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International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 12, Issue 1 | Pages 154-159 | e-ISSN: 2347-470X

Classification of Lung Cancer in Segmented CT Images Using Pre-Trained Deep Learning Models

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ABSTRACT- Many Diagnosis systems have been designed and used for diagnosing different types of cancer. Identification of carcinoma at an earlier stage is more important, and it is made possible due to the use of processing of medical images and deep learning techniques. Lung cancer is seen to develop often to be increased, and Computed Tomography (CT) scan images were utilized in the investigation to locate and classify lung cancer and also to determine the severity of cancer. This work is aimed at employing pre-trained deep neural networks for lung cancer classification. A Gaussian-based approach is used to segment CT scan images. This work exploits a transfer learning-based classification method for the chest CT images acquired from Cancer Image Archive and available in the Kaggle platform. The dataset includes lung CT images from the Cancer Image Archive for classifying lung cancer types. Pre-trained models such as VGG, RESNET, and INCEPTION were used to classify segmented chest CT images, and their performance was evaluated using different optimization algorithms.

Keywords: Computer-Aided Diagnosis, lung cancer, Deep learning, CT image, Gaussian, VGG, RESNET, and INCEPTION.

ARTICLE INFORMATION
Author(s): P. Deepa, M. Arulselvi, S. Meenakshi Sundaram;
Received: 28-01-2024; **Accepted**: 29-02-2024; **Published**: 15-03-2024;
E- ISSN: 2347-470X;
Paper Id: IJEER240105;
Citation: 10.37391/IJEER.120122
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-12/ijeer-120122.html

crossref member
CROSSREF.ORG THE CITATION LINKING BACKBONE

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1. INTRODUCTION

The association between both tobacco and lung cancer was originally proposed in 1912, and it continues to be a public health concern. In India, it is estimated that 10-15% of the population has been exposed to tobacco. Lung carcinoma is a disease that originates in the lung region and may spread to other human organs. In addition to historic links between tobacco and lung cancer, recent statistics highlight the study's urgency. As of 2024, global lung cancer rates have surged by 15%, emphasizing the critical need for early detection and diagnosis.

Computer-aided diagnostics (CAD), a subset of Artificial Intelligence (AI), facilitates pathologic malignancy diagnosis. AI complements clinical decision-making by transforming qualitative image input into quantitative information. Deep Learning (DL) in medical imaging shows potential, with applications in diagnosing cutaneous malignant melanoma [1] and diabetic retinopathy [2]. DL's progressive application in lung cancer pathology detection is evident. Recent studies highlight its capability to analyze tumor information qualitatively or quantitatively. To overcome limited image samples, transfer learning, inspired by human knowledge transfer, is explored for efficient lung cancer classification [3]. The study employs pre-trained CNN models (Inception V3, VGG16, ResNet-50) for multiclass classification of lung cancer images.

2. RELATED WORK

Accurate assessment or detection of disorders or anomalies is a difficult task in medicine. Where machine learning approaches based on automated or semi-automatic computer-aided diagnostic (CAD) systems can help medical experts forecast or diagnose diseases or anomalies. The deep learning-based CAD systems work commendably, and the system's output supports specialists in making appropriate selections. According to a thorough review of the literature, deep learning can be used in a wide range of research fields in medical health monitoring. Deep learning is the study to classify lung cancer because it is a popular and powerful machine intelligence and classification technology [4, 5]. If merely a massive quantity of data is inferred, deep learning conspicuously CNN is considered to have a high success rate. Although numerous deep learning-based lung cancer algorithms have been proposed [6 - 11], their accuracy can still be improved. In [12], they introduced a weakly supervised strategy for classifying whole-slide lung cancer images quickly and effectively. For discriminative block retrieval, their solution uses a patch-based fully convolutional network.
Furthermore, context-aware extraction of features and aggregation algorithms were developed to build a globally holistic WSI descriptor. The suggested method in [13] intends

to investigate the efficiency of pre-trained deep models for malignancy classification of lung nodules.

