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Research Article

A Deep Learning Network for Classification of Lung Cancer from Computer Tomography Images Using Fine-Tuned Visual Geometric Group-16

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ABSTRACT

Many deaths from cancer are caused by lung cancer, of the most prevalent and deadly forms of the illness. Although lung cancer remains a significant health issue, improvements in research, early detection techniques, and current treatments give hope for improved outcomes. To diagnosis a wide range of diseases, numerous Computer Aided Diagnosis (CAD) systems have been created recently. Early lung cancer detection is now crucial and simple thanks to deep learning and image processing methods. For radiologists, identifying cancerous lung nodules is a difficult and time-consuming process that involves computed tomography (CT) scans. Kaggle was used to gather the lung cancer CT scans. Two essential techniques used in DL to improve the quality, diversity, and generalization capabilities of images during training are image pre-processing and augmentation. This article presents an improved Deep Learning (DL) model that effectively classifies lung cancer from CT scans. The foundation model was a modified VGG-16 model. By applying the fine-tuning process, the suggested model's efficacy is greatly enhanced. In the categorization report, metrics such as F1-score, recall, accuracy, and precision are frequently provided. After adjustments, the suggested model's accuracy rose dramatically from 81.91% to 96.78%. According to the experimental findings, the suggested approach outperformed the current methods for classifying lung cancer.

Keywords: Lung Cancer, Lung Cancer Classification, Artificial Intelligence, Deep Learning, Fine-tuning.

1. Introduction

The deadly cancer disease can affect individuals of all age groups. Cancer is the medical word for the abnormal cell proliferation. [1] Any portion of the human body is susceptible to cancer, which can then spread to surrounding areas. The lung, which is the primary component of the respiratory system, aids in the exchange of air between the bodies and the outside environment. An aggravating problem that could result in mortality is the aberrant cell development within the lungs. [2] In the present world, there are only a few things that might cause lung cancer such as smoking, alcohol, being around harmful gases, asbestos, air pollution, and hereditary issues.

The major cause of the large number of deaths occurring globally is lung cancer. [3] According to data provided by WHO, terrible lung cancer would be the cause of 1.7 million fatalities in 2025. The chances of survival from lung cancer will significantly improve if it is diagnosed in its early stages, leading to a considerable reduction in the likelihood of dying. Technologies of information and imaging techniques can be developed to do this. Even for experienced radiologists and doctors, distinguishing between lung cancer-related nodules and normal forms can be challenging [4].

Lung adenocarcinomas and squamous cell carcinomas of the lungs makeup the majority of the varied group of cancers referred to as non-small cell lung cancer (NSCLC) [5]. However, 70% of cases are found after the local disease and metastatic disease, and NSCLC's five-year survival rate is not extremely low.

Lung cancer is a unique kind of tumour that diffuses unevenly, grows quickly, and also takes over the body's other organs [6]. Recently, a terrible lung disease has claimed the lives of numerous people throughout the world. Therefore, in order to lower the mortality rate, it is necessary to implement preventative measures against such diseases.[7] Additionally, early detection of lung disorders helps doctors to predict the severity of diseases and give patients the right treatments to recover from fatal diseases.

Several modalities are available to detect lung cancer. But most of these are expensive and time-consuming [8]. Lung cancer can be detected in all of its phases using a variety of techniques, but the prognosis for patients is often dismal. In order to improve manual cancer analysis, image processing is a useful technique. Many medical experts have found that studying sputum cells can help them to find early signs of lung cancer. The best imaging method for use in the medical area is CT, which aids in the accurate identification of malignant cells. X-ray films are commonly utilized in a mass screening approach to identify cases of lung cancer. Due to the shadow created by the organ and the overlap of the bones. Through the use of specialized X-ray equipment to collect imaging data from various angles throughout the human body, a cross section of these tissues and organs can be seen utilizing CT.

The exact detection of aberrant cells in chest CT scan pictures is made possible by the application of CAD technology, or computer-aided diagnosis. [9] As the most sensitive imaging modality, CT provides several competitive advantages, including quick collection, cost-effectiveness, and accessibility. [10] Due to its potential to enhance the effectiveness of treatment and hence increase survival, low dose CT-based early identification of lung cancer has acquired more interest in recent times. Therefore, in the current clinical atmosphere, lung nodule identification in chest CT images becomes particularly important. The enormous advancement in the field of CAD has made it possible to analyse lung cancer suspect areas more effectively [11]. Early detection of lung cancer depends on the CAD system. A CT scan can be used to get a more accurate diagnosis to more effectively capture the intricacies of the lung nodules and the tissues around them. Because the lung nodules are so intricate, it is important to do a thorough analysis to determine whether they are malignant or not. Improvement of medical image processing methods provides the path for more accurate cancer detection. The establishment of computer-aided diagnostic algorithms and the appropriate planning of the disease's treatment schedule require accurate lung segmentation and area separation. Due to the physical features of the lung, this issue is still not simple.

The remainder of the paper is structured as follows: Section 2 describes the literature review and research gaps; Section 4 discusses the experimental results; Section 3 explains the methodology; and the work is concluded and future directions are outlined in Section 5.

2. Related Works

There are numerous methods for detecting lung cancer. This section provides a briefing for a few. An ANN model was created by Ibrahim M. Nasser and Samy S. Abu-Naser [12] to evaluate the presence of lung cancer in humans. The algorithm was trained using the dataset, and its effectiveness was assessed. The experiment's findings showed that the suggested ANN model can accurately and successfully identify lung cancer. The main flaw in the suggested method is that ANNs usually need enormous amounts of training data.

