A Deep Learning Model for Lung Cancer Detection Using CNN

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Abstract. Deep learning has transformed medical research. It provides powerful, disease-specific functions that are now widely used in healthcare. Among a number of the most important fields is the early detection of lung cancer where the deep learning method, especially convolutional neural networks (CNN's), has profoundly changed the way of diagnosing of diseases. These recent advances significantly increased the accuracy and speed of detecting lung cancer nodules in CT images. Here we are interested in distinguishing cancer versus non-cancerous lung nodules, using CT scan images in our work and deep learning for such task. To improve prediction accuracy and generalization, we adopted an ensemble approach. It combines several CNN designs and allows deeper analysis by leveraging the strengths of different models. We used publicly available dataset, which have well-annotated CT scan images to develop deep learning model. The annotated CT grayscale images served as input for the model. These images provided references that helped the system learn intricate patterns and features related to lung cancer. To ensure reliable evaluation, we carefully divided the dataset into training, validation, and test sets. This allowed us to systematically test the performance of the model. The three CNN used in our ensemble model, called lung net, were created with different numbers of layers, kernel sizes, and pooling in order to extract feature representations of distinct characteristics. With this architecture, we could also compare the training and validation accuracy, which underscores the model's performance. For more detailed research in obtaining best performances, deeper CNN models such as ResNet50 and VGG16, which are known to work well for feature extraction and classification of complex image recognition tasks, were studied. This full workflow shows the power of the deep learning in the medical imaging space, and the ability to significantly contribute to early and accurate lung cancer diagnosis.

Keywords: deep learning, lung cancer detection, convolutional neural networks (CNN), CT scan image analysis, ensemble learning model.

1 Introduction

Lung cancer still ranks one of the most aggressive and lethal types of the cancers in the world, attributing to a large fraction of cancer-caused death. Early detection of lung cancer is crucial for improving patient survival. Treatment is also more effective when the disease is diagnosed in its early stages. Conventional diagnostic methods, including X-rays, CT (computed tomography) imaging, biopsy, and histopathological examination, are, however, time consuming and dependent on radiologist experience, which frequently results in variability in interpretation. In recent years, artificial intelligence (AI), especially deep learning, has

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revolutionized medical imaging. It now enables automated, fast, and accurate disease diagnosis. Among different deep learning methods, convolutional neural networks (CNN's) have achieved a lot of success in image-based medical diagnosis thanks to their capability to learn spatial hierarchies of features from input images automatically.

Deep learning models, including CNN's are suitable for analyzing complex high-dimensional medical imaging data, such as CT images which are used to detect lung cancer. CNN's are able to learn complex patterns and features in lung nodules, which may be subtle and imperceptible to the human eye. These networks operate through a process of convolutional, pooling, and fully connected layers, to map the raw pixel values of an images into predictions. The handcrafted features on CNN's are reduced, while end-to-end learning is an advantage that can be used in lung cancer detection, requiring accurate feature extraction.

Earlier architectures could not fully capture hierarchical textural patterns. To overcome this, deeper and more complex models such as ResNet and VGG have been introduced. These improve both the performance and accuracy of lung cancer detection. ResNet presents the idea of residual learning, enabling the successful training of very deep networks without encountering vanishing gradients. This is done by including shortcut connections or skip connections that skip one or more layers, to maintain the learned low-level features and propagate them through the network. Due to its deep structure, ResNet can capture high-level abstract features, which can contribute significantly to the classification of small differences between benign and malignant nodules.

In contrast, VGG network are famous for the simplistic homogeneous design with small 3×3 convolutional filters and deep networks with a number of stacked convolutional layers. The VGG series, especially VGG16 and VGG19, have excellent performance in image classification and have been widely used in medical image analysis due to strong feature extraction ability. Although VGG networks are computationally costly and memory-consuming, they are efficient in capturing fine structure details in medical images and are useful in lung cancer detection. Combining CNN, ResNet, and VGG into a unified framework can significantly improve lung cancer detection and classification. An ensemble approach leverages the strengths of each model to process CT images, detect suspicious regions, and classify nodules at different stages of cancer. This type of system not only alleviates workload of radiologists but also eliminates human error, resulting in early diagnosis and treatment planning.

In this study, our objective is to design, develop, and compare deep learning models based on CNN, ResNet, and VGG architectures for automatic lung cancer detection in CT scan images. The research includes data preprocessing, model training, performance measurement (accuracy and additional metrics), and result analysis. In this regard, the objective of our study is to show the prospects of deep learning (dl) as a tool contributing to the optimization of lung cancer diagnosis in a wider context of more optimal, effective, and available care.