Machine learning techniques, such as deep learning-based CAD systems, are useful in diagnosing and forecasting diseases in the medical field. This study uses transfer learning to classify lung cancer, building on the advances made by CNNs in medical image classification. Although existing algorithms show promise, higher accuracy rates are needed. The demand for more precise and efficient methodologies in lung cancer diagnosis is accentuated by this need for improvement.

3. PROPOSED METHOD

The proposed work shown in Figure 1 utilizes input images to perform lung cancer classification using Transfer Learning; it processes a model that is trained to solve one problem concerning the samples collected from that respective problem domain and is utilized to solve a problem in another distinct domain using the knowledge gained from the earlier domain. It involves the trained model to solve the problem in a newer domain without having to retrain the model with samples from the newer domain. It is believed that the parameters learned from training the model in a domain can be reused to solve a problem in a newer or fresh domain.

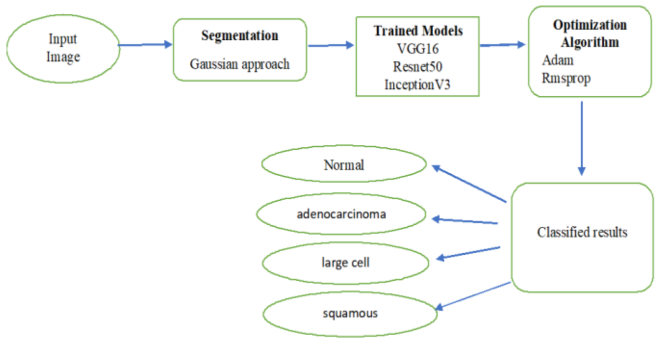

Figure 1: Block diagram of the proposed work

Currently, numerous pre-trained models are available to solve image classification and other computer vision applications. VGG, GoogLeNet, and Residual Network are the more prominent models. As these pre-trained models are considered to be more efficient and consistent, they are used extensively in transfer learning tasks. VGG-16/ 19 which is known as the first exclusive deep neural network with numerous layers, residual network-based models (Resnet-50), and inception v3 – a model with symmetric- asymmetric building blocks are used in this study. To improve lung cancer classification, strategies such as handling imbalanced classes, domain-specific augmentation, and hyperparameter tuning can be used to improve the model's robustness.

3.1 Dataset

For evaluating the performance of the proposed lung image feature extraction and classification method, commonly available lung CT images from the Kaggle platform are used. The dataset comprises 1200 images, where, 288 Adenocarcinoma, 316 Large cell carcinoma, 294 Normal images, and 302 Squamous cell carcinomas. The train test split was fixed at 70% and 30%. Thus, 360 images are used for testing, and 840 images are used for training. Initially, the images are normalized and then segmented using the Gaussian approach. Segmented images (lung region) from the CT images are used for training the models (VGG-16, Resnet50, and Inception v3). Pre-trained models were used as feature extractors; though they are trained using the ImageNet dataset and connected neural layers, the images are classified as either cancerous or normal image.

Gaussian-Based Segmentation of CT Lung Image

Gaussian-based segmentation is utilized to isolate lung regions, improving the accuracy of deep learning models for lung CT image classification. The selection of VGG, RESNET, and INCEPTION pre-trained models is based on their demonstrated effectiveness in image classification tasks. These models possess unique architectural features that render them suitable for classification tasks. Leveraging their learned hierarchical features allows for the identification of complex patterns within lung CT images.

Consider a pixel from a color image represented as $x_i=(x_i^R,x_i^G,x_i^B)$ and the segmentation of the color image with N number of pixels can be summarized as follows:

(a) Choose the number of segments in the image represented as M and initialize

$$\theta = (\pi_1, \pi_2, \ldots, \pi_M, \mu_1, \mu_2, \ldots, \mu_M, C_1, C_2, \ldots, C_M)$$

where μ and C represents the mean and center of the cluster.

