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RESEARCH ARTICLE

High-Precision Detection of Lung Adenocarcinoma Using Augmented VGG16 and Transfer Learning

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Abstract

Objectives: The research aims to enhance the effectiveness of the deep learning model for detecting lung adenocarcinoma using VGG16 CNN with transfer learning on medical images. The proposed model addresses the overfitting issues of existing models, thereby improving lung cancer detection accuracy. **Methods:** The lung CT scan images are analyzed for detection and classification using VGG16, leveraging transfer learning techniques. The dataset includes labeled lung images from LUNA 16, Kaggle, and other datasets, which are augmented to introduce variability and reduce overfitting. The images are resized format to 224 × 224 pixels. During the validation and training phases, the model's performance is evaluated based on accuracy, and precision. **Findings:** The adjusted VGG16 model attains a training accuracy of 99.42%, a validation accuracy of 99.13%, and a validation precision of 95.45%, indicating strong generalization capabilities, outperforming other existing models. **Novelty:** This research presents a new method for detecting lung cancer by combining advanced preprocessing and data augmentation techniques with the VGG16 architecture using transfer learning. This combination greatly enhances the model's ability to detect cancer accurately, setting a new standard in the field.

Keywords: Lung cancer; VGG16; Transfer learning; Data augmentation; medical imaging; CT (Computer Tomography)

1 Introduction

Lung cancer is a leading cause of death worldwide. Recent advancements in deep learning and medical imaging have significantly enhanced the accuracy and early diagnosis of lung cancer. Traditional methods suffer from high rates of false positives and delayed diagnosis. While deep learning techniques, especially convolutional neural networks (CNNs), have shown outstanding performance in image classification, many existing models suffer from overfitting, leading to reduced performance on unseen data. Techniques like data augmentation and transfer learning can increase model performance and accuracy. The research aims to develop a lung adenocarcinoma detection system using the VGG16 CNN model, integrating techniques like data augmentation and transfer learning to improve model generalizability, avoid overfitting,

and achieve overall improved performance.

Current studies on lung cancer detection using deep learning face several limitations. Many models suffer from issues related to overfitting due to small dataset sizes, which reduces their generalizability and reliability on unseen data. For instance, the VGG16 model's low accuracy in certain studies can be attributed to insufficient dataset size, limiting its ability to generalize well. Additionally, some studies struggle with high rates of false positives and false negatives [(1)], indicating a need for more advanced data augmentation techniques and better model validation processes. Furthermore, research comparing different architectures shows varying accuracy levels, pointing to the necessity for optimized model configurations and improved data handling strategies. Overall, these limitations underscore the need for incorporating advanced data augmentation, transfer learning techniques, and larger, more diverse datasets to enhance model performance and accuracy.

In the research by Mst. Farhana Khatun, Moshfiqur Rahman Ajmain, and Md. Assaduzzaman, ResNet50, EfficientNetB7, VGG19, and MobileNetV2 used a dataset of histopathology images and the ResNet50 model and achieved the highest accuracy of 98% [(2)].Another study comparing CNN, ResNet50, and DenseNet121 architectures using chest CT-Scan images found that DenseNet121 has an accuracy of 71.74%, while CNN achieves 56.19%, and ResNet50 achieves 56.51%, indicating the need for better model optimization and data handling techniques [(3)].

The paper [(4)] by Sumithra B, G. Vallathan, M. Raman Kumar, and K. Govindharaju introduced a custom CNN model for classifying non-small cell lung cancer (NSCLC) images, achieving 85% accuracy. This custom model could benefit from incorporating transfer learning. Research [(5)] on lung cancer detection methods found the VGG16 model achieves 77.62% accuracy, but due to their small dataset, the model's generalizability can be low. A study comparing various 3D CNN models in lung cancer classification from CT and PET scans found that their Custom-2 model achieved 92.3% accuracy but could not address potential overfitting issues [(6)].The research uses chest CT scans and machine learning techniques for detecting and classifying lung cancer with Local Binary Pattern (LBP) and Discrete Cosine Transform (DCT) and classification using K-nearest neighbors (KNN) and Support Vector Machine (SVM), achieving 93% accuracy for SVM [(7)]. This approach might not fully utilize deep learning's capabilities.