By incorporating genetic characteristics, Jacob J. Chabon et al. [13] introduced an effective technique for lung cancer identification. It brings about advancements in deep sequencing for cancer personalized profiling. Finally, a machine learning model is constructed, integrated, and prospectively validated using the molecular features. Early-stage lung cancer patients can be success- fully distinguished from risk-matched controls using the suggested model. The first drawback of the suggested methodology is that more patients must be assessed in order to accurately determine the recommended strategy's efficacy. The second drawback is a potential reduction in clinical screening sensitivity. Third, the performance in non-smokers can be poorer.

Siddharth Bhatia et al. [14] employed deep residual learning as part of their strategy to deal with lung cancer CT image detection. The suggested approach outlines many pre-processing methods to identify lung regions at risk for cancer and extract relevant features. The feature collection is passed to a number of classifiers to ascertain the likelihood that a CT scan contains cancer, and the individual predictions are then aggregated. A combination of Random Forest and XGBoost classifiers produced the best ac- curacy of 84 percent. By reducing misclassification, P. Mohamed Shakeel et al.'s the two main goals are to improve the quality of lung images and detect lung cancer. [15]. An improved profuse clustering method is utilized to divide the impacted area, contributing to the advancement of image quality. The impacted area yields a number of spectral signatures. The suggested method produced highest accuracy with the lowest error rate. In order to diagnose lung cancer using CT scans, A reproducible machine learning technique was presented by Kun-Hsing Yu and colleagues. [16] The introduced techniques are rarely compared or duplicated because of the stated methodologies' various software dependencies. In the proposed study, existing lung nodule segmentation and classification modules were compared and replicated. The findings indicated that a variety of transfer learning techniques have a respectable level of diagnostic accuracy when used with chest CT images.

Jafar A. ALzubi et al. [17] suggested a combination of Maximum Likelihood Boosting and Weight Optimized Neural Networks to identify lung cancer in large data sets. Kanchan Pradhan and Priyanka Chawla [18] have conducted an empirical examination of the different ML techniques that can be utilized in combination with IoT devices so that lung cancer can be identified. The investigation's focus is on analysing the main objective in the identification of different diseases, with a particular focus on identifying a gap for future advancements in lung cancer identification within the medical Internet of Things (IoT).

A DCNN based lung cancer identification module was introduced by Chao Zhang et al. [19]. By relying on verified clinical and laboratory results, a 3D- CNN architecture was constructed to correctly determine if lung nodules are cancerous or benign. Improved sensitivity and specificity values were obtained for the suggested model. Comparing manual evaluations completed by various levels of physicians with those carried out by 3D CNN served as additional model validation. The main disadvantage of the suggested strategy is its restricted applicability, as it solely investigated a small subset of ground glass nodules that corresponded to early-stage disease and was not explicitly designed for screening purposes. Another significant drawback related to deep neural network architecture.

Research by AR Bushara et al. [20] has demonstrated that capsule networks are a successful approach to medical imaging problems. Gur Amrit Pal Singh and P. K. Gupta [21] introduced an efficient method for identifying and classifying lung CT scan images into categories. The results demonstrate that VGG-CapsNet, A new VGG and Capsule Network-based capsule network combination performs better than CNN's capsule network combination or a simple capsule network. The initial step involves ap- plying image processing methods to the images, followed by classification using learning algorithms. The process involves extracting textural features and statistical data, which are then fed to classifiers along with a variety of extracted features. Classification is done using seven different classifiers. According to the results, compared to the other classifiers, 88.55 percent is the superior accuracy value of the Multi-Layer Perceptron classifier (Tafadzwa L. Chaunzwa et al. [22]. The tumour histology might be predicted using CNNs. The study demonstrated that ML classifiers, specifically SVM and KNN, performed equally well when applied to quantitative radiomics features derived from CNN. According to the experimental findings, the Convolutional Neural Network proved to be a dependable probabilistic classifier in different test sets. Moreover, the network's ability to detect objects was supported by visually understandable reasons. The small sample size is the main drawback of the suggested strategy.

An ideal lung cancer classification model based on DL was created by Lakshmanaprabu S.K. et al. [23]. The suggested approach offers an original automatic classification approach for lung CT images. Optimal DNN and Linear Discriminant the CT scan lung pictures were analysed in this study using analysis. The comparative results show that the recommended classifier has improved classification performance.

An approach to learning that is minimally supervised was developed by Fahdi Kanavati et al. [24]. The EfcientNet-B3 architecture was utilized to train a CNN using TL and cancer detection in entire slide photos using weakly supervised learning. The proposed method demonstrated outstanding performance in differentiating between non-neoplastic tissue with high ROCAUC and lung cancer on four separate test sets.