(b) Let us assume that the color image is formed by a mixture of M. The initial value of it can be fixed by

$$\pi^0_1 = \pi^0_2 = \ldots = \pi^0_M$$

$$\mu_l^{(t+1)} = 1/N\pi_l^{(t+1)} \Sigma^N_{i=1} x_l \gamma(Z_{il}) \quad (1)$$

$$C_l^{(t+1)} = 1/N\pi_l^{(t+1)} \Sigma^N_{i=1}(x_l - \mu_l^{(t+1)})^2 \gamma(Z_{il}) \quad (2)$$

$$l=1,2,\ldots, M \text{ and } i= 1, 2, \ldots, N$$

where M is the number of segments in the image, N is the number of pixels.

(c) Using iterative Expectation and Maximization (EM) algorithm the optimal value of θ was calculated and is the difference between the current and the previous iteration results are less than 10^{-6} then the iterative procedure is stopped.

(d) The optimal value of the θ obtained by the iterative process, each pixel x_i in the color image is clustered by following mathematical expression:

$$\max\{E[\ln p(X, Z|\pi,\mu,C)] = \Sigma^N_{i=1}\Sigma^M_{l=1}\gamma(Z_{il})$$

$$\{\ln \pi_l + \ln N(x_i|\mu_l,C_l)\}, l= 1, 2, \ldots, M\} I_l \quad (3)$$

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Where μ is the means, C is the covariances, π is the mixing coefficients (probabilities), EM is used to evaluate the responsibilities of given current parameters and Re-estimate the parameters of given current responsibilities, p(X,Z) is the conditional probabilities of variable X and Z.

The number of clusters (M) in the Gaussian mixture model plays a pivotal role in defining the complexity of segmentation, influencing how distinct patterns are identified within the image.

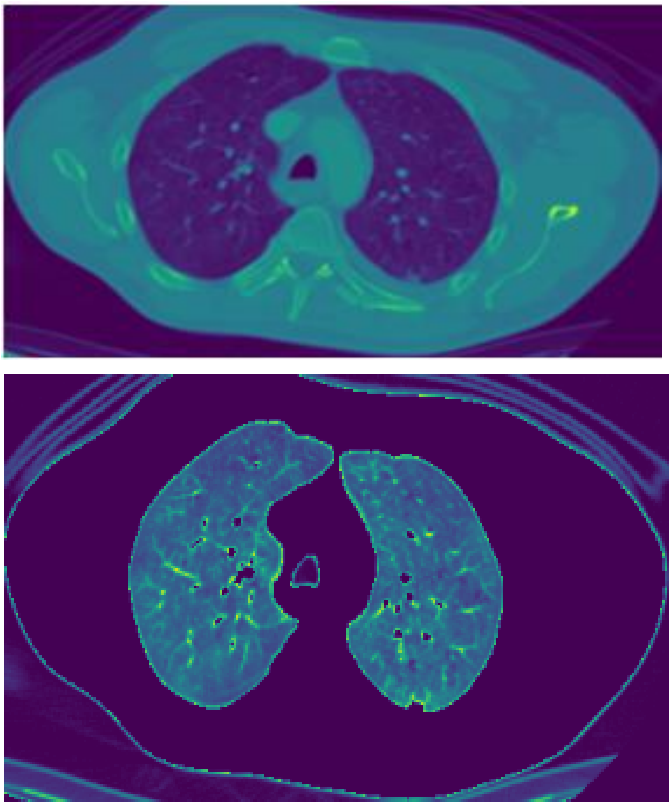


Figure 2: Result of Gaussian Segmentation (CT image | segmented lung region)

The Gaussian mixture model is combines the benefits of parameter estimation and non-parametric estimation while ignoring the probability density function's specific form. Furthermore, the model's complexity is primarily related to solution issues and has nothing to do with the volume of the training samples. To perform image segmentation, the Gaussian mixture model was used to describe a color image and the EM technique to estimate the various parameters of the Gaussian model.