Research on differentiating invasive adenocarcinoma (IA) and non-IA using transfer learning and CNNs showed that the CNN feature extractor-based transfer learning strategy performs better than other models [(8)]. This study could have used more advanced data augmentation techniques for better performance. Another study proposed a custom Depth Residual Network model (DRNN) for identifying lung cancer types from CT scans. It achieved 85.71% accuracy performance could have improved using advanced techniques [(9)]. A study using a deep learning-based algorithm for lung cancer detection on chest radiographs faced challenges with false positives and false negatives [(10)].

In conclusion, here are the main contributions of the paper:

1. Integration of VGG16 CNN Model: Utilizes the VGG16 CNN model for lung adenocarcinoma detection, leveraging its pre-trained features for enhanced performance in medical imaging tasks.
2. Data Augmentation: Applies advanced data augmentation techniques to increase the variability and quantity of the training data, improving the model's ability to generalize and reducing the risk of overfitting.
3. Transfer Learning: Incorporates transfer learning to leverage knowledge from pre-trained models, enhancing feature extraction and boosting the model's accuracy and efficiency in detecting lung cancer.
4. Improved Model Generalizability: Focuses on improving the generalizability of the model to make it more effective in detecting lung cancer in new, unseen data, addressing common issues related to overfitting and dataset limitations.
5. Comprehensive Validation: Employs thorough validation processes to ensure the model's reliability and robustness, including cross-validation and evaluation on diverse datasets.
6. Enhanced Performance Metrics: Aim to achieve higher accuracy and lower false positive/negative rates compared to existing models, contributing to more reliable and early detection of lung adenocarcinoma.

2 Methodology

Classifying lung adenocarcinoma using a pre-trained model like VGG16 involves several essential steps. The process begins with gathering a large, well-labeled dataset of lung images that specify the existence of cancer. These images undergo preprocessing, including resizing to 224x224 pixels to fit VGG16's input requirements, normalizing pixel values, and applying data augmentation to improve model robustness. The VGG16 model, pre-trained on a dataset such as ImageNet, is then adapted to the lung cancer dataset by replacing its top layers with custom layers tailored for classification tasks. The model is trained to fine-tune its weights based on this new dataset. Ultimately, the model's effectiveness is evaluated using metrics such as precision and accuracy to ensure its capability to accurately identify lung adenocarcinoma from images.

2.1 Model Flow

The flow diagram for the fundamental system model and its different sub-systems is shown in the diagram below Figure 1.