To predict lung cancer, P. Mohamed Shakeel et al. [25] created a new, improved image processing and ML approach. The NSCLC CT image dataset was assembled specifically in order to diagnose lung cancer. By employing the multilayer brightness-preserving technique, the obtained images can undergo a comprehensive examination, resulting in the elimination of noise and enhancement of the lung image quality. An improved DNN that divides the region into layers and extracts multiple features is used to isolate the impacted region from the lung CT imaging using noise-cancelling. The effective qualities are then selected using an ensemble classifier and a hybrid intelligent-generalized rough set strategy for spiral optimization. Lung cancer detection rates are increased with the new technique. P. Mohamed Shakeel [26] developed using the bin smoothing normalization technique, the noise has been removed. In order to lower the selection approach concentrated on selecting the least repetitious and Wolf heuristic criteria, taking into account the dimensionality and complexity of the data. Using a mix of generalized neural networks, ensemble learning, and discrete AdaBoost optimization, the biological lung data was successfully analysed, leading to the successful identification and categorization of normal and abnormal features. By carefully selecting cancer attributes and reducing the dimensionality of features, the issue of overfitting cancer characteristics was effectively mitigated.

An automatic 3-D lung segmentation method for CT images was described by Gopi Kasinathan et al. [27] using an active contour framework. The suggested segmentation model combines the formulation of the bias field of the local picture and the active contour model. When homogenous CT images are reconciled severely, a local energy term is provided and employed to effectively predict and segment tumor locations with intensity inhomogeneity. The evolution process was slowed down and characteristics were identified applying the CT pictures to a Gaussian distribution with many scales. The photos that were recovered were categorized using an enhanced CNN. It can be deduced from the results that the recommended approach has a significant ability to achieve superior performance and enable automated diagnosis of lung cancer. It was created by A. R. Bushara and associates. [28]. By leveraging the capabilities of several classifiers to counteract their individual shortcomings, ensemble methods provide a potent approach to improving accuracy and performance. With a 98% prediction accuracy, the outcomes demonstrate that our ensemble technique outperforms previous ensemble approaches and single-model tactics. Using already-existing datasets and resources, the suggested approach improves accuracy and offers a workable solution by Quasar et al. (2024) [29]. It fared better than Google Neural Network and ImageNet and showed similar accuracy to Multivariable Regression and Neural Network and GrayNet. Its potential utility in medical applications is further supported by its sensitivity and specificity, which indicate that it may be able to detect malignancies that other techniques could overlook by Gayathri et al. (2023) [30].

2.1. Research Gaps

There is a significant limitation due to the nature of DNN. For training, ANNs often need a lot of data. Performance of the model is directly influenced by training data quality and representativeness. Another challenge was the small sample size. Some investigations, not designed for screening, contained a small quantity of powdered glass nodules. So, the clinical screening sensitivity may be less than the ideal. Additional research involving a larger sample size of patients to address these limitations and completely demonstrate the performance features. While lung cancer detection methods have improved, no screening approach is perfect. The possibility of false positives and false negatives might result in both over diagnosis and missing diagnoses. The early stages of lung cancer may be difficult to detect using some detection techniques, when it is most curable. This may lead to a delayed diagnosis and possibly poorer patient outcomes. Healthcare personnel must interpret radiological imaging, as CT scans and chest X-rays. The precision of detection may be affected by variations in skill and subjective interpretation. Different histological kinds of lung cancers are included in the disease. The effectiveness of detection techniques may vary for each type, resulting in differences in accuracy and dependability. Some sophisticated detection techniques, such as genetic profiling or liquid biopsies, can be expensive or require specialized tools and training. The availability and broad use of these procedures could be hampered by a lack of resources. In order to overcome these limitations, a useful lung cancer categorization method was presented in this paper.

3. Materials and Methods

Getting the dataset is the first step in the suggested approach. After gathering the dataset, data pre-processing and data augmentation were carried out. The pretrained models, which had already been trained on pictures from the CT picture dataset were trained using the ImageNet dataset. Lung cancer classification was carried out using the proposed fine-tuning architecture. The CT scans were divided into four groups by the model. The effectiveness of the proposed strategy is assessed and contrasted with current strategies. Figure 1 displays the block architecture for the suggested approach.

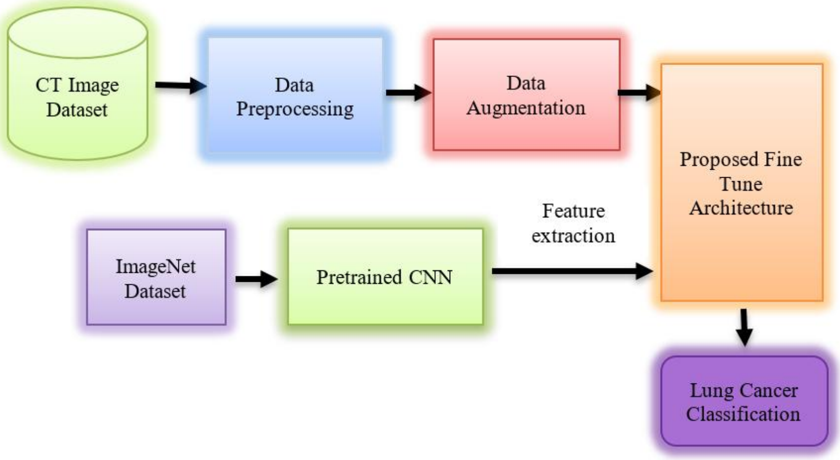


Fig. 1 The suggested approach is represented by a block diagram.