3.2 Transfer Learning Models

By transfer learning process, a model that is trained to solve one problem with respect to the samples collected from that respective problem domain is utilized to solve a problem in another distinct domain using the knowledge gained from the earlier domain. It involves the trained model to solve the problem in an original domain without having to retrain the model with samples from the newer domain. It is believed that the parameters learned from training the model in a domain can be reused to solve a problem in a newer or fresh domain. Currently numerous pre-trained models are available to solve image classification and other computer vision applications. VGG, GoogLeNet, and Residual Network are three of the more prominent models. As these pre-trained models are considered to be more efficient and consistent, they are used extensively in transfer learning tasks. VGG-16/ 19 which is known as the first exclusive deep neural network with numerous layers, residual network-based models (Resnet-50) – a model with symmetric- asymmetric building blocks are used in this study.

3.2.1. Inception v3

The architecture design of inception v3 differs from its previous versions with a major focus on reducing computational complexity. In general inception, models are more well-organized both in terms of the trainable parameters and the resource consumption (storage and other resources) when compared to the VGG networks. Efforts to restructure or improvise the inception network must not affect the computational efficiency of the network. Else the suitability of the altered model for different applications will become an issue. An Inception v3 network's architecture is described below with a schematic diagram (*fig. 3*) and it includes the following essential components:

1. *Factorized Convolutions*: This supports to reduce the count of trainable parameters available in the system thus improving the computational efficiency.
2. *Smaller convolutions*: Substituting the larger convolutions with smaller convolutions makes the training process faster. A 5x5 filter has 25 parameters in total and using two 3x3 filters instead of a 5x5 convolution, requires 18 (3*3 + 3*3) parameters only.
3. *Asymmetric convolutions*: Instead of a 3x3 convolution, a 1x3 convolution followed by a 3x1 Convolution may be employed. If a 3x3 convolution was switched for a 2x2 convolution, the number of parameters would be much more than the asymmetric convolution mentioned.
4. *Auxiliary classifier*: a small convolution network is used as an auxiliary classifier. It is inserted between layers during the training process and considered to make the network deeper in the case of GoogLeNet, but in turn, it acts as a regularizer in Inception v3.

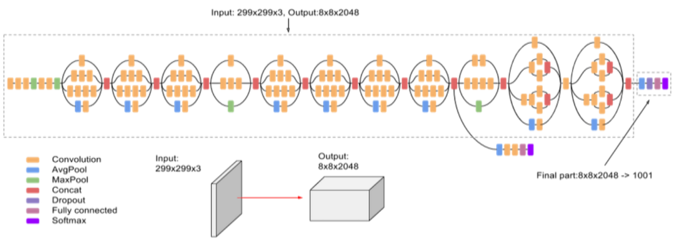


Figure 3: Proposed Architecture of Inception V3

3.2.2. Resnet50

Deep neural networks require a longer training time and likelihood of overfitting is high. To overcome such issues a residual learning approach was proposed to diminish the training time of the model that are significantly deeper when compared to the conventional neural models. During the neural training the accuracy reaches a saturation point and tends to decrease if model training is continued further. This term is "degradation problem". This demonstrates that not all neural network topologies are created equal. To overcome this problem, ResNet follows residual mapping. Instead of assuming that stacking of layers will suffice to map a input to output, the residual network allows explicit mapping of residuals. A Resnet50 network architecture is described below with a schematic diagram (*Fig. 4*)

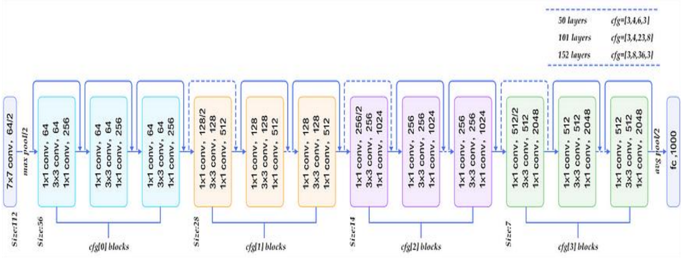


Figure 4: Proposed Architecture of ResNet 50

3.2.3. VGG16

VGG16 is a variant of CNN architecture (presented in *fig. 5*) considered to be one of the most efficient deep neural models. An important and unique feature of VGG16 is the usage of convolutional layers with 3x3 size filters, and a maximum pooling using a 2x2 size filter. The convolution and max pooling layers are arranged uniformly in the architecture. The classification layer consists of two fully connected layers configured with softmax activation. The network has in total 138 million trainable parameters.

