International Journal of Scientific Research in Computer Science, Engineering and Information Technology
ISSN : 2456-3307 OPEN ACCESS
Available Online at : www.ijsrcseit.com
doi : https://doi.org/10.32628/CSEIT25112820

A Comparison of Transfer Learning Techniques in Lung Cancer Nodule Detection

S.Saranya*, R.Rajeswari
*Department of Computer Application, Bharathiar University, CBE, Tamil Nadu, India

ARTICLEINFO

Article History:

Accepted : 05 April 2025
Published: 09 April 2025

Publication Issue
Volume 11, Issue 2
March-April-2025

Page Number
3422-3432

ABSTRACT

Lung Cancer continues to be a major global health hazard, contributing to around 1.8 million fatalities per year. This number is anticipated to increase, with projections forecasting 17 million deaths by 2030. Major risk factors include asbestos, tobacco smoke, air pollution, radon exposure, previous radiation treatment, and the family history of the disease. The recent Covid-19 pandemic has worsened the situation for lung cancer patients, making them more vulnerable to complications. In this study, two Convolutional Neural Network (CNN) models, SqueezeNet and Resnet-50, were evaluated for lung nodule classification in Computed Tomography (CT) images. These CNN models differ in architecture, depth, and feature extraction abilities. Key performance indicators such as classification sensitivity, specificity, accuracy, and computational efficiency are the main focus of the comparison. The Luna 16 database, which comprise CT images and labeled lung nodules, was used for model training and validation. The results showed that SqueezeNet outperformed ResNet-50, achieving a Train-accuracy of 88.07% and a Test-accuracy of 89.62%, while ResNet-50 achieved a Train-accuracy of 83.81% and a Test-accuracy of 86.18%. Both models demonstrated strong performance in evaluation metrics like F1-score, Precision and Recall, highlighting the effectiveness of CNN-based models in enhancing lung nodule detection.

Keywords: Lung Cancer, resnet50, squeezenet, comparative analysis, Deep Learning(DL)

Introduction

Lung Cancer remains the most serious and widespread diseases worldwide, consistently being the leading cause of death for many years, with approximately 1.9 million fatalities annually. It is projected that death rates from lung cancer will continue to increase, with an estimated 17 million deaths globally by 2030 [1]. Several factors contribute to the development of lung cancer, including exposure to asbestos, radon, and tobacco smoke, as well as tobacco product use. Other

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significant risk factors include high levels of air pollution, prior radiation therapy, and a family history of the disease. The recent Covid-19 pandemic has further complicated the situation for individuals with lung cancer, who are more susceptible to consequences[4]. The virus can damage the lungs, increasing the risk of developing other diseases like lung cancer [5]. Common manifestation of lung cancer include shortness of breath, chest pain, respiratory infections weight loss, and persistent cough. The 5 year survival rate for lung cancer patients is currently about 23.7%, largely due to late-stage diagnoses, which often delay treatment. Early detection, however, can substantially improve survival rates, potentially increasing them to 50-70%.

Lung cancer is generally categorized into two primary catergory: Small-Cell-Lung Cancer (SCLC) and Non-Small-Cell-Lung Cancer (NSCLC). Of all incidences of lung cancer, 80–85% are NSCLC, with the remaining 15-20% being SCLC[2]. The detection of lung cancer is typically done using X-rays or CT scans. However, these methods can be time-consuming and difficult for radiologists, often leading to potential inaccuracies. Research has shown that false positive rates in lung cancer screenings evaluated by human experts can be as high as 54%[19]. This process requires substantial focus, expertise, and experience.

To identify lung cancer, a number of diagnostic methods are employed, such as CT, MRI (Magnetic-Resonance Imaging), PET (Positron-Emission-Tomography), and chest X-rays. Because of their greater tumor identification accuracy and lower noise levels, chest CT scans are preferred among these [6]. For the early detection and treatment of lung cancer, CT scans offer vital clinical imaging data [8]. Our study uses CT scan pictures to predict lung cancer because of their efficacy.