3.1. Dataset Description

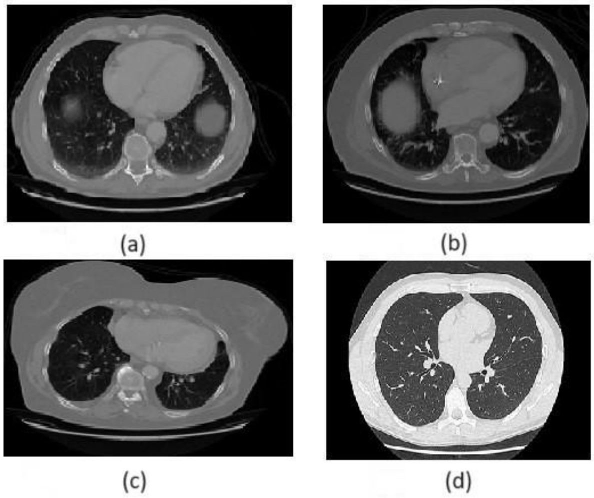


Fig. 2 Sample Lung images from Kaggle Dataset. (a) Adenocarcinoma, (b) Large Cell Carcinoma, (c) Squamous Cell Carcinoma, (d) Normal

Lung cancer CT scans were gathered using Kaggle. In order for the CT images to function with the model, they need to be in JPG format. The three forms of chest cancer that are covered in the dataset are squamous cell carcinoma, adenocarcinoma and big cell carcinoma. Furthermore, normal cells are classified in a different group. The primary folder, which contains all of the subfolders, is called the data folder. The data folder has three subfolders: train, evaluate, and confirm Ten percent of the picture dataset is utilized for validation, twenty percent is used for testing, and seventy percent is used for training. There are 613 CT pictures in the train dataset. There are 315 CT pictures in the test and 72 in the valid data. A few samples of the sample image are displayed in Figure 2.

3.2. Data Pre-processing and Data Augmentation

Image pre-processing and augmentation are two crucial strategies utilized in DL in order to increase the quality, variety, and generalization capabilities of image during training. Image pre-processing concentrates on improving the input images prior to training, whereas data augmentation provides additional training instances by subjecting the original images to random changes. DL models are able to learn from a more varied and representative set of training samples by combining methods for data augmentation and image pre-processing. Pre-processing makes sure that the incoming images are of a high grade and are uniform, whereas augmentation creates additional samples with variances that mimic real-world events. Together, these methods enhance the effectiveness of the performance of the framework on untested data and its generalization.

3.3. Proposed Architecture

A technique used in Transfer Learning is called fine-tuning, in which a previously learned model is further trained on a novel, related problem. By using fine-tuning, the model can modify its previously acquired representations to fit the requirements of the current task or dataset without having to be trained from the start. Initially, a sizable dataset pertinent is used to train the model that was previously educated on a similar problem. In this pre-training stage, a large dataset is used to train the model, such as ImageNet, in order to discover general features and representations that are applicable to a range of tasks involving images. To preserve the knowledge gained during the pre-training phase, The pre-trained model's parameters and weights have been preserved. These pre-trained weights act as the initial point.

The pre-trained model is altered by stacking additional layers on top of the old layers, the exact task determines the number and arrangement of these new levels. To manage the degree of alteration during fine-tuning, the additional layers are randomly initialized, and the current layers may be frozen or have their learning rates changed. The newly created the revised model is then trained using a task-specific dataset. The freshly added layers' weights are updated during the training process, and weights of certain previous layers may also be changed. Improving the model's functionality on the novel task is the aim while retaining the crucial characteristics and representations identified during pre-training. In contrast to the pre-training phase, a slower learning rate is typically used during fine-tuning. This makes it possible for the new layers to revise the particular task while maintaining the past features. In order to enable the new layers to adapt to the new task more quickly, the learning rate for those layers may be increased. An optimisation approach is used to adjust the weights of the model after computing the loss during training. To ascertain how well the model can forecast the future and generalize to new data, its efficacy is evaluated on an alternative validation set following training. The knowledge and representations acquired during pre-training on a large dataset can be employed during fine-tuning. Compared to developing a model from scratch, starting with a pre-trained model allows for significant training time savings. The pre-trained method has already gathered generic qualities, which may be helpful for the new assignment.

A lot of labelled data is often needed while training deep neural networks. However, it may be difficult or expensive to acquire a sizable labelled dataset for a particular task in many real-world settings. Fine-tuning makes it possible to obtain good performance with a smaller dataset, because the pre-trained model already has valuable learning representations. A large and diverse dataset has already taught genetic features to pre-trained models. These acquired characteristics can transfer easily to various tasks or sectors. It can increase generalization and performance by adjusting the pre-trained model's representations to the unique details of the new task. An effective approach called fine-tuning speeds up model training, lowers the amount of data needed, increases generalization, and makes it easier to apply pre-trained information to new tasks. Algorithm 1 offers the general fine-tuning algorithm. This study used a revised modified VGG-16 model to classify lung cancer from CT scans.

Algorithm 1: Fine Tuning for enhanced performance of the proposed model

Input:

- VGG-16 is a pre-trained CNN model.
- A new dataset for fine-tuning
- Hyper parameters for fine-tuning (eg: learning rates, number of epochs etc.)

Output:

• An improved method for classifying lung cancer.

1. Start by loading the pre-trained model. Then, load the model's weights and architecture.
2. Make the lowest layers frozen.

• Determine which pre-trained model's lowest layers best capture broad characteristics.

• To stop these layers' weights from being changed while fine-tuning, freeze them.

3. Retrain or swap out the upper layers.

• Determine which pre-trained model's upper layers are in charge of the features unique to the assignment. .

