which in turn allows for early medical intervention. We put these models through a great deal of testing which we then evaluated via key performance indicators. ResNet-50 we saw to do the best in our classification task, which we put down to its residual learning which improves feature extraction and also, in terms of computation time, is a great thing. Although EfficientNet-B0 does very well in terms of resource use, ResNet-50 outperformed the rest in total. Also, by helping radiologists to make better and faster diagnoses, this application may totally transform clinical practices. In conclusion, this project provides a method for detecting lung cancer effectively, with ResNet-50 showing outstanding classification performance and emerging as the most accurate and dependable model.

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