Advanced technologies like machine learning, artificial intelligence, and image processing are significant for enabling the early identification and diagnosis of lung cancer. By providing technical solutions for medical data analysis, these technologies improve lung cancer diagnosis and detection [9]. Even though eight different studies have been done on image processing techniques for early cancer detection, their ability to diagnose early-stage cancer is still restricted and has to be improved. Neural networks are useful tools for early lung cancer diagnosis because they have the potential to identify cancer cells in healthy tissues [7]. The success of these methods in comparable domains is leveraged in this study, which focuses on a deep learning-based categorization strategy [27]. Dataset collecting, data pre-processing, lung segmentation, feature extraction, and lung classification are commonly included in the methodology[13].

CNN, a kind of deep learning algorithm, has shown great success in medical image analysis, especially when it comes to tasks like classifying lung nodules. CNN models are designed to learn hierarchical features from raw picture data on their own, which renders them especially effective for the analysis of intricate medical images, including CT scans. Below is an overview of some key CNN models and their important characteristics.

LeNet-5[25], developed by Yann LeCun and his team in 1998 stands as the foundational architectures of CNNs. Initially designed for recognizing handwritten digits with the MNIST dataset, this model comprises seven layers, including two subsampling (or pooling) layers, two convolutional layers, two fully connected layers, and an output layer. As one of the earliest successful implementations of CNNs, LeNet-5 significantly contributed to the progress of computer vision by showcasing the efficacy of Deep Learning methods in image recognition tasks.

AlexNet [3] is a pioneering convolutional neural network that marked a significant advancement in the field of computer vision. Its architecture comprises eight layers, which include three fully connected layers and five convolutional layers. This net is made a substantial impact in the ImageNet-Large-Scale-Visual Recognition Challenge (ILSVRC), establishing a benchmark for images classification. Notable characteristics of AlexNet are the implementation of ReLU activation functions to incorporate non-linearity, the inclusion of dropout layers to mitigate overfitting, and the application of data augmentation methods to improve this model's robustness and generalization capabilities.

In 2014 VGGNet [22], developed by Karen Simonyan and Andrew Zisserman, is renowned for its deep architecture, with either 16 or 19 layers, depending on whether the VGG16 or VGG19 variant is used. Its distinctive characteristic is the use of miniature 3x3 convolution filters throughout the network, contributing to its simplicity and uniform structure. In the same year, Google introduced GoogLeNet (Inception), an architecture with 22 layers based on the Inception module. This design enabled the use of multiple filter sizes at the same level, reducing the number of parameters and introducing auxiliary classifiers.

In 2015, Kaiming He and his research team unveiled ResNet (Residual Networks) [21], a model that utilized residual connections to facilitate the training of extremely deep networks, effectively mitigating the vanishing gradient issue. This architecture is available in several configurations, including 18, 34, 50, 101, and 152 layers. Two years later, in 2017, Gao Huang and his colleagues introduced DenseNet [12], which further advanced the field by implementing dense connections between layers. This design promotes to enhances overall performance and feature reuse.

That same year, Google Inc. released MobileNet [17], followed by the MobileNetV2 and MobileNetV3 versions. These models are designed for mobile and embedded vision applications, focusing on efficiency and low computational cost through depthwise separable convolutions. Additionally, François Chollet developed Xception in 2017[15], an extension of the Inception Architecture that substitute standard convolutions with depthwise separable convolutions, resulting in a 71-layer network aimed at improving both performance and efficiency.

This study compares two different CNN models, ResNet-50 and SqueezeNet, to classify lung nodules in CT scans. To find the best architecture for this application, we will assess these models using a range of performance characteristics, including sensitivity, specificity, accuracy, and computing efficiency.