• These layers can be retrained using the new dataset, or they can be swapped out for new ones that are suitable for the new purpose.

• Randomly initializes the new layers' weights.

4. Adjust the model.

• Compile the updated version using a new optimizer and loss function suitable for the new task.

• Use the new dataset to train the revised model using the fine-tuning hyperparameters.

• The lower layers are unfrozen during training, and their weights are updated using a slower rate of learning than the more advanced levels.

5. Assess the adjusted model.

• Assess how well the improved model performs on a validation set.

• To maximize performance, modify the fine-tuning hyperparameters as necessary.

6. Store the adjusted model.

One popular convolutional neural network design is VGG-16. Its performance in competition garnered a lot of attention on image categorization tasks and ease of use. The sixteen layers that comprise the VGG-16 model consist of three fully linked layers and thirteen convolutional layers It has a simple design with small receptive fields (3×3) and maximum pooling layers (2×2) for down sampling.

$$(M * N * d) + 1) * Z \tag{1}$$

The calculation has been modelled into a mathematical equation as shown in Equation (1).

Where, (M), height (N), the previous layer (d), and filters (Z) in the proposed layer.

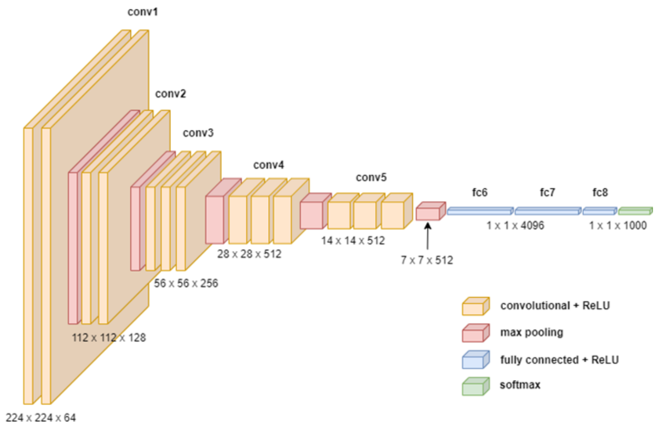


Fig. 3 Block diagram illustration of the suggested improved VGG-16

The image data with the desired input dimensions is accepted by the in- put layer. Two or more convolutional layers make up each convolutional block in the model, and consequently, these layers are A max pooling layer comes next. The layers of convolution employ the rectified linear activation function to create non-linearity, and small receptive fields (3×3) are used as the size of the receptive fields. The collected Following the convolutional blocks, features are flattened and sent through 4096 units in three fully connected levels. These layers are also subjected to ReLU's activation function. The VGG-16 architecture's last layer is made up of a SoftMax layer with an equal number of units as the classification task's classes. The likelihood of each class is displayed via the probability distribution it creates over the classes. Figure 3 depicts the fundamental architecture of VGG-16.

$$w_2 = (w_1 - f) \div s + 1 \tag{2}$$

$$H_2 = (H_1 - f) \div s + 1 \tag{3}$$

$$d_2 = d_1 \tag{4}$$

Where w- width, H-height and d-depth.

This work used a revised modified VGG-16 model to classify lung cancer from a collection of CT scans. To avoid both overfitting and underfitting during training, the VGG-16 model was updated. A process of fine-tuning was applied to the suggested modified VGG-16 model. During feature extraction, two successive small convolutional kernels were used instead of a single large one, maintaining the VGG-16 convolutional network's original architecture. As a result of fewer parameters and the preservation of the VGG-16 perceptual effects, training is sped up while maintaining network depth. In below equation c- current layer, and P-previous layer.

$$c * P * c + 1 \quad (5)$$

Table 1. Parameter details of the Proposed Fine-tuned VGG-16 Model

Item	Before Fine-tuning	After Fine-tuning
Trainable Parameters	25,093,004	39,252,364
Total parameters	39,807,692	39,807,692
Non-trainable Parameters	14,714,688	555,328

Table 2. Parameter details of the Proposed Fine-tuned VGG-16 Model

Parameters	Before Fine-tuning	After Fine-tuning
Optimizer	Adam	RMSprop
Learning Rate	0.0001	0.00001
Number of Epochs	10	25
Data set	Kaggle	Kaggle
Loss	Categorical cross entropy	Categorical cross entropy

The dimensions of the input image were 224×224. The hidden layer contained five blocks. The flattened layer was responsible for lowering the feature maps' dimensions, whereas the pooling layers were in charge of reducing the image size. Ten training epochs were performed on the altered VGG-16 model before. After tuning starting with the ninth layer, the images provided a low l rate. It was trained for 25 epochs following the fine-tuning process. The fine-tuning process was conducted independently on the 8th, 10th, and 12th layers, and it was determined that fine- tuning from the best degree of precision was obtained from the eighth layer. Table 1 displays a summary of the suggested model's fine-tuning before and after.

4. Experimental Results and Discussion

4.1. Hardware and Software Setup

Following the collection of the dataset, the proposed model was run. The entire procedure was carried out in Python and TensorFlow on Google Collaboratory, where the model was built and trained. The different hyper parameters utilized by the proposed model are in Table 2.

