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Deep learning-based approach to diagnose lung cancer using CT-scan images

Mohammad Q. Shatnawi *, Qusai Abuein, Romesaa Al-Quraan

Faculty of Computer and Information Technology, Jordan University of Science and Technology, Irbid, Jordan

A R T I C L E I N F O

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A B S T R A C T

The work in this research focuses on the automatic classification and prediction of lung cancer using computed tomography (CT) scans, employing Deep Learning (DL) strategies, specifically Enhanced Convolutional Neural Networks (CNNs), to enable rapid and accurate image analysis. This research designed and developed pre-trained models, including ConvNeXtSmall, VGG16, ResNet50, InceptionV3, and EfficientNetB0, to classify lung cancer. The dataset was divided into four classes, consisting of 338 images of adenocarcinoma, 187 images of large cell carcinoma, 260 images of squamous cell carcinoma, and 215 normal images. Notably, The Enhanced CNN model achieved an unprecedented testing accuracy of 100 %, outperforming all other models, which included ConvNeXt at 87 %, VGG16 at 99 %, ResNet50 at 94.5 %, InceptionV3 at 76.9 %, and EfficientNetB0 at 97.9 %. The study of this research is considered the first one that hits 100 % testing accuracy with an Enhanced CNN, demonstrating significant advancements in lung cancer detection through the application of sophisticated image enhancement techniques and innovative model architectures. This highlights the potential of Enhanced CNN models in transforming lung cancer diagnostics and emphasizes the importance of integrating advanced image processing techniques into clinical practice.

1. Introduction

In the past few years, artificial intelligence has taken a keen interest in discovering the relationship between inputs and outputs, which is obtained from a dynamic resistance signal, rather than finding their relationships using mathematical models without any prior assumptions [1]. Modern artificial intelligence (AI) captures interaction effects and nonlinear relationships [2]. Nowadays a wide range of applications has been developed by artificial intelligence (AI) and expanded into previously human experts-only domains, thanks to advances in digitized data acquisition, including clinical decision-making, predictive medicine, patient data analysis, and health services management [3,4].

Currently, Artificial intelligence has attracted great interest in medicine, especially when used to analyze medical images for diagnostic or predictive purposes [5]. Radiologists interpret medical images, which requires good image quality and good interpretation skills. However, the interpretation of images by humans is limited by the presence of noise, fatigue, aberrations, etc. All of these problems have been solved by developments in both imaging and computers based on the use of intelligence. Artificial intelligence is used in various radiographic tasks, such as risk evaluation, prognosis, diagnosis, detection, and response to treatment, as well as in multi-scale disease detection [6,7]. Machine learning and deep learning are the main technologies that underpin these developments. In the branch of AI known as machine learning, predictions are based on prior data [8,9]. Using the input data, machine learning may change the data in meaningful ways and discover insightful patterns and representations [10]. A subset of machine learning known as deep learning can be defined as a machine learning technique having numerous layers of easy-to-use computational components [8,11].

In recent years, deep learning has established itself as a leading machine learning tool for detecting objects and for advanced medical image analysis [12]Machine learning algorithms were first applied to the analysis and interpretation of medical images in the middle of the 1960s, and they are still in use today [13] to enhance the accuracy and effectiveness of medical imaging interpretation, computer-aided detection/diagnosis algorithms were developed [14]. In medical image processing, machine learning is frequently used to detect, classify, and diagnose cancer [12].

Cancer is a disease when a few of the body's cells grow out of control

* Corresponding author.
E-mail addresses: mshatnawi@just.edu.jo (M.Q. Shatnawi), qabuein@just.edu.jo (Q. Abuein), rmalqaran20@cit.just.edu.jo (R. Al-Quraan).