RELATED WORKS

A novel approach, the "Denoising First" Two-Path CNN (DFD-Net) [23], tackles the challenges associated with lung cancer detection in CT scans. This model seamlessly integrates denoising and detection into a single end-to-end framework. Initially, noise is eliminated during preprocessing using DR-Net, a residual learning-based denoising model. The enhanced image is then processed by a two-path CNN, which is specifically designed to detect lung cancer by simultaneously capturing local and global features through paths with varied receptive field sizes, enabling the modeling of complex dependencies.

Additionally a study that compared DL models for pneumonia diagnosis highlighted the Inception-ResNet model's superiority [16]. Among the models evaluated, Inception-ResNet-V2 achieved the highest classification accuracy, surpassing ResNet152V2, MobileNet-V3 (both large and small), EfficientNetV2 (both large and small), InceptionV3, and NASNet-Mobile by margins of 2.6%, 6.5%, 7.1%, 13%, 16.1%, 3.9%, and 1.6%, respectively, demonstrating its effectiveness in providing accurate results.

The EOSA-CNN hybrid model [11] showed exceptional performance following training. When assessed on the publicly accessible IQOTH and NCCD lung cancer dataset from the Iraq-Oncology Teaching Hospital and the National Center for Cancer Diseases, the EOSA metaheuristic algorithm achieved a classification accuracy of 93.21%. In comparison to other methods, including GA-CNN, LCBO-CNN, MVO-CNN, SBO-CNN, WOA-CNN, and traditional CNN, EOSA-CNN excelled in specificity, recording values of 0.7941 for normal cases, 0.9795 for benign cases, and 0.9328 for malignant cases. These findings validate the effectiveness of the EOSA-CNN hybrid algorithm in lung cancer classification.

EfficientNet-B3, a convolutional neural network (CNN) that leverages transfer learning and weakly-supervised learning methodologies, was utilized to predict carcinoma in Whole Slide Images (WSIs) [6]. Trained on 3,554 WSIs, this model excelled at distinguishing lung carcinoma from non-neoplastic conditions, achieving impressive ROC AUC scores across four independent test sets (0.975, 0.974, 0.988, and 0.981). The model's successful validation marks a significant step toward developing software to assist pathologists in routine workflows, enhancing diagnostic accuracy while reducing workloads.

A neural network-based methodology for identifying abnormal lung tissue growth, focusing on high detection accuracy, is presented in [18]. The approach leverages textural characteristics to distinguish between normal and malignant tissues. Enhanced detection is achieved through CNN and GoogleNet algorithms, with both the region proposal and classifier networks utilizing VGG-16 as their foundation. This model demonstrated exceptional detection and classification precision of 98%, supported by confusion matrix analysis and classification accuracy metrics.

A 3D multipath VGG-like network was employed to analyze 3D cubes from the LIDC-IDRI and Lung Bowl 2017 datasets [26]. This approach integrated U-Net predictions with the VGG-like network to detect and classify lung nodules and assess malignancy levels. The combined architecture achieved a 95.6% accuracy and a log loss of 0.387732, showcasing its capability in lung nodule classification and malignancy evaluation.The YOLOv5 deep learning framework [10] significantly enhances diagnostic precision and efficiency, with implications for improved patient outcomes. This model not only delivers high classification accuracy (97.77%) but also accelerates the process, making it ideal for clinical settings. Its training and test loss curves illustrate consistent improvements in accuracy over time, reinforcing its reliability.

Finally, a model detailed in [14] demonstrated exceptional performance in lung nodule detection and staging (STG-1 to STG-4) using the ResNet-18 convolutional neural network classifier. It achieved a detection accuracy of 98.2%, sensitivity of 96.4%, and a notably low false positive rate of 1.8 per scan. These results suggest the model's potential for clinical integration, aiding early cancer detection and minimizing false positives.