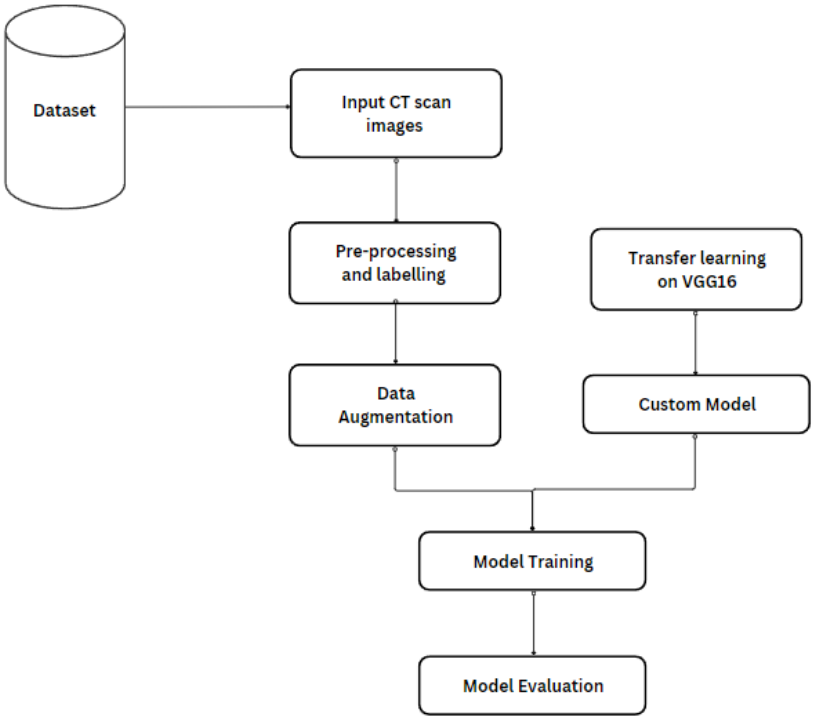

Fig 1. Proposed Model for Detecting Lung Adenocarcinoma Cancer

2.2 System Model Description

The Lung Cancer detection system consists of interconnected sub-systems, each playing the main role in the system's overall functionality. These sub-systems are engineered to accurately differentiate between the presence and absence of cancer.

2.2.1 Dataset

The dataset consists of Lung adenocarcinoma CT (computed tomography) scan images which is the most commonly found of lung cancer. Adenocarcinomas in the lung typically occur in the outer areas of the lung, within glands that produce mucus and assist in respiration. The data set is divided into 2 with 80% of data in training and 20% in validation. The data is collected from various sources such as Kaggle, LUNA 16, and PubMed Central (PMC). The Figure 2 shows lung CT Scan image.

2.2.2 Preprocessing and Labelling

The collected dataset from various sources is processed and merged to ensure accurate classification and labeling of every image. The data is kept in two folders labeled "normal" for images without cancer and "adenocarcinoma" for images with cancer. This is done to train the model on these folders.

2.2.3 Data Augmentation

Data augmentation is a technique employed to increase the diversity of available data for training models. It involves altering the original dataset by applying different transformations, such as rotation, width shift, and height shift, to produce new, altered representations of the information. In addition to preventing overfitting, this enhances the model's capacity for generalization. The attributes like "rotation_range" of 40, "width_shift_range" of 0.2, "height_shift_range" of 0.2, "shear_range" of 0.2, "zoom_range" of 0.2, "horizontal_flip" of True, is used in the proposed model.

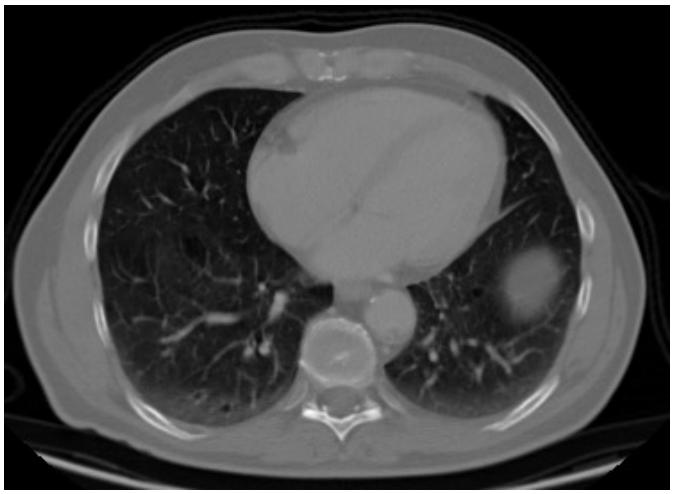

Fig 2. CT scan of Adenocarcinoma Lung

2.2.4 Transfer Learning on VGG16

VGG16 (Figure 3) is a widely recognized convolutional neural network (CNN) model. The designation "VGG16" describes the model's structure, featuring 16 layers with weights, consisting of 13 convolutional layers followed by 3 fully connected layers. VGG16's architecture emphasizes simplicity and consistency in design. It processes an input image of size 224x224 pixels and includes three color channels (RGB).

The model's 13 convolutional layers employ 3x3 filters with a stride of 1 and padding, ensuring the preservation of spatial resolution, critical for detecting various features within the input image. To effectively manage spatial dimensions, the network includes five max-pooling layers, each using a 2x2 filter and a stride of 2, placed strategically after every two or three convolutional layers. This pooling operation reduces spatial dimensions while preserving essential information. The final part of the network consists of three fully connected layers. In the context of transfer learning (Figure 3), these final layers are adapted as required by the specific model. Two extra fully connected layers are incorporated: the initial layer features 256 nodes and uses 'relu' activation, while the subsequent layer, serving as the output layer, consists of a single node activated by 'sigmoid'. The activation function, 'sigmoid' is utilized to produce output probabilities ranging from 0 to 1, indicating the probability of a specific class in binary classification tasks like cancer detection.