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and spread to other bodily regions [15]. The human body consists of more than 30 trillion cells [16], but when the cells age or become damaged, the human body sends signals to the cells telling them to grow through a process called cell division, which results in new cells that the body needs to function normally [17]. But when the body ignores these signals which tell cells to stop dividing through a process called programmed cell death, abnormal cells continue to multiply, leading to the formation of squamous cells known as cancerous tumors [18]. Nearly any part of the human body can develop cancer, and tumors can be classified as either malignant or non (benign) [19]. Malignant tumors, also known as cancerous tumors, can invade or spread to surrounding tissues as well as distant regions of the body, where they might grow into new tumors [20]. However benign tumors do not penetrate or spread to neighboring tissues. Benign tumors typically don't recur after removal [21].

In our study, we will focus on one of the popular Malignant cancerous tumors which are one of the leading reasons for mortality around the world which are lung cancer [22]. Cancer of the lung is a malignant tumor that produces uncontrolled growth of cells in the lung's tissues [23]If left untreated, this tumor may spread to adjacent tissues or other parts of the body [24]. The vast majority of lung cancers are carcinomas [25]. Most lung cancers are caused by tobacco smoke, smoking, air pollution, environmental exposure, mutations, and single nucleotide polymorphisms (SNPs) known to cause lung cancer [26]. When the disease affects the lungs, it leads to Pain, dyspnoea, and anorexia are the most prevalent and severe symptoms, followed by easy weariness, taste alterations, sleep issues, cough, weight gain, and loss of lowest performance status [27].

Since the past decade, lung cancer has become a sign of fear among people in all countries of the world [28]. Cancer has been described as a deadly chronic disease due to its destructive nature. This disease develops very quickly, 49%–53 % of the cancer cells are detected in stage 4 which is the last advanced stage of the disease, where the percentage of their survival does not exceed 6 % [29]. Patients with lung cancer can increase their chances of survival by a whopping 82 % if they are diagnosed early with stage 1 non-small cell lung cancer. But there are many reasons why it cannot be detected early. The most important reason is that doctors are not able to detect lung cancer manually easily from CT images in a reasonable period [30] due to the poor quality of medical images in addition to several other factors that prevent early detection of the disease, including the lack of sufficient information for diagnosis. Inappropriateness, physician stress, high diagnostic complexity, poor communication between the patient and the physician, and other factors lead to increased medical bills and deterioration of the patient's health. During this time, the malignant disease may have progressed to dangerous and difficult-to-treat stages.

As a result, machine detection has become a prerequisite for the early prediction of lung cancer, allowing doctors to diagnose lung cancer early to save patients' lives. Although previous recent research has achieved satisfactory results when using deep learning models, there is still a need to improve them to a higher level. And the efficiency of the work of the system by increasing the size and realism of the database related to lung cancer [31,32] and improving the accuracy and clarity of the lung cancer image dataset [33], thus achieving better results in terms of time and accuracy to predict this malignancy in the least amount of time and effort.

This study solves the challenge of automatic classification and prediction of CT data to distinguish between patients with lung cancer and it is types and healthy subjects. we will use different deep learning algorithms such as ConvNeXt to train our dataset that will be taken from Kaggle and compare the findings to other previous research results, trying to achieve more accurate and valuable results. before all of that, we will apply Image Enhancement techniques such as (HE, CLAHE, and noise reduction.) preprocessing methodologies such as Augmentation will be used to improve the robustness and generalization of the dataset. This will attempt to bridge the gap of blurring images found in most of the previous research. As a result, an expected accurate model will increase the chance of survival.

2. Related works

In the last decade, growing research used deep learning models to predict Lung Cancer in the early stages. The abundance of these researchers indicates that lung cancer is an interesting topic. In this chapter, the authors highlight the other researchers' works.

2.1. Related work with different datasets

Ratika et al [34] evaluated performance scores for daily activities with advanced lung cancer based on classification techniques, including Artificial neural network, Logistic Regression, Naive Bayes, Kernel SVM, KNN, and Random Forest. The results showed that Random Forest algorithms performed well in terms of accuracy at 88 %, and the Artificial neural network was found in the best prediction, giving an accuracy of 89 %.