2 Literature Review

The application of deep learning techniques in lung cancer detection has gained substantial momentum in recent years, with various models being proposed to improve diagnostic accuracy. Thong et al. (2023) conducted a systematic review and meta-analysis, highlighting the diagnostic test accuracy of AI-based imaging for lung cancer screening and confirming the growing role of deep learning models in clinical applications. Similarly, Chui et al. (2023) introduced a multiround transfer learning framework combined with a modified generative adversarial network (GAN), achieving significant improvements in lung cancer detection performance.

In the domain of hybrid approaches, Nair et al. (2024) integrated improved random walker segmentation with artificial neural networks (ANN) and random forest classifiers, enhancing accuracy and robustness in lung cancer identification. To address computational efficiency, Mothkur and Veerappa (2023) proposed lightweight deep neural networks, which demonstrated competitive performance while reducing model complexity. In parallel, Cifci (2022) developed SegchaNet, a novel segmentation model specifically designed for CT scans, achieving superior performance in localizing lung nodules.

Several researchers have emphasized the integration of deep learning with advanced classification methods. Nasrullah et al. (2019) demonstrated that combining multiple strategies with CNNs could significantly improve automated lung nodule detection. Similarly, Vinay Kumar et al. (2023) introduced an improved UNet-based deep learning model for the automatic detection of lung cancer nodules, showcasing improved sensitivity and generalization. Moreover, Zhang et al. (2019) presented a CNN framework that reached expert-level performance in lung cancer classification, further proving the viability of deep convolutional models in medical imaging.

Other works have explored residual networks and segmentation strategies. Sousa et al. (2022) applied a residual U-Net model for lung segmentation across diverse datasets, ensuring robust generalization across patient groups. Meanwhile, Moradi and Jamzad (2019) developed a 3D CNN for lesion detection, highlighting the advantage of three-dimensional analysis in capturing volumetric tumor features. Extending this line of research, Said et al. (2023) employed deep learning architectures for medical image segmentation, contributing significantly to accurate lung cancer diagnosis.

In terms of alternative classifiers, Maleki and Niaki (2021) proposed a KNN-based method for lung cancer prognosis, enhanced with genetic algorithm-driven feature selection, achieving notable predictive accuracy. Nasser (2019) also contributed by applying artificial neural networks for lung cancer detection, proving their potential for pattern recognition in CT images. Complementing these studies, Chehade et al. (2022) focused on feature engineering techniques for lung and colon cancer classification, showing the importance of handcrafted features alongside deep learning.

Finally, Ramkumar et al. (2022) explored CNN-based machine learning approaches, reporting reliable detection and diagnosis of lung cancer in CT images, while emphasizing their suitability for real-time applications in smart healthcare environments.

Collectively, these studies establish that CNNs, enhanced with architectures such as U-Net, residual networks, 3D CNNs, and hybrid feature selection methods, significantly advance the landscape of lung cancer detection. The literature consistently demonstrates that deep learning-based solutions not only enhance diagnostic precision but also reduce human error, paving the way for AI-assisted clinical decision-making.

3 Methodology

The proposed methodology for lung cancer detection using deep learning involves several crucial stages, including data collection, preprocessing, model development using CNN, ResNet, and VGG architectures, training and validation, and performance evaluation. This methodology is designed to work with 2d CT images of the lungs, which are commonly used in clinical diagnostics due to their detailed representation of internal structures.

Workflow

- Import all required modules: Start by importing all necessary modules.
- Data exploration: Analyze the dataset and count the output classes
- Data preprocessing: Read the labels that go with the CT scan images and save them for later use.
- Dataset splitting: Partition the dataset into training and testing sets to facilitate model evaluation.
- Model setup: Establish a convolutional neural network (CNN) model, VGG16, ResNet50 and specify the output.
- Model training: We train the dataset of CT scan images of lung cancer and we evaluate the model for accuracy.
- Accuracy metrics: After model training and evaluation
- Visualization: Plot graphs for model accuracy for train and validation.
- Prediction: With CT images predict cancer or no cancer