This modified VGG16 model (Figure 4), is tailored for cancer detection. It leverages the powerful feature extraction capabilities of the original VGG16 architecture. By replacing the final layers, the model has improved performance in identifying cancerous images.

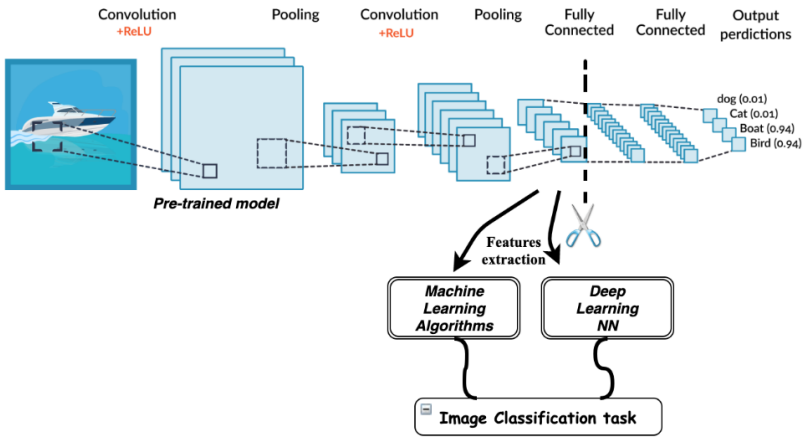

Fig 3. Transfer Learning

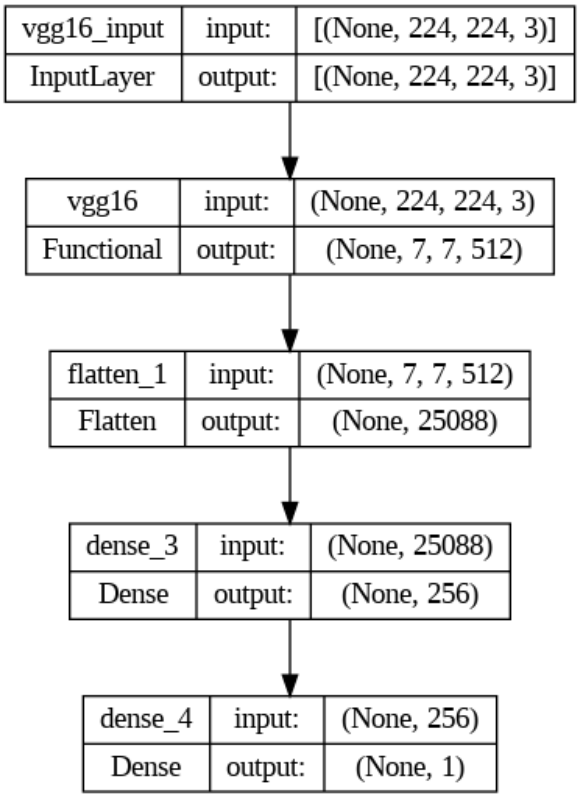

Fig 4. Proposed Model

2.2.5 Model Training

For VGG16, the photos are downsized to 224 x 224 pixel dimensions. After then further classified into batches of 32, which facilitates memory management and speeds up the training process, referred to as a binary classification problem, which means that the labels are either 0 or 1. This indicates that the "class_mode" parameter is set to "binary".

2.2.6 Model Evaluation

Similarly, the test data is used to generate the "validation_generator". Additionally, it reads images, resizes them and binary labels will be applied to every batch of 32 images. As training progresses, the model's accuracy and loss for training and validation are computed and plotted.