Figure 5: Proposed Architecture of VGG16

While VGG-16 excels in simplicity and interpretability, RESNET-50 offers advantages in learning intricate features, and Inception V3 balances computational efficiency.

3.3 Optimization Algorithm

The study builds upon this established foundation by incorporating a weakly supervised strategy, as outlined in [12], for the swift and effective classification of whole-slide lung cancer images. This novel approach employs a patch-based, fully convolutional network, representing a significant advancement in techniques for lung cancer classification. In alignment with the insights articulated in [13], the study directs its focus toward evaluating the efficiency of pre-trained deep models in the classification of lung nodules with malignancy. The utilization of pre-trained models, encompassing VGG-16, ResNet50, and Inception v3, emerges as a critical strategy to augment classification accuracy, harnessing the acquired hierarchical features.

In this work, the CNN classifier with the various optimizer algorithms such as the Root Mean Squared Propagation (RMSprop) and Adaptive Moment Estimation (Adam).

A technique Adaptive Moment Estimation (Adam) is a method for determining adaptive learning rates for each parameter [14]. Adam, like Adadelta and RMSprop, the average of previous squared gradients, with exponential decay, is stored. v_t and an exponentially decaying average of past gradients m_t.

$$m_t = \beta_1 m_{t-1} + (1- \beta_1)\, g_t \tag{4}$$

$$v_t = \beta_2 v_{t-1} + (1- \beta_2)\, g_t^2 \tag{5}$$

The optimization methods Adam and Rmsprop are very similar, although there are a few important distinctions among RMSProp with momentum and Adam, whereas RMSProp with momentum creates parameter changes using a momentum on the rescaled gradient. For gradient normalization, RMSprop [15] uses the mean square of the gradient. This balances the step size and reduces the step for large gradients to avert the Exploding Gradient and increases the step for small gradients to sidestep the Vanishing Gradient. *Equation (6)* is used to calculate the running time parameter $[g^2]_t$.

$$[g^2]_t = \beta E[g^2]_{t-1} + (1-\beta)\, g_t^2 \tag{6}$$

$$W_{t+1} = W_t - [\, \eta / \sqrt{(E[g^2]_t)}\,] \cdot g_t \tag{7}$$

3.4 Performance Metrics

Confusion Matrix: A Confusion matrix is used to find the performance of the classifier.

The accuracy shows the classification to which the model correctly identified the classifier.

$$Accuracy = (TP+TN)/(TP+FP+TN+FN) \tag{8}$$

Table 1. Confusion Matrix

Classes	Normal	Adeno	Squamous	Largecell
Normal	*TP*	*FP*	*TN*	*TN*
Adeno	*FN*	*TP*	*FN*	*FN*
Squamous	*TN*	*FP*	*TP*	*TN*
Largecell	*TN*	*FP*	*TN*	*TP*

4. EXPERIMENTAL RESULTS AND DISCUSSION

The dataset comprises 1200 images for training and testing the deep learning models. Initially, the images are normalized and then segmented using the Gaussian approach. Segmented images (lung region) from the CT images are used for training the models (VGG-16, Resnet50, and Inception v3). The optimal number of epochs was determined based on average validation accuracy and the accuracy of the model obtained for different epochs is summarized. With the ADAM optimization algorithm, the VGG-16 yields an accuracy of 96% after the 100th epoch. Though the VGG model can achieve better accuracy with more layers, it cannot converge to global minima when the number of layers is increased beyond 20. This is due to the vanishing gradient problem, and the learning rate becomes less than that there are no updates to the model weights. Using batch normalization, the gradient explosion is controlled. The vanishing and gradient problem can be limited by using the residual learning network (RESNET-50). But from the tabulated results, it can be seen that the RESNET yields poor performance since, in the original implementation of RESNET, the stochastic gradient descent optimization technique was used. ADAM algorithm has issues in converging to the optimal solution and the SGD with a learning rate scheduler may outperform it. The results presented in the plots of Fig.6 and 7 shall present the performance comparison of ADAM and RMSprop algorithms. ADAM yields better performance in the case of all pre-trained models considered in the experiments.