4.2. Performance Parameters

The effectiveness of the proposed strategy is assessed and quantified using four performance measures. Performance metrics provide an assessment of the effectiveness of the suggested model. They allow us to assess the correctness of the model, reliability, and efficiency while making predictions or producing outputs. Numerous evaluation measures that provide insight into the effectiveness of the model can be computed according to the matrix of confusion. The confusion matrix's values are used to generate these measures. The evaluation metrics used in this work are tabulated in Table 3. Assessment of Performance Metrics of the Suggested Adjusted Improved VGG-16 The following is a mathematical expression for the model:

Equation (1) is used to express correctness in the proposed study.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

Precision is expressed as in Equation (2)

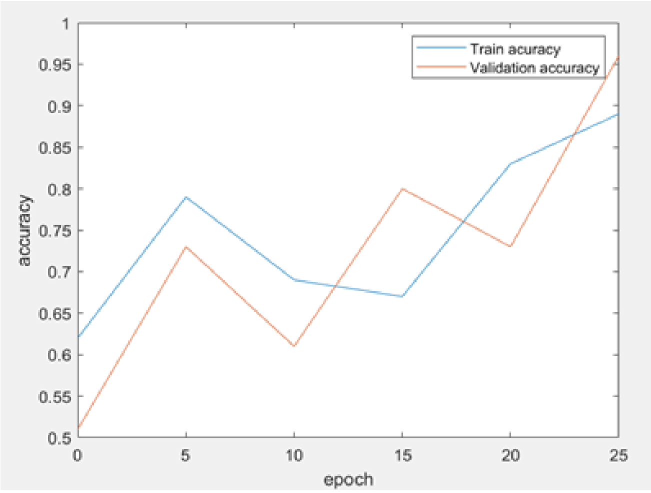
$$Precision = \frac{TP}{TP+FP} \quad (7)$$

Recall is expressed as in Equation (3)

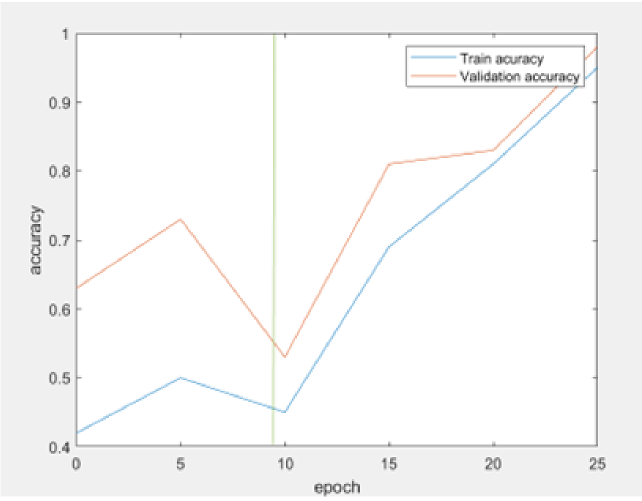
$$Recall = \frac{TP}{TP+FN} \quad (8)$$

F1-Score is expressed as in Equation (4)

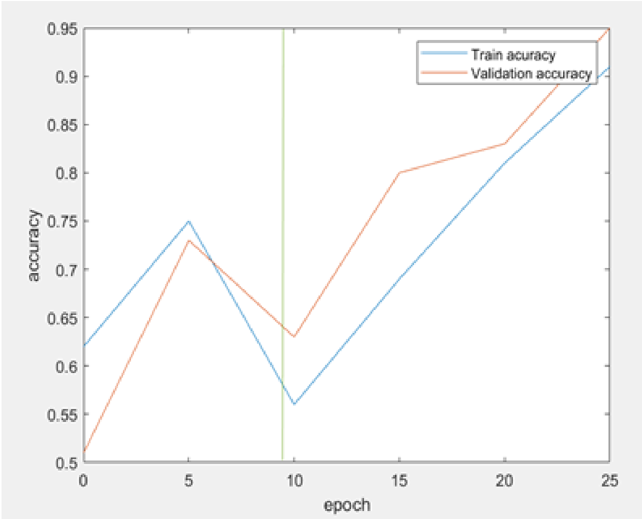
$$F_1\,Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (9)$$



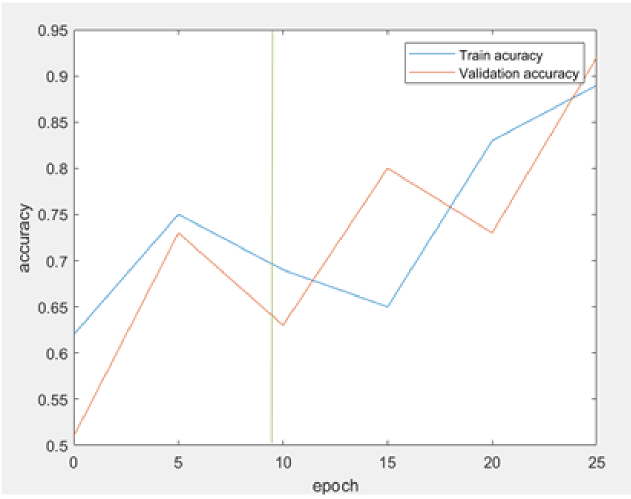
(a)



(b)