Training accuracy (Equation (1)) assesses the model's efficiency on the training dataset by comparing predicted labels to actual labels. High training accuracy signifies effective learning of patterns within the training data.

$$Training\ Accuracy = \left(\frac{number\ of\ correct\ predictions\ on\ trainingdata}{total\ training\ data\ instances}\right) X\ 100 \tag{1}$$

Validation accuracy (Equation (2)) measures the model's efficiency on the validation dataset, which is not applicable for training but for tuning hyperparameters and monitoring overfitting. It helps ensure the model generalizes well to new data.

$$Validation\ Accuracy = \left(\frac{number\ of\ correct\ predictions\ on\ validation\ data}{total\ validation\ data\ instances}\right) X\ 100 \tag{2}$$

Training loss (Equation (3)) gauges the effectiveness of the model on the training dataset by quantifying the difference between predicted and actual targets. A lower training loss signifies better performance on the training data.

$$Training\ Loss = 1\ X\ (\sum_{i=1}^{N} L(yi, yi'))/N \tag{3}$$

where:

- N denotes the quantity of training samples.
- yidenotes the actual label for the i-th sample,
- yi' signifies the predicted label for the i-th sample,
- L denotes the loss function (cross-entropy loss).

Validation loss (Equation (4)) measures how the model functions on the validation dataset. It is calculated similarly to training loss but uses the validation data. Monitoring validation loss helps in detecting overfitting.

$$Training\ Loss = 1\ X\ (\sum_{i=1}^{M} L(yi, yi'))/M \tag{4}$$

where:

- M represents the number of validation samples,
- yidenotes the actual label for the i-th validation sample,
- yi' signifies the predicted label for the i-th validation sample,
- L denotes the loss function.

Training precision (Equation (5)) quantifies the proportion of accurately predicted positive outcomes by the model on the training dataset. High training precision indicates the model's reliability and accuracy in positive predictions.

$$Training\ Precision = \left(\frac{True\ Positives\ on\ training\ data}{True\ Positives\ on\ training\ data + False\ Positives\ on\ training\ data}\right) X\ 100 \tag{5}$$

Validation precision (Equation (6)) assesses the capability of the model to correctly identify positive instances in the validation dataset. This dataset is not used for training but for tuning hyperparameters and monitoring overfitting. High validation precision ensures that the model makes accurate positive predictions on new data.

$$Validation\ Precision = \left(\frac{True\ Positives\ on\ validation\ data}{True\ Positives\ on\ validation\ data + False\ Positives\ on\ validation\ data}\right) X\ 100 \tag{6}$$

3 Results and Discussion

This analysis explores the performance metrics and behavior of our modified VGG16 model during the training and validation phases, highlighting key aspects such as accuracy, loss reduction, and model robustness.

Performance Metrics

- **Accuracy**: This model attained a total training accuracy of 99.42% and a validation accuracy of 99.13%. The high accuracy rates show that the model has learned to distinguish between cancerous and non-cancerous images with high precision.
- **Loss**: The loss function used for binary cross-entropy. During training, the loss decreased to 0.23%, while the validation loss stabilized at 0.27%. These minimal loss values indicate that the model's predictions match the actual outcomes.
- **Precision:** The model attained a training precision of 96.5% and a validation precision of 95.45%. These high precision rates indicate that the model's positive predictions are highly accurate, effectively distinguishing between cancerous and non-cancerous images with minimal false positives.

Epoch-wise Performance Analysis

- **Training and Validation Accuracy**: This graph (Figure 5) demonstrates the model's learning progression, with both accuracies increasing steadily. The proximity of these two curves suggests minimal overfitting and robust model generalization.
- **Training and Validation Loss**: This graph (Figure 6) illustrates the reduction in loss for both validation and training datasets over successive epochs. The convergence of validation and training loss curves designate that the model is effectively learning without significant overfitting.
- **Training and Validation Precision**: This graph (Figure 7) illustrates the precision for both validation and training datasets over successive epochs. The convergence of validation and training precision curves designate that the model is accurately learning to identify positive instances without significant overfitting.

The consistent reduction in loss and convergence of validation and training metrics underscore the efficacy of our approach. By employing data augmentation and transfer learning, we enhanced the model's capability to generalize, leading to high accuracy and low loss on unseen data.