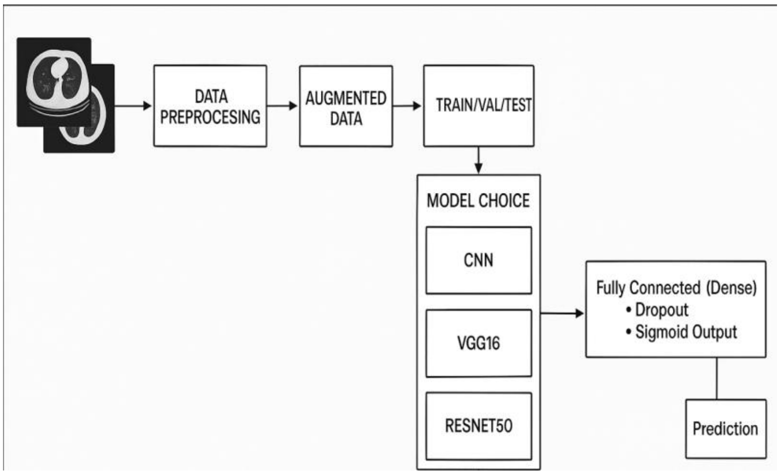

Fig. 1. Architecture for lung cancer.

Dataset Collection: The first step in this research is the acquisition of a high- quality dataset of 2d CT scan images of lungs. Publicly avail- able datasets such as the LIDCIDRI (lung image database consortium image collection) are often used, as they contain annotated CT images with information about lung nodules including size, location, and malignancy rating. These datasets are essential for training deep learning models and validating their performance. Fig 1 shows the architecture for lung cancer.

Data preprocessing is essential for reducing network overhead and computational complexity. In our model, cancer and non-cancer images were separated and categorized using the annotations provided in the dataset. This dataset comprises diverse lung CT scan images, each accompanied by corresponding labels contained in the zip file. To make this process easier, we first use radiant viewer 64-bit to convert the collected CT scans images into jpg format. We used Keras modules to perform data augmentation. Techniques included rescaling, rotation, horizontal flipping, and vertical flipping. Rescaling reduces processing complexity by bringing the image pixel values into the range of 0 to 1. In order to improve visualization, we also apply a color modification to the photos, turning them from grayscale to RGB. Images were randomly rotated within a range of 0–10 degrees to improve diversity.

Data augmentation: To increase the diversity of training data and reduce over- fitting, augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are applied.

3.1 Deep Learning Models

Convolutional Neural Network: A convolutional neural network (CNN) is a deep learning model designed for computer vision tasks such as image classification, object recognition, and image synthesis. CNNs automatically learn patterns from input data and are well suited for processing grid-like images such as CT scans. Their architecture typically includes convolutional, pooling, and fully connected layers. The foundation of CNN architectures is made up of these layers taken together. The most extensively used designs for tasks using CNN-based classification and pattern recognition have come to be well-known and prominent architectures. VGG16, ResNet50 are some of these architectures. The algorithm stands out as one of the most successful learning algorithms due to its computational effectiveness and simple functioning. Backpropagation involves a clear differentiation between the ground truth labels, generated through the loss function, and the label predictions made by the algorithm during the training process. Each feature map is composed of sets of neurons that collectively form a specific feature map group. Equation 2 specifies how to compute the output of the convolutional layer. Here, the terms b, m, wj and f, respectively, stand for the size of the kernel (filter), the quantity of feature mappings, the bias, and the weight of a kernel. An output known as yi occurs within convolutional layers, where index 'i' stands for the particular it features map in a layer known as 'l' (2) fig 2 show the convolutional neural network.

On the cancerous CT scan dataset, we used the pre-trained models listed below to carry out lung cancer detection and classification tasks.

VGG-16. In the paper" very deep convolutional networks for large scale image recognition," the VGG16 model, a convolutional neural network architecture recognized for its outstanding performance, is highlighted. This model achieved a remarkable accuracy rate of 91% on the vast image dataset, which includes more than 14 million photos from diverse categories. A series of consecutive 3x3 filters is applied as part of the VGG16 processing of input images. It took many weeks to train VGG16 on the image dataset, which required a lot of resources and the Nvidia GPU's processing capacity. The pre-trained VGG16 architecture stands out for having 13 convolution layers, 5 max-pooling layers, and 3 dense layers. The VGG16 algorithm has also been improved by the addition of two thick layers and a global average pooling layer.