This table below provides an overview of various studies that have utilized transfer learning for lung nodule classification. A groundbreaking method, the "Denoising First" Two-Path Convolutional Neural Network (DFD-Net) [2], addresses the challenges of lung cancer detection in CT scans. This model seamlessly integrates denoising and detection into a single end-to-end framework. Initially, noise is eliminated during preprocessing using DR-Net, a residual learning-based denoising model. The enhanced image is then processed by a two-path convolutional neural network, which is specifically designed to detect lung cancer by simultaneously capturing local and global features through paths with varied receptive field sizes, enabling the modeling of complex dependencies.

This below table provides an overview of various studies that have utilized transfer learning for lung nodule classification.

TABLE I. RELATIVE WORKS ON LUNG NODULE CLASSIFICATION USING TRANSFER LEARNING

Methodology	Datasets	Re Results	Author
MobileNet, VGG16, VGG19, DenseNet-201 and ResNet-101	1190 CT scan	Accuracy 56% Precision 43% Recall 42% Specificity 42%	Aashka Mohite et al [11]
CNN, DTC, KNN, SVM, NB, MLP, GBM, GBRT, ABC	QOTH/NCCD 1190 images	Accuracy, precision, recall, and f1-score are on average 99.71%.	Alihan Suiçmez et al [24]
VGG16, ResNet50, CNN	ACDC LUNGH	Overall Accuracy 97.9 % 93 %	Šarić M et al. [22]
VGG16, ResNet50, CNN	Luna 16	97.1% accuracy, 95.9% sensitivity, 98.1% specificity	-Pragya Chaturvedi et al [1]
AlexNet and ResNet	1,532 images Shengjing of China Medical University	95.6%. ResNet	Chengquan Guo et al [3]
3D-ResNet, 3D-VNet	LIDC-IDRI LUNA16 dataset	Accuracy, sensitivity, and specificity of 99.2%, 98.8%, and 99.6%	Lavina Jean Crasta et al [2]
ResNet50, VGG 16, EfficientNet-B5	LC15000 dataset	91%ResNet50, VGG 16 94%, EfficientNet-B5 97%	Suvarna G Kanakaraddia et al [5]
ResNet-50 EfficientNet-B0,	Multi-centric dataset from Kaggle	Maximum epoch 0.9962 and 9.9978	Kajal Kansal et al [7]

DATASETS

This research employs LUNA16 (Lung Nodule Analysis 2016)[20] dataset for the diagnosis of lung nodules. LUNA16 acts as a standard for evaluating the effectiveness of various lung nodule detection algorithms. The data utilized in this study has undergone preprocessing and is partially derived from the LUNA16 competition dataset. It consists of a diverse set of CT scan images featuring lung nodules of varying sizes and stages. These images are annotated with detailed information regarding the location, size, and type of each nodule, with annotations provided by radiologists to serve as the ground truth for evaluating the detection algorithms.

COMPARATIVE ANALYSIS WITH TRANSFER LEARNING OF LUNG NODULE

A Convolutional Neural Network (CNN) built on SqueezeNet is ideal for situations with limited computational resources. SqueezeNet is a lightweight CNN architecture designed to deliver high performance with fewer parameters and reduced computational demands. It utilizes fire modules, which include a squeeze layer and an expand layer, significantly reducing the number of parameters compared to conventional CNN models. Due to its computational efficiency and smaller model size, SqueezeNet is an excellent choice for training on resource-constrained platforms, such as Kaggle.