Shaji et al [35] develop smart computer-aided systems to Improve the accuracy of diagnoses based on machine learning algorithms including Decision Tree, SVC, Logistic Regression, XgBoost, K-Nearest Neighbour, Gradient boosting, and Random Forest. Comparing various methods, the results showed that the logistic regression produced the highest accuracy of 94 %.

Wan [36]implemented Visual analyses to display the distribution and correlation between the characteristics of patients and lung cancer risk by using machine learning algorithms including logistic regression, K-nearest neighbors, random forest, and decision tree. The results showed that the accuracy values ranged from 84 % to 90 %.

Al-Tawalbeh et al [37] predicted lung cancer disease based on symptoms that appear in patients by using machine learning algorithms including support vector machine (SVM), K-Nearest Neighbour (KNN), Naïve Bayes, and narrow neural network (NNN) classifiers. The results showed that SVM achieved the highest accuracy with 92.6 % and KNN achieved the lowest accuracy with 85.87 %.

Zheng et al [38] (KD_ConvNeXt) proposed approach, KD_ConvNeXt, leverages a knowledge distillation mechanism with a Swin Transformer as the teacher network and a ConvNeXt as the student network, achieving a superior classification accuracy of 85.64 % and an F1-score of 0.7717. Our results demonstrate the effectiveness of combining knowledge distillation and convolutional neural networks for lung tumour subtype classification, outperforming existing state-of-the-art methods in terms of accuracy and robustness.

Doppalapudi et al [39]created multiple survival prediction models by comparing the performance of three of the most common deep learning architectures -Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and Artificial Neural Networks (ANN)- while comparing the performance of deep learning models against traditional machine learning models. The results showed that The deep learning models outperformed traditional machine learning models across both classifications and regression approaches. they achieved a best of 71.18 % accuracy for the classification approach and Root Mean Squared Error (RMSE) of 13.5 % and R2 value of 0.5 for the regression approach for the deep learning models while the traditional machine learning models saturated at 61.12 % classification accuracy and 14.87 % RMSE in regression.

Chaunzwa et al [40] proposed a radiomics technique to predict non-small cell lung cancer (NSCLC) tumor histology from non-invasive standard-of-care computed tomography (CT) data (CNNs) by using convolutional neural networks. The results showed that the best-performing CNN with an accuracy of 0.71($p = 0.018$) functioned as a robust probabilistic classifier in heterogeneous test sets, with qualitatively interpretable visual explanations for its predictions, according to the findings.