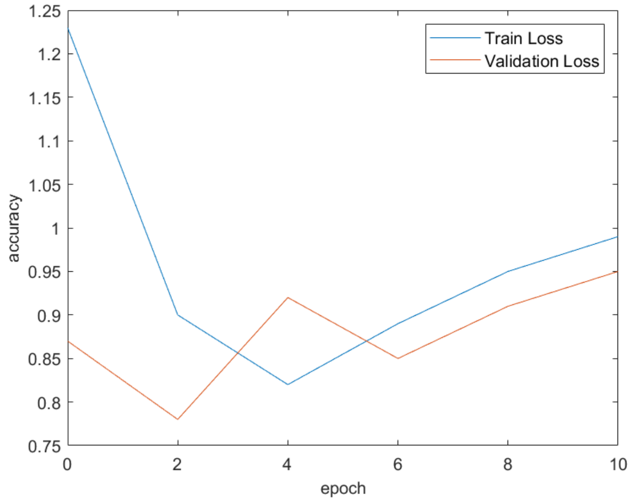
(c)



(d)

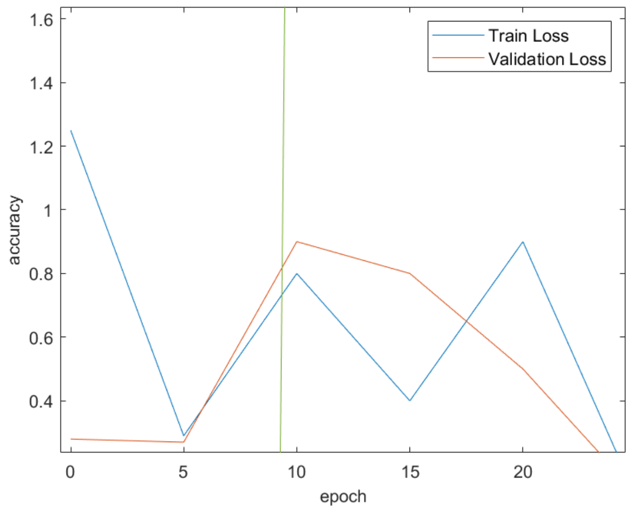
Fig. 4 The accuracy of the proposed fine-tuned VGG-16 model (a) before fine-tuning (b) and after fine-tuning from the eighth layer (c) after fine-tuning of the tenth layer (d) after fine-tuning of the twelfth layer.

A graphical representation of a model's accuracy over time or across training epochs is called an accuracy plot. It is useful to see how the accuracy of the model develops and gets better as training goes on. The percentage accuracy implies the proportion of accurately predicted cases out of all instances, and is typically given as a number. A comparison of the accuracy plot of the suggested model before and after fine-tuning can be seen in Figure 4. Fine tuning is performed for three cases namely, from 8th layer, from 10th layer and from 12th layer and the accuracy plots are shown in Figure 4 (a), (b), (c) and (d).



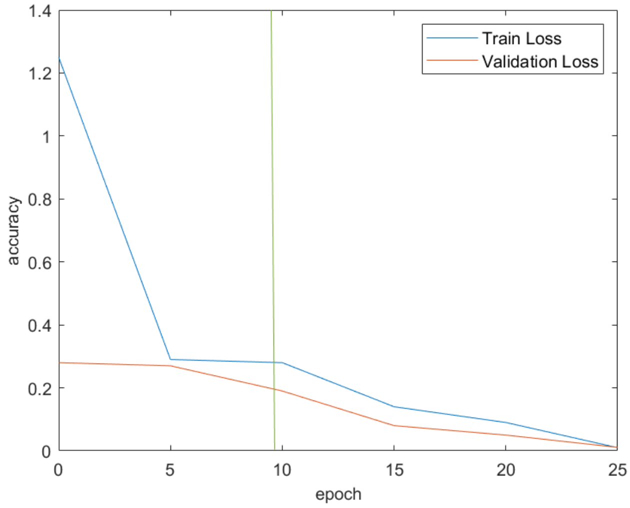
1.25
1.2
1.15
1.1
1.05
1
0.95
0.9
0.85
0.8
0.75
accuracy
0
2
4
6
8
10
epoch
Train Loss
Validation Loss

(a)



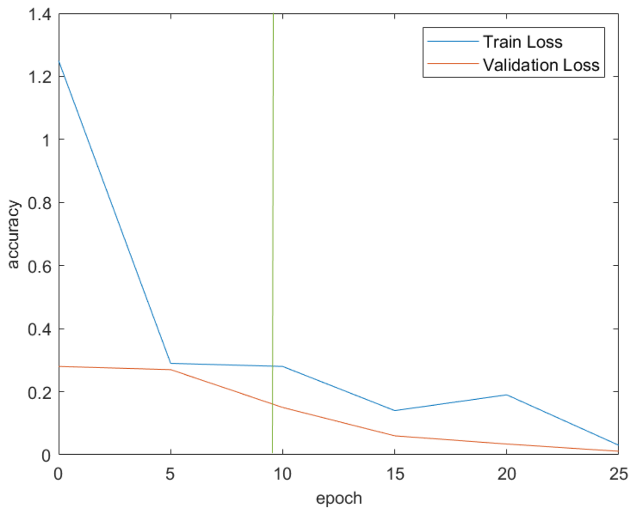
1.6
1.4
1.2
1
0.8
0.6
0.4
accuracy
0
5
10
15
20
epoch
Train Loss
Validation Loss

(b)



1.4
1.2
1
0.8
0.6
0.4
0.2
0
accuracy
0
5
10
15
20
25
epoch
Train Loss
Validation Loss

(c)



(d)

Fig. 5 The loss of the suggested fine-tuned VGG-16 model displays (a) before fine-tuning, (b) the model of eighth layer fine-tuning, (c) the model of tenth layer fine-tuning, and (d) the model of level twelve fine-tuning.