While fine-tuning a pre-trained model can offer advantages, in this case, the model will be trained from scratch. This approach starts with randomly initialized model weights, followed by training on the dataset. Training from scratch requires a sufficiently large dataset to ensure the model can learn meaningful features. Additionally, it involves defining the model architecture, loss functions, and optimization methods. The dataset is to be split into training and validation subsets, typically following an 80-20 split. This division is requisite for assessing the model's performance on previously unseen data and for minimizing the likelihood of overfitting. Normalizing the image data is essential for neural network training, as it accelerates convergence and enhances model performance. Pixel values are scaled to a standard range, making it easier for the model to learn. In this case, the original pixel values range from -3000 to 2000, which could cause issues like slower convergence and numerical instability during training. ResNet supports the training of very deep networks by mitigating the vanishing gradient issue. Its design features residual blocks that facilitate the smoother passage of gradients throughout the network. Even with limited resources, using a simplified version of ResNet is advantageous as it offers a strong framework for feature learning without demanding excessive computational power. It strikes a good balance between depth and efficiency. The model will be trained from scratch by initializing weights randomly and learning from the dataset. While fine-tuning a pretrained model is typically beneficial, it is not utilized here due to resource constraints. Figure 1 presents a comparative analysis of deep learning architectures, specifically ResNet50 and CNN, in the context of classifying lung nodules using imaging data related to lung cancer. The purpose could be to evaluate which model provides better accuracy, computational efficiency, or interpretability.

RESULTS AND DISCUSSION

In this study, the Keras and TensorFlow frameworks were employed to implement models using multi-centric data from the Luna16 database. Two well-known CNN architectures, SqueezeNet and ResNet-50, were evaluated for their effectiveness in lung nodule detection. The Outcome indicated that the SqueezeNet model achieved a Train Accuracy of 0.8807 and a Test Accuracy of 0.8962, while the ResNet-50 model achieved a Train Accuracy of 0.8681 and a Test Accuracy of 0.9867. Although both models performed well, ResNet-50 surpassed SqueezeNet in terms of both training and testing accuracy results.

TABLE II METRICS EVALUATION OF RESNET50 AND SQUEEZENET

Evaluation metrics	**Resnet50**	**Squeeze net**
Precision	**0.98**	**0.90**
Recall	**0.97**	**0.88**
Fi score	**0.98**	**0.89**
Accuracy	**0.98**	**0.88**

Overall, the outcomes across both datasets were noteworthy, reflecting strong performance across multiple evaluation metrics, such as precision, recall, and F1-score, as outlined in Table II, highlighting the effectiveness of both models.