Beck et al [41]the author applied Deep learning-based AI algorithms

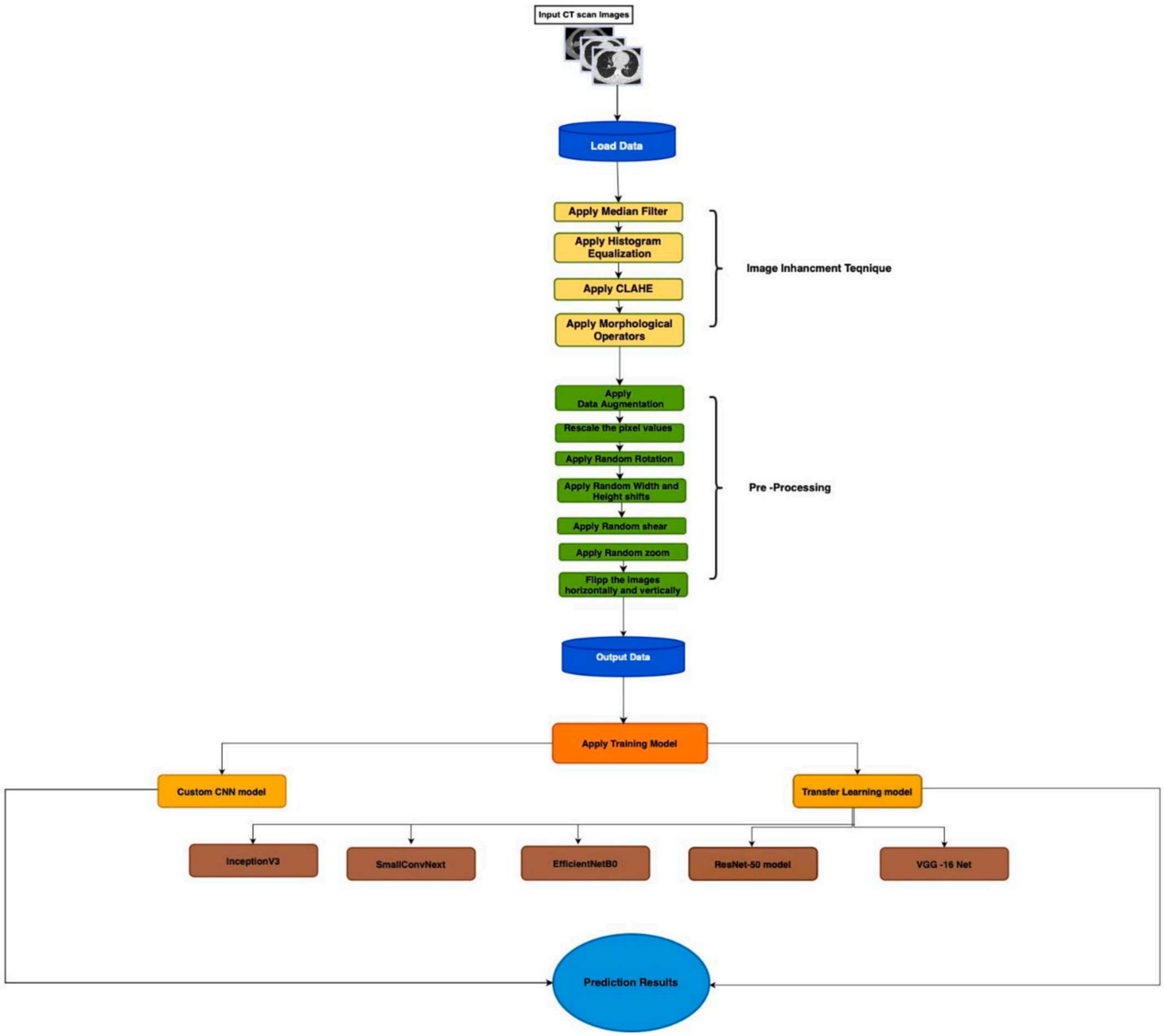

Fig. 1. Study Flow chart.

using convolutional neural networks (CNN) for pulmonary nodule (PN) detection and classification. The results show that Deep Cubical Nodule Transfer Learning Algorithm (DeepCUBIT) outperformed Deep 3D CNN without transfer learning by a wide margin. This finding highlights the importance of transfer learning in the training of domains that predict lymphovascular invasion (LVI) or nodal involvement of nodules.

Wang et al [42]proposed a Deep Learning method based on Dual-scale Categorization (DSC) with two VGG16 neural networks, one network for each scale, to evaluate PD-L1 expression critically. The result showed that the DSC-based deep learning technique had an 88 % pathologist concordance, which was greater than the 1-scale categorization-based method's 83 % concordance.

2.2. Related work with the same and similar dataset

The authors in Ref. [43]used a unique Deep Learning (DL) based method to identify lung cancer in four categories: large cell carcinoma, adenocarcinoma, squamous cell carcinoma, and normal cell. The models are trained with 1000 lung CT scan images. The dataset was collected from Kaggle chest CT-scan images. We provided a unique Deep Learning (DL) based method that was suggested by modifying the DenseNet201 model and adding layers to the original DenseNet framework to identify lung cancer disease. The best features retrieved from DenseNet201 were chosen using two feature selection techniques, and these features were then applied to several ML classifiers. Confusion matrix, ROC curve, Cohen's Matthews Correlation Coefficient (MCC), Kappa score (KS), 5-fold technique, and p-value were used to assess the system's performance. The result showed that the suggested system reached a high accuracy of 100 %, and an average accuracy of 95 % after using a 5-fold technique, a p-value of less than 0.001.