A model's loss function value over training iterations or epochs is shown visually in a loss plot. As the model learns and modifies its parameters during the epochs, the loss starts at a very high value and eventually declines. The loss plot of the suggested model is shown in Figure 5 (a) before to and (b) following the fine-tuning of the eighth layer. Figure 5 (c) and (d) show the loss of the suggested VGG-16 model following fine-tuning from the 10th and 12th layers, respectively.

A classification report is a thorough analysis that offers different metrics for each class in a classification challenge. It is frequently employed to evaluate a performance on the classification. In the categorization report, often included are measurements like F1-score, recall, accuracy, and precision. The model's categorization report prior to and after fine-tuning from the eighth, tenth, and twelfth layers is shown in Table 3. The table demonstrates how fine-tuning improves the recommended model's performance. More minute details and higher accuracy can be obtained by modifying the learning rate to run over these layers in smaller steps. After fine-tuning, the model’s accuracy has increased dramatically from 81.91% to 96.8%. It was found that the fine tuning from the eighth layer provided the highest level of accuracy than fine tuning the model from its 10th or 12th layer which is evident from Table 3.

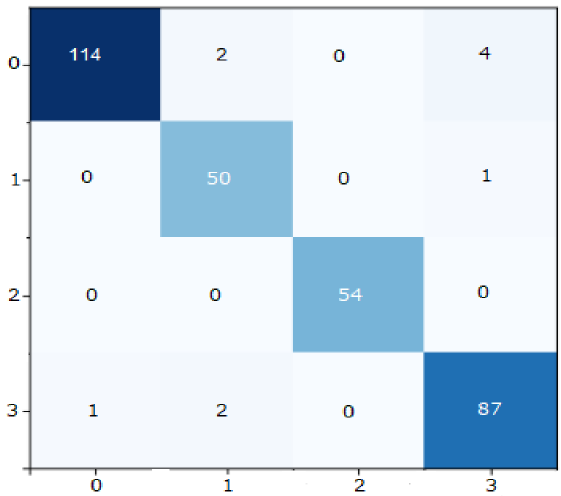


Fig. 6 The suggested algorithm's confusion matrix following fine-tuning from the eighth layer.

The confusion matrix for the suggested lung cancer classification model is shown in Figure 6. Different classes in the dataset are indicated by the values 0, 1, 2, and 3. Adenocarcinoma is represented by value 0 and Large Cell Carcinoma by value 1. The values of 2 and 3 represent normal and squamous cell carcinoma respectively.

Table 3. Performance metrics of the suggested optimized VGG-16 model

Parameters	**Before Fine Tuning**	**8th Layer**	**10th Layer**	**12th Layer**
Accuracy	81.91 %	**96.70** %	95.55 %	94.65%
Precision	74.68 %	**97.64**%	97.48 %	96.23%
Recall	75.16 %	**96.85** %	96.69 %	95.59 %
F1-Score	76.73 %	**96.38** %	96.85 %	95.00 %
Specificity	87.28 %	**97.38**%	86.87 %	86.38%
MC	0.726	**0.946**	0.931	0.929
KP	0.723	**0.946**	0.932	0.911

Table 4. Comparison of the suggested improved VGG-16 model's performance with previous studies

State of the Art Networks	**Methodology**	**Accuracy (%)**
Jinsa Kuruvilla et al. [24]	Feed Forward and Feed Back Propagation Network	93.3
Devinder Kumar et al. [25]	Autoencoder	75.01
Jinsa Kuruvilla et al. [26]	Fuzzy Logic	94
Lakshmanaprabhu et al. [18]	Deep Neural Network	94.56
Ruchita Tekade et al. [27]	DCNN	95.66
P.B.Sangamitra et al [28]	EK-Mean clustering and Back Propagation	90.87
Baihua Zhang et.al [29]	Ensemble Learning	84
Proposed model	**Fine-tuned modified VGG-16**	**96.08**

The model's performance with seven distinct techniques to lung cancer classification is used to assess its efficacy, as shown in Table 4. The comparison table makes it evident that the suggested lung cancer classification model performed better than the ones already in use.

5. Conclusion

For patients, researchers, and healthcare providers, lung cancer is a severe and complicated disease that poses numerous challenges. The intricacy of lung cancer has been extensively studied over time, improving patient care, available treatments, and diagnostic techniques. Furthermore, there is considerable promise for advancing lung cancer research and clinical therapy through the merging of AI and DL. There are still certain limitations, though. This research proposed an effective DL-based lung cancer classification model. A modified VGG-16 model served as the foundation for the suggested system. The underlying algorithm underwent a fine-tuning procedure. The collected CT scan data was used to assess the suggested algorithm's performance. The results of the experiment show that the proposed approach's efficacy is enhanced by the fine-tuning technique, outperforming the performance of the models that are currently available for Lung cancer's classification. The model's accuracy rose sharply from 81.91% to 96.8% after fine-tuning. When the tenth, twelfth, and twelfth layers were fine-tuned separately, the maximum accuracy was obtained from the ninth layer. The findings indicate that the proposed brain tumortype classification system based on the fine-tuned modified VGG-16 technique performs better than the other model classifiers. In the future, lung cancer categorization might make use of hybrid models based on deep learning.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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