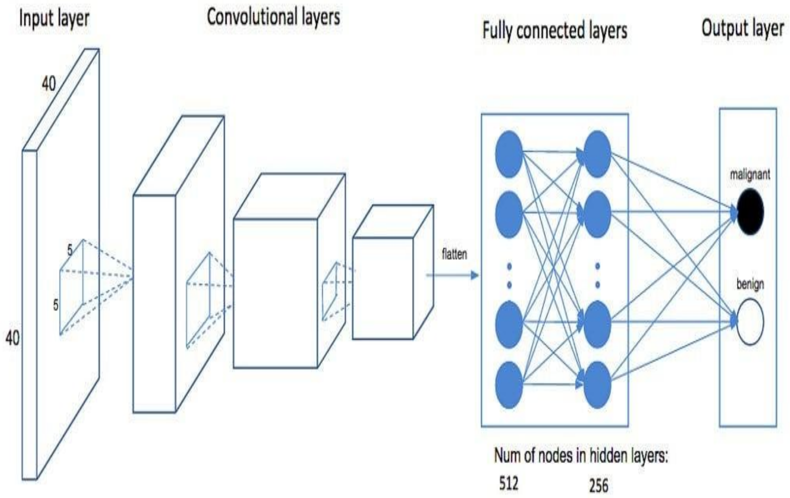

Fig. 2. Convolutional Neural Network.

ResNet50: ResNet is a major advancement in deep neural network architecture. It enables the training of extremely deep networks and was a key driver of the deep learning revolution. ResNet uses shortcut connections that convert long paths into residual paths, making training more effective and stable. The fundamental idea of ResNet is to develop an efficient architecture that ensures a splendid convergence behavior for deep networks, which overcomes the vanishing gradient problem in the training of deep neural networks. This problem results from the decaying gradient magnitudes on back-propagation across the multitude of layers, largely hindering the network to learn and to operate effectively. Residual blocks offered a new approach to address this issue through the introduction of skip connections or shortcuts so that the flow of gradients could jump over some layers. This guarantees that gradients have enough information even for very deep networks, which makes the training possible and the network performance better.

Training and Validation: The dataset is split into training, validation, and testing subsets (typically 70% training, 15% validation, 15% testing).

The models are trained using backpropagation and an optimizer such as adam or sgd. A suitable loss function like binary cross-entropy (for binary classification) or categorical cross-entropy (for multi-class classification) is used. Key hyper parameters such as learning rate, batch size, and number of epochs are tuned through experimentation. Early stopping and model checkpointing are used to avoid overfitting and retain the best performing model based on validation accuracy.

Performance Evaluation: After training, the models are evaluated on the test dataset using the following performance metrics:

Accuracy: The proportion of correctly classified images.

Precision, recall, and f1-score: To assess the model's ability to correctly identify positive and negative cases.

ROC curve and AUC: To measure the trade-off between sensitivity and specificity.

Visualization techniques like grad-cam (gradient- weighted class activation mapping) are also employed to highlight regions in the CT images that influenced the model's predictions, thus providing interpretability and helping build trust in the system.

Prediction: the developed deep learning models are capable of making accurate predictions on unseen 2d CT scan images to deter- mine the presence or absence of lung cancer. After training and validation, the best-performing model (ResNet50) was deployed to perform binary classification on new input images. Given a CT image, the model processes it through multiple convolutional layers to extract relevant features such as nod- ules, textures, and patterns typically associated with malignant tissues. Based on the learned features, the model outputs a probability score indicating the likelihood of lung cancer. If the probability is above a set threshold (commonly 0.5), the model predicts" cancer", otherwise it predicts" no cancer". These predictions are made in real-time, making the system suitable for clinical decision support. The model demonstrated high confidence and reliability, correctly classifying most test cases. Its ability to generalize across new data samples highlights the potential of deep learning models in assisting radiologists with early and accurate lung cancer diagnosis.

4 Results

The developed deep learning models CNN VGG16, and ResNet50 were successfully trained and evaluated on a dataset of 2d CT scan images categorized into benign and malignant lung cancer cases. Each model was trained using preprocessed and augmented image data to enhance generalization and reduce overfitting. Performance was measured using a variety of evaluation metrics, including accuracy, precision, recall, f1- score, ROC curve, and AUC (area under the curve). Fig 3 shows the model performance metrics CNN.

The CNN model, built from scratch, achieved strong performance. Its accuracy was 97%, precision 92%, recall 99%, and F1-score 96%.