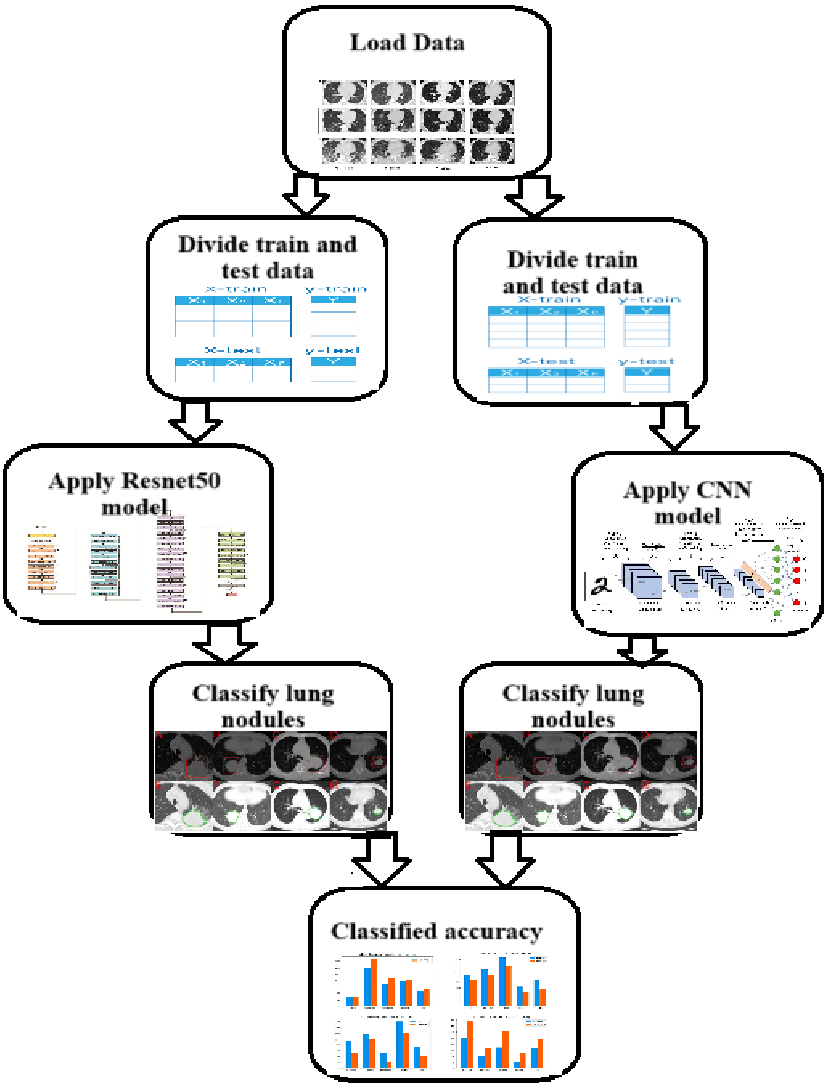

Figure 1. Comparative study of deep learning architectures (ResNet50 vs. CNN) for lung nodule classification

Figures 2 and 3 illustrate the accuracy and loss curves of the SqueezeNet and ResNet-50 models for lung nodule classification using both training and validation datasets. The validation loss for SqueezeNet decreases but exhibits significant fluctuations, indicating a potential degree of overfitting. In contrast, the ResNet-50 model appears to be well-optimized, with both training and validation losses steadily decreasing and accuracy increasing consistently.

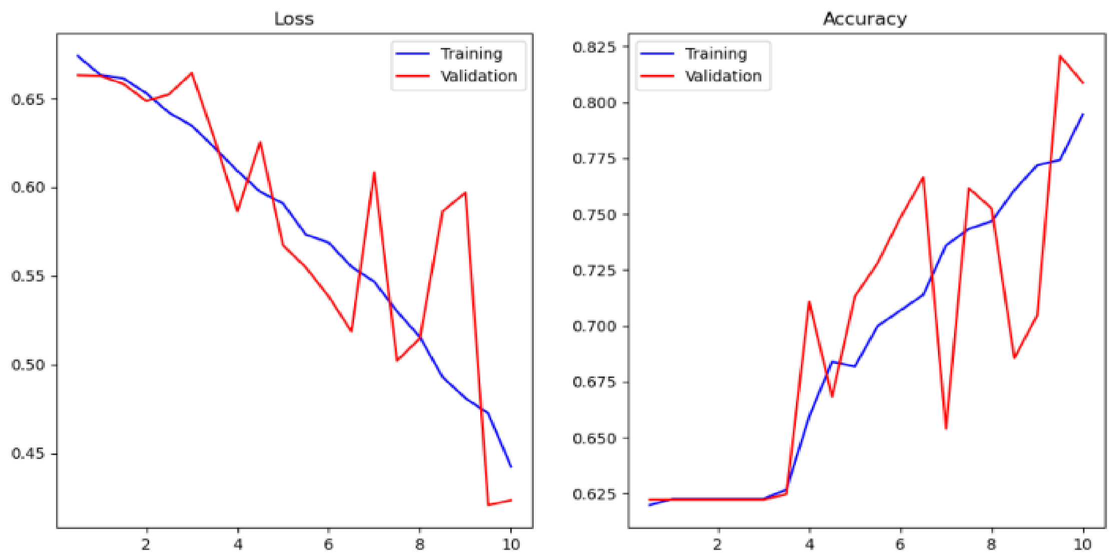

Figure 2. Loss and Accuracy of Squeezenet using Training and validation data for lung nodule classification