Visualizing the Learning Process

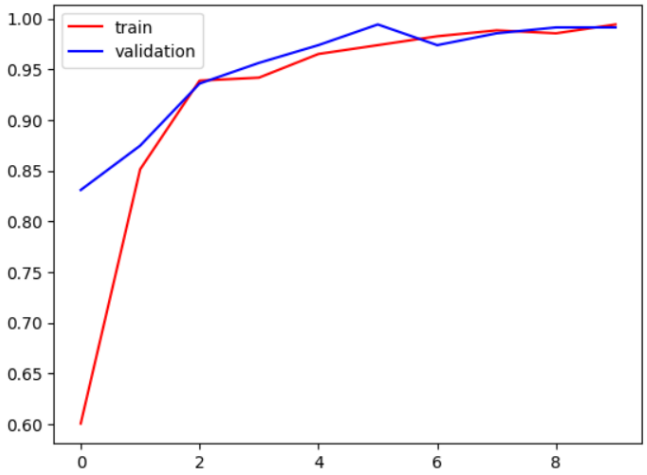

Fig 5. Training and Validation Accuracy vs. Epoch

Figure 5 illustrates the training and validation accuracy, demonstrating a consistent improvement for both datasets. The training accuracy stabilizes around 99.42%, with validation accuracy closely trailing, suggesting the model learns effectively without overfitting the training data.

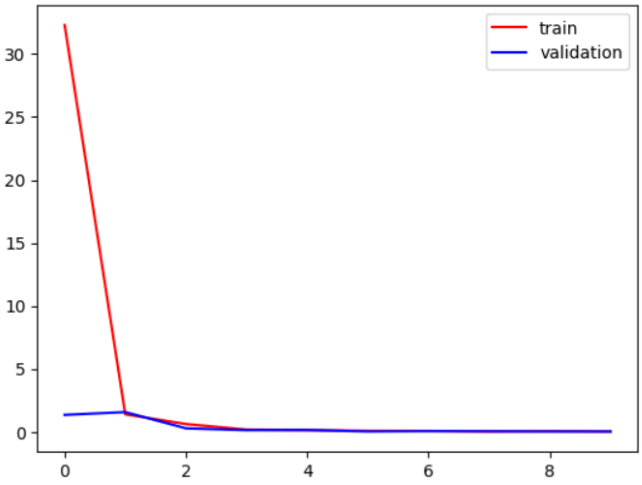

Fig 6. Training and Validation Loss vs. Epoch

Figure 6, portraying training and validation loss, demonstrates a downward trend to both curves. The training loss reaches a lower value (0.23%) contrasted to the validation loss (0.27%), which is expected as the model optimizes for the training data. However, the small gap between the curves further emphasizes the model's capability to generalize on unseen data.

Figure 7, depicting training and validation precision, shows a steady increase in precision for both datasets over successive epochs. This indicates the model's improving ability to accurately identify positive instances. Training precision starts lower but rapidly increases, reaching approximately 96.5%, while validation precision begins higher and stabilizes around 95.45%. The close alignment of training and validation precision curves suggests that the model is learning effectively without overfitting, maintaining high accuracy in its predictions across both datasets.

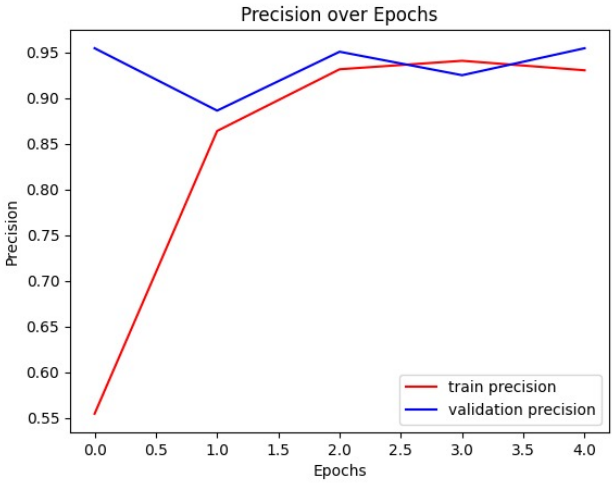

Fig 7. Training and Validation Precision vs. Epoch

Key Insights

- **Weight Updates**: Proper weight amendments during training are crucial for model performance, as they refine the model's ability to make accurate predictions.
- **Overfitting Mitigation**: Our approach effectively mitigated overfitting through data augmentation and careful validation, ensuring that the model performs well on new data.
- **Binary Cross-Entropy**: This loss function was well-suited for the binary classification task, contributing to the model's high accuracy and low loss.