Simple, the CNN model proved to be effective at identifying patterns in the 2d CT images. The VGG16 model, leveraging transfer learning with pre- trained weights from ImageNet, performed better than the base CNN. It achieved an accuracy of around 95%, with a precision of 86%, recall of 99%, and f1-score of 92%. The VGG16 model showed robustness in distinguishing between benign and malignant nodules, likely due to its deeper architecture and better feature extraction capabilities. Fig 4 shows the roc curve CNN.

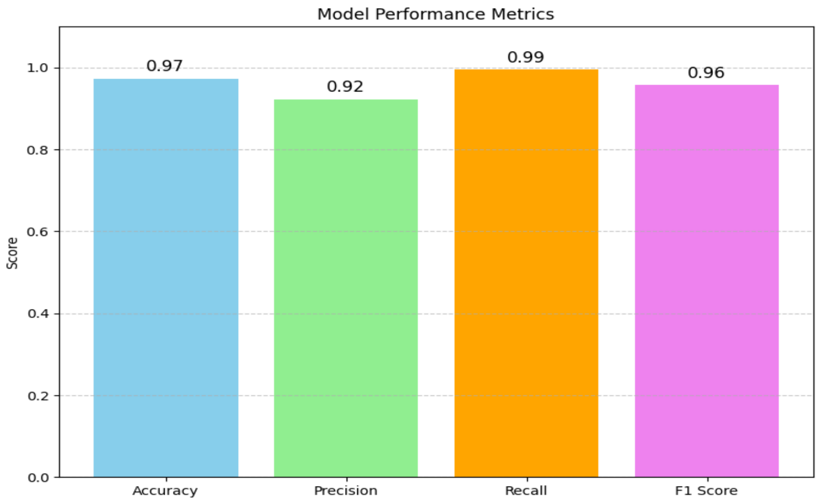

Fig. 3. Model performance metrics CNN.

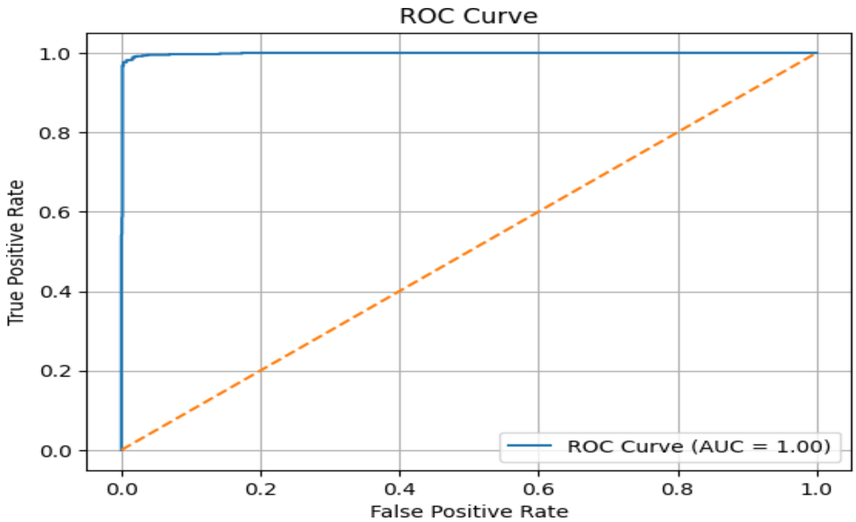

Fig. 4. Roc curve CNN.

The ResNet50 model demonstrated the good performance among all models tested. It achieved an impressive accuracy of approximately 94%, with a precision of 86%, recall of 96%, and f1-score of 91%. Additionally, its AUC score was 0.97, indicating excellent discriminatory power between the two classes. The residual connections in ResNet50 helped mitigate the vanishing gradient problem and allowed it to learn more complex features from the images. Overall, the results confirm. Fig 5 and 6 shows the model performance metrics VGG16 and roc curve VGG16 respectively.