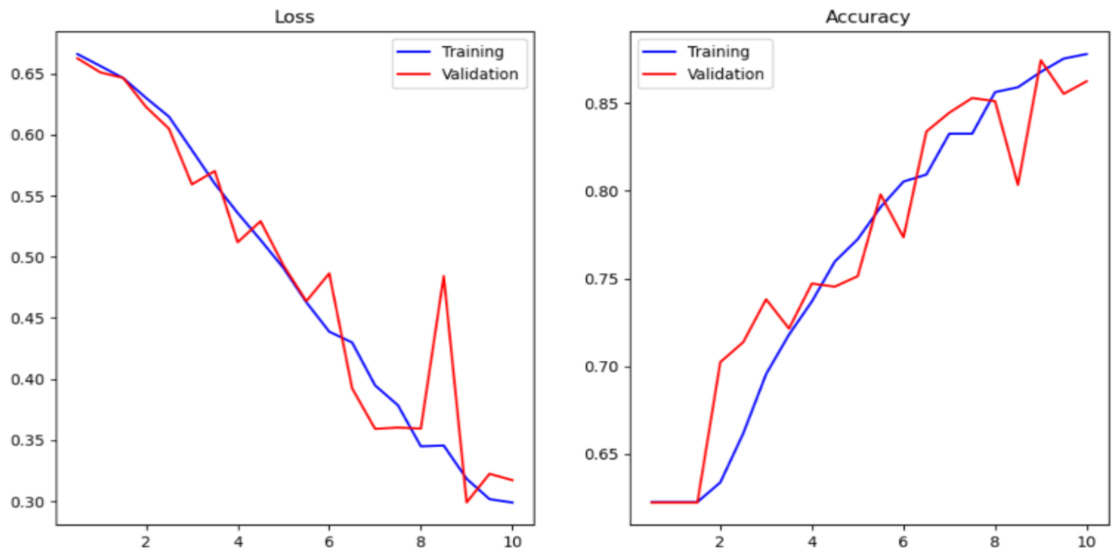

Figure 3. Loss and Accuracy of Resnet50 using Training and validation data for lung nodule classification

Figures 4 and 5 present the ROC curves for the SqueezeNet and ResNet-50 models. The ROC curve for ResNet-50 is positioned near the Upper-Left corner, with an AUC. of 1.00, indicating perfect classification performance for lung nodules, with no false positives or false negatives. In comparison, SqueezeNet achieves an AUC of 0.93, demonstrating very strong classification performance. Figures 6 and 7 display the confusion matrices for SqueezeNet and ResNet-50, providing a detailed breakdown of each model's performance in lung nodule classification.