Limited variations in the dataset posed challenges during the experimental phase, particularly in rare lung cancer types. The RESNET model's performance exhibited fluctuations during certain epochs, and the imbalance in class distribution within the dataset affected the model's ability to generalize. These limitations emphasize the need for robust strategies to handle imbalanced data and refine model training protocols. Future work should explore techniques to address dataset imbalances and incorporate more diverse samples for improved model generalization.

The confusion matrix is a vital tool for evaluating model performance in multiclass classification. It comprises TP, FP, TN, and FN values, providing a detailed breakdown of the model's predictions. Accuracy is calculated as TP divided by total instances. Precision, recall, and F1-score for each class are derived from the confusion matrix. It helps detect model biases towards certain classes, making it easier to identify and mitigate potential biases. By analyzing the information provided by the confusion matrix, we gain a comprehensive understanding of the model's strengths and weaknesses in classifying different categories.

Table 2. Confusion Matrix of Multiclass Classification

Classes	Normal	Adenocarcinoma	Largecell carcinoma	Squamous carcinoma
Normal	0	105	10	0
Adenocarcinoma	0	3	74	0
Largecell carcinoma	77	1	0	0
Squamous carcinoma	0	0	0	90

Table 3. Performance accuracy under various optimizers

	VGG 16	Inception V3	Resnet 50
RMSProp	0.613636	0.861742	0.774621
ADAM	0.960227	0.945076	0.776515

Table 4. Classifier results for Multiclass Classification

	Normal	Adenocarcinoma	Largecell carcinoma	Squamous cell carcinoma
Training	217	179	232	212
Testing	77	109	84	90

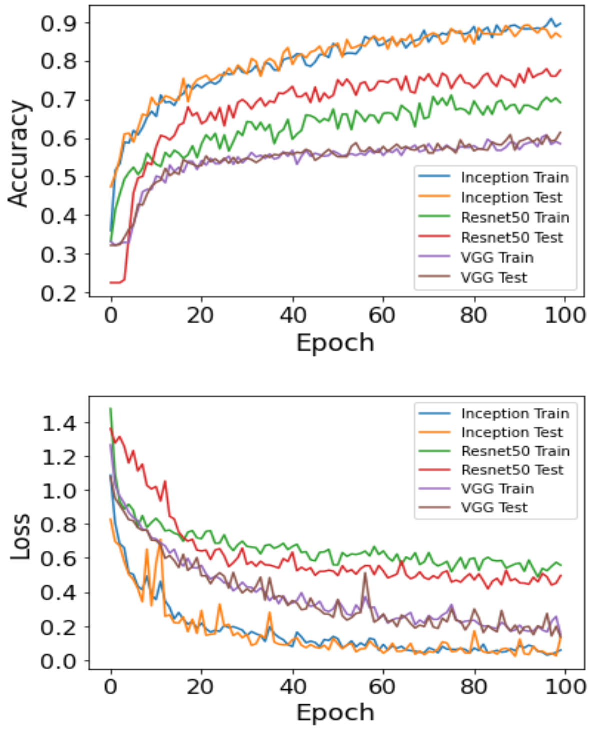
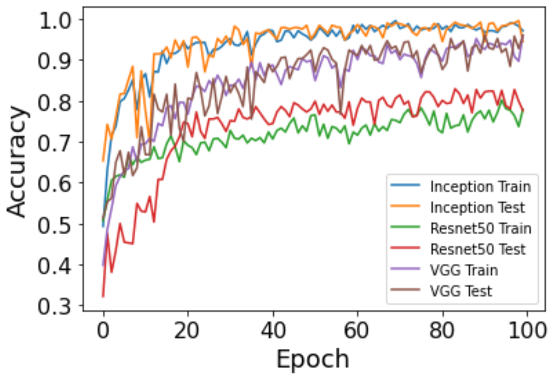


Figure 6: Performance comparison of pre-trained models with RMSprop Optimization

In this medical imaging study, pre-trained models (VGG, RESNET, and INCEPTION) were finetuned by modifying their fully connected layers for optimal lung cancer classification. Hyperparameter tuning was performed to enhance model performance and transfer learning with a reduced learning rate to fine-tune weights on the medical imaging dataset.