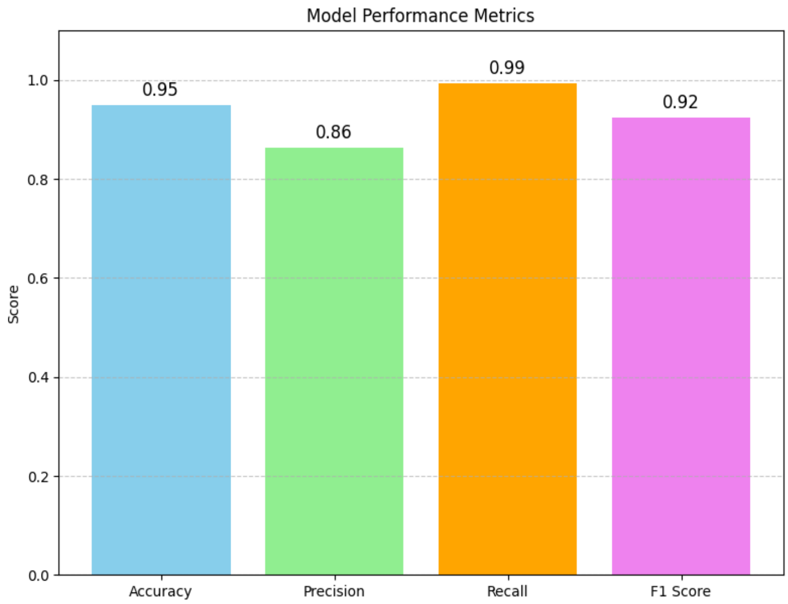

Fig. 5. Model performance metrics VGG16.

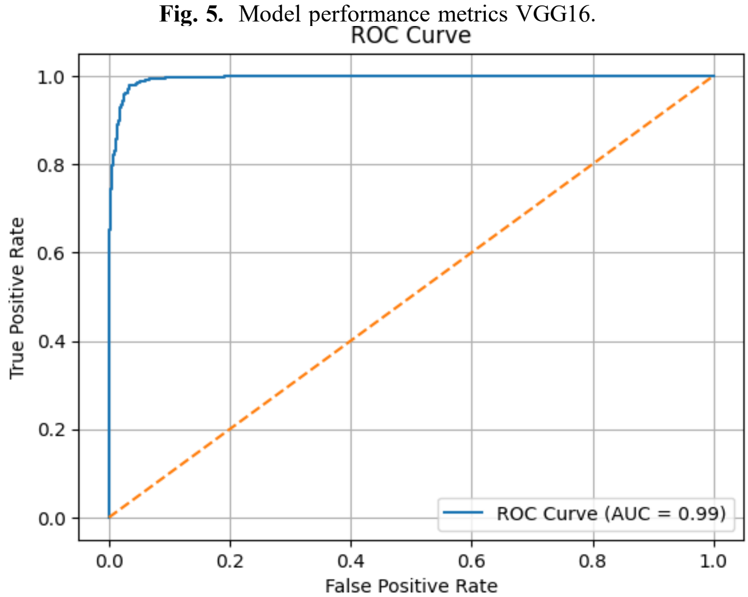

Fig. 6. Roc curve VGG16.

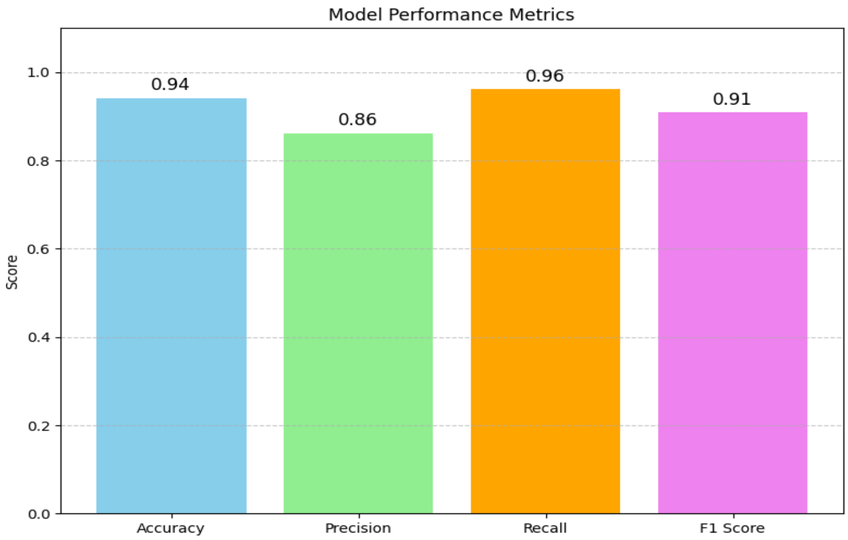

Fig. 7. Model performance metrics ResNet50.