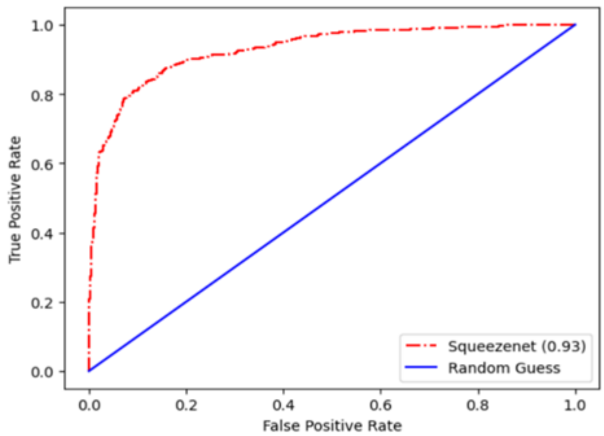

Figure 4. Squeezenet ROC curve for lung nodule classification

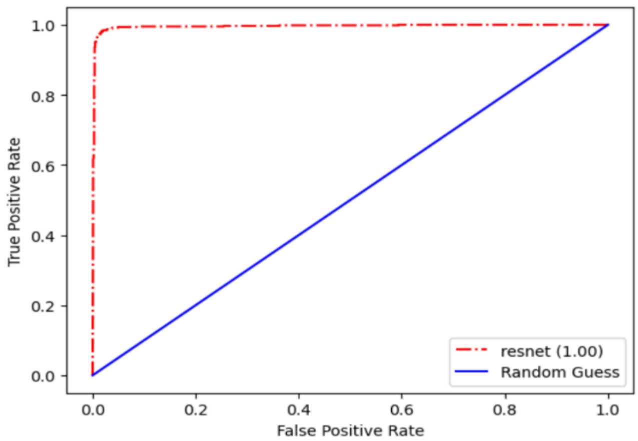

Figure 5. Resnet50 ROC curve for lung nodule classification

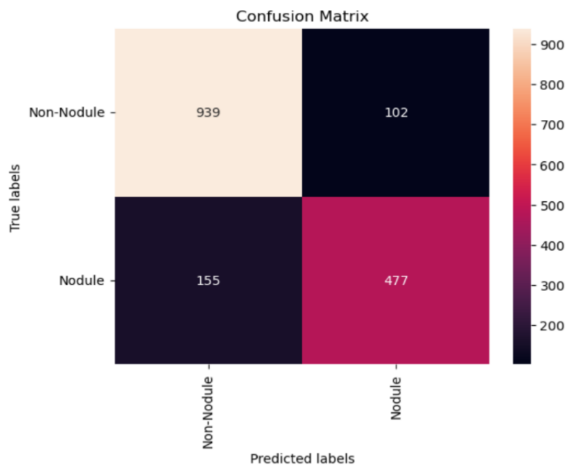

Figure 6. Matrix Confusion of Squeezenet for lung nodule classification

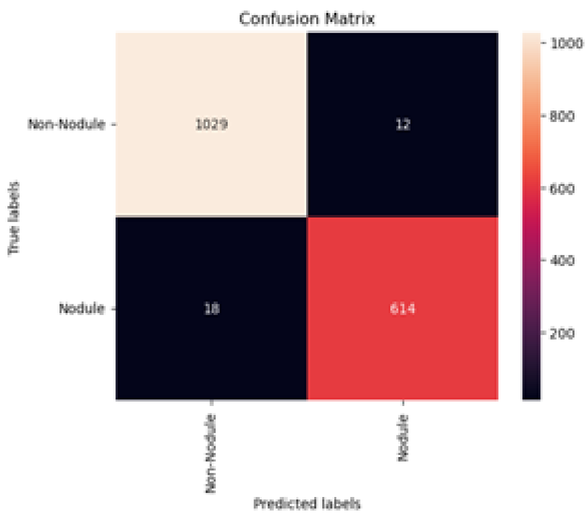

Figure 7: Matrix Confusion of Resnet50 for lung nodule classification

CONCLUSION

This study reviews and presents the application of Transfer Learning techniques for lung nodule classification. The literature on this topic highlights significant advancements and persistent challenges within the field. Recent studies highlight the growing significance of sophisticated ML and DL methods, especially CNN, in improving the precision and dependability of lung nodule detection and classification.

This study demonstrates the effectiveness of CNN architectures, specifically SqueezeNet and ResNet-50, for lung nodule detection using multi-centric data from the Luna16 database. Results indicate that ResNet-50 consistently outperforms SqueezeNet in both training and testing accuracies across various datasets. With higher training accuracy and superior testing performance, ResNet-50 proves to be a more effective model for this task. While SqueezeNet delivers commendable results, particularly in testing accuracy, ResNet-50's overall superior performance makes it the preferred choice for this application. Both models exhibit robust performance across evaluation metrics such as F1-score, precision, and Recall, demonstrating their effectiveness in lung nodule detection. This study highlights ResNet-50's potential as a tool for improving diagnostic accuracy in lung cancer detection while affirming the solid performance of both models in clinical contexts.

The current body of literature on lung nodule classification underscores the importance of ongoing innovation in algorithm design and data management. It also emphasizes the need for collaborative efforts to validate and standardize these models across diverse populations and imaging protocols. Future research should aim to address these challenges, enhance model generalizability, and explore emerging technologies to further advance lung nodule classification.

ACKNOWLEDGEMENT

The second author wishes to express gratitude and recognition for the project funding received from MHRD – RUSA 2.0 – BCTRC, Bharathiar University, Coimbatore, India.

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