In conclusion, our modified VGG16 model demonstrates substantial improvements in lung cancer detection, evidenced by high accuracy and low loss values during both training and validation phases. These results highlight the potential of integrating advanced machine-learning techniques in clinical practice to enhance diagnostic accuracy and reliability.

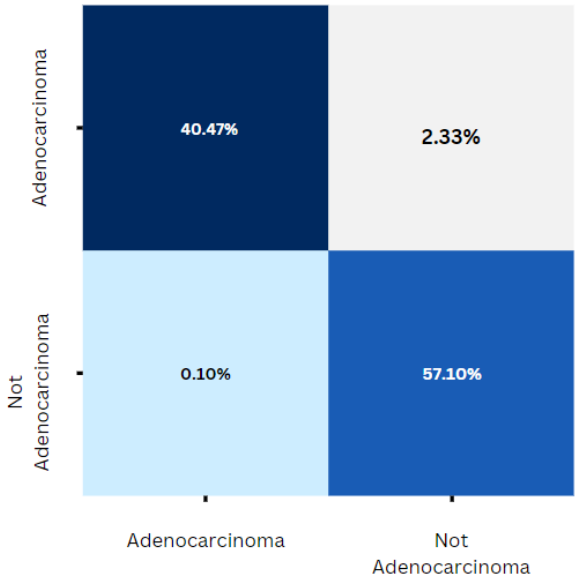

Fig 8. Confusion matrix

The confusion matrix (Figure 8) visualizes the performance of the lung adenocarcinoma detection model by presenting the distribution of TN, TP, FN, and FP predictions for each class. The matrix is classified into four quadrants:

- True Positives (TP) (Adenocarcinoma accurately identified as Adenocarcinoma) (40.47%)
- False Positives (FP) (Not Adenocarcinoma incorrectly identified as Adenocarcinoma) (2.33%)
- False Negatives (FN) (Adenocarcinoma incorrectly identified as Not Adenocarcinoma) (0.10%)
- True Negatives (TN) (Not Adenocarcinoma accurately identified as Not Adenocarcinoma) (57.10%)

The model shows high accuracy in distinguishing between Adenocarcinoma and Non-Adenocarcinoma cases, as indicated by high values in the True Negatives and True Positives quadrants, along with low values in False Positives and False Negatives quadrants.

Comparison Study

Table 1. Comparison study of the existing model with the proposed model

Model	Accuracy	Precision
VGG16 model (proposed model)	99.13%	95.45%
SVM [11]	83.33%	-
EffetientNet-B7 [12]	79.32 %	87.86%
LDA [13]	84%	53.33% (Specificity)
VGG19 [14]	96.22%	91%
Xception [15]	89.68%	-
VGG16 [16]	92.53%	97.0%

The above comparative study shows that the VGG16 model presented in this study outperforms alternative models in terms of both precision and accuracy, highlighting its effectiveness for lung adenocarcinoma detection (Table 1).

4 Conclusion

This study presents a dependable early detection system for lung cancer utilizing the VGG16 CNN model enhanced with transfer learning and data augmentation. The adapted model achieves a training accuracy of 99.42% and a validation accuracy of 99.13%, with a precision of 95.45% on validation data, indicating significant enhancement in diagnostic efficacy. Our approach integrates robust data augmentation techniques and transfer learning, effectively addressing overfitting and setting a new benchmark for early detection systems in lung cancer diagnostics. The primary strength of our research lies in its high accuracy and precision, but reliance on a specific dataset may limit the model's generalizability to other datasets or real-world scenarios, necessitating further validation. Future research should expand the dataset to include more diverse samples and explore other CNN architectures such as ResNet or Inception for potentially better results. Open questions remain regarding the model's performance in clinical settings and its ability to generalize across diverse patient populations. Integrating multi-modal data, such as genetic and clinical information, could provide a more holistic approach to lung cancer detection. Continuous improvement and validation are essential, and collaboration with medical professionals for clinical trials and real-world testing will be crucial.

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