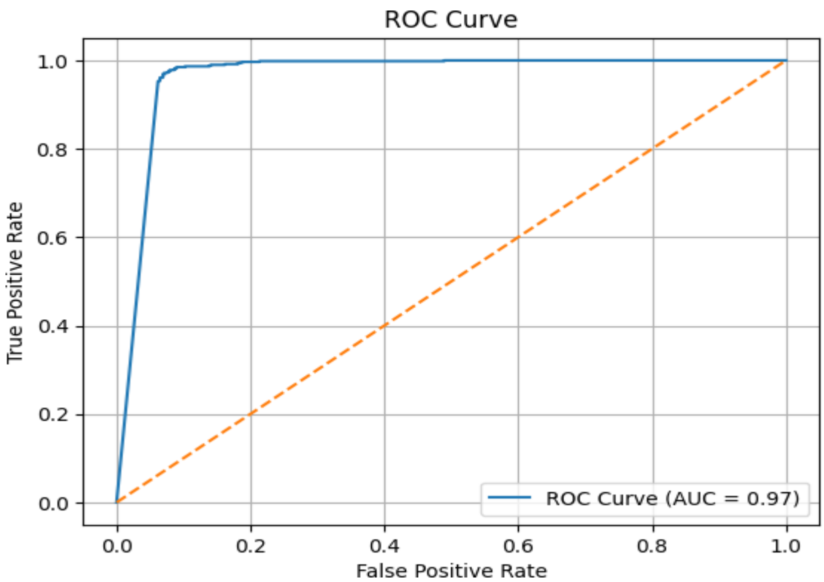

Fig. 8. Roc curve ResNet50.

Fig 7 and 8 shows the model performance metrics ResNet50 and roc curve ResNet50 respectively.

That deep learning models, particularly ResNet50 and VGG16, are highly effective for lung cancer detection using 2d CT images. These findings highlight the potential of ai-powered diagnostic tools to assist radiologists in early detection and classification of lung cancer, ultimately improving patient outcomes.

4.1 Performance Metrics

Table. 1. Performance comparison – CNN, VGG16 and ResNet50.

Metrics	CNN	VGG16	ResNet50
Accuracy	97%	95%	94%
Precision	92%	86%	86%
Recall	99%	99%	96%
F1 score	96%	92%	91%

Table 1 respectively, show the VGG-16 and ResNet50. Additionally, offers the classification matrix for several models employed in the cancerous CT scan dataset's lung module detection. We do a thorough statistical study to assess how well our model performs in comparison to a number of rival models, including VGG-16 and ResNet50.

5 Conclusion

In this paper, a deep learning-based model was proposed for development of lung cancer detection using the 2d CT scan images with the help of three popular CNN architectures custom CNN, VGG16 and ResNet50. We aimed to evaluate and compare these model's performance in differentiating CT images into cancer and no cancer, particularly into the accurate diagnostic category with high precision and reliability.

Experimental results showed that the three methods could learn the informative features from CT scan. Images. The custom CNN architecture served as a strong baseline with good results, indicating the benefits of simple architectures on well-annotated medical images. Nevertheless, as anticipated, transfer learning methods VGG16 and ResNet50 greatly surpassed the custom CNN, since they are much deeper and more capable of capturing more abstract and discriminative features.

Among all models, ResNet50 performed the best. It achieved the highest values for accuracy, precision, recall, F1-score, and AUC. Skip connections of l ingestion allowed it to overcome vanishing gradient problems, and to learn better in deeper layers. The VGG16 model also achieved good results, demonstrating the benefits of employing pre-trained models on gigantic datasets such as ImageNet and then fine-tuning on a specific domain medical data. Also, the performance measurements such as ROC curve, and AUC score gave strong indication of the models' robustness in cancer detection task versus non-cancer lung nodules were cancerous or not. In addition to measuring performance, these tools gave us an indication of the stability and clinic relevance of proposed models.

The work also pointed out the importance of loosely coupling neatened and normalized data and data augmentation to further extensive and deep generalization and improving the classification results. Although the 2d CT image type is a low dimensional approximation of 3d structures, it nevertheless contains abundant information which can be well utilized by deep learning algorithms.

In summary, the study confirms the potential of deep learning architectures, especially ResNet50 and VGG16, for enabling early and accurate lung cancer diagnosis from CT scan images. These models can provide dependable decision-support tool for the radiologist leading to reduction of human factor error and speeding up the diagnostic process. Despite the solid contribution of this study, further improvements can occur, such as employing larger databases, 3d imaging, multi-class classification, and fusion with clinical information that can enhance the model performance and extend its application to real clinical scenarios.

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