Optimization algorithms, like ADAM and RMSprop, have a significant impact on model convergence and performance. ADAM shows rapid convergence due to adaptive learning rates but may overshoot the optimal solution. RMSprop maintains a moving average of squared gradients, resulting in a smoother convergence trajectory. Choosing the right algorithm depends on the dataset and model architecture. ADAM is adaptable and ideal for swift convergence, while RMSprop is stable and ensures reliable convergence.



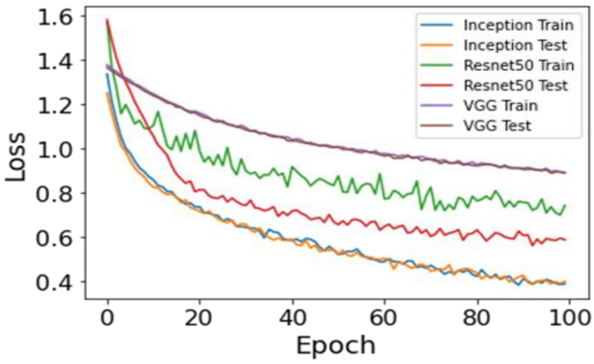


Figure 7: Performance comparison of pre-trained models with ADAM Optimization

Efficient integration of lung cancer classification models into medical workflows is critical. To achieve optimal efficiency, various optimization techniques can be used, including model pruning, quantization, hardware acceleration, batch size optimization, caching and memoization, and asynchronous inference. These optimizations facilitate swift and accurate diagnoses in real-time clinical scenarios.

Table 5. Comparison of existing and proposed models

	Accuracy	Precision	Recall	F1-Score
CNN-based Classification	0.92	0.94	0.90	0.92
ResNet Lung Classifier [13]	0.88	0.91	0.85	0.88
VGG-16 LungNet [5]	0.89	0.92	0.87	0.90
InceptionV3 LungDetect [7]	0.91	0.93	0.89	0.91

Table 5 compares existing and proposed lung cancer classification models based on Accuracy, Precision, Recall, and F1-Score. The CNN-based Classification model achieves an impressive Accuracy of 0.92 with high precision (0.94), recall (0.90), and F1-Score (0.92). ResNet Lung Classifier [13], VGG-16 LungNet [5], and InceptionV3 LungDetect [7] exhibit competitive performance with varying scores. Deploying successful lung cancer classification systems requires strategic approaches to overcome challenges such as limited dataset diversity, imbalanced class distribution, model reliability, model interpretation, and trust, adapting to evolving data, handling sensitive medical data, bridging the gap between technology and healthcare expertise, and resource constraints during deployment. By addressing these challenges, similar systems can meaningfully contribute to medical imaging, improving diagnostic capabilities and patient outcomes.

5. CONCLUSION

As a response to the growth of lung cancer, pathologists and physicians need an assistive mechanism such as computer-aided diagnosis for an efficient diagnosis and treatment. This work analyzes the scope and limitations of different optimization algorithms and their performance in combination with the pre-trained models. It is observed in case of VGG-16 and Inception v3 models the use of ADAM optimization has helped to achieve better accuracy and whereas in case of RESNET model the ADAM or the RMSprop algorithm does not helped the model to converge to an optimal solution. Despite the suggested method's great performance, it could benefit from being tested with a larger number of images from various databases. In future we plan to add more images for training the model from scratch to validate the model performance more accurately. By embracing ensemble models and tapping into the potential of diverse imaging modalities, future studies can elevate the accuracy and reliability of diagnostic systems, ultimately benefiting clinical decision-making processes.

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