The authors in Ref. [44]used deep learning techniques. The models were trained with 1000 lung CT scan images, collected from Kaggle chest CT scan images. We provided deep learning approaches, including VGG16, InceptionV3, and Resnet50. The technique comprises accuracy levels and loss values. The result showed that the proposed CNN model achieves a better accuracy of 94.2 %, GG16 accuracy is 88.5 %, InceptionV3 accuracy is 91.4 %, and Resnet50 accuracy is 91.4 %.

The authors in Ref. [45] used deep learning techniques. This

Fig. 2. CT scan images for lung cancer patients with it types taken from the Dataset [49].

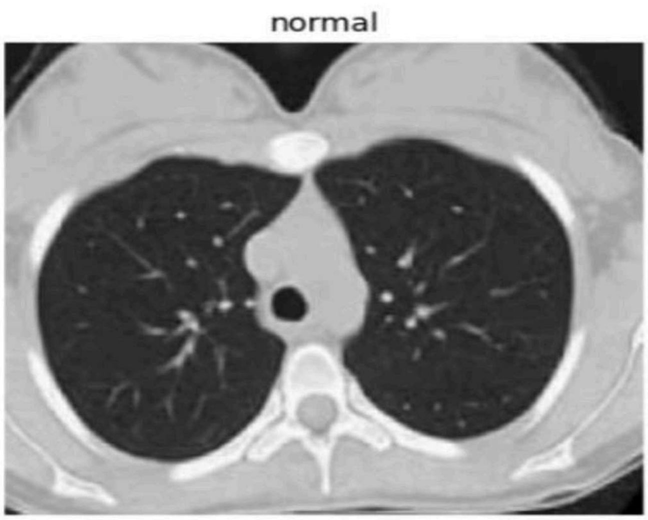

Fig. 3. CT scan image for non-lung cancer patient taken from the Dataset [49].

approach employs a collaborative deep learning (CDL) model to distinguish between cancerous and non-cancerous nodules in chest CT scans, leveraging limited available data. The models are trained with 1000 lung CT scan images. The dataset was collected from Kaggle chest CT-scan images. We provided a CDL deep-learning learning approach the CDL sub-model incorporates six feature patches to refine a network previously trained with ResNet-50. The technique comprises accuracy levels. The result showed that the proposed CDL model demonstrated a high accuracy of 93.24 %.

The authors in Ref. [46] used deep learning techniques. This research focuses on classifying lung cancer cells based on tumor cells, shapes, and biological traits in images processed through convolutional layers, and further classifies them into adenocarcinoma, large cell carcinoma, squamous cell carcinoma, or normal cell carcinoma. The models are trained with 1000 lung CT scan images. The dataset was collected from Kaggle chest CT-scan images. We provided Normalizer-Free Networks (NFNets) and EfficientNetB4, which are trained, validated, and tested over CT-Scan images. The technique comprises accuracy levels. The result showed that NFNets model classifies lung cancer images with 96 % accuracy and EfficientNetB4 with 94 % accuracy.

The authors in Ref. [47] used deep learning techniques. identify lung cancer in a dataset into the cases on the slides as one of three classes: normal, benign, or malignant. A computer system has been proposed that utilizes advanced image processing and computer-vision methods. The models are trained with more than 1100 lung CT scan images. The dataset was collected in two Iraqi hospitals and development/analysis of the IQ-OTH/NCCD lung cancer Kaggle dataset. We provided a support vector machine (SVM) after applying image-processing (feature extraction, image enhancement, and image segmentation, techniques)/computer-vision techniques. several SVM kernels and feature extraction techniques are evaluated. The result showed that the highest accuracy achieved by using this procedure on the new dataset was 89.8 % accuracy.

The authors [48] used deep learning techniques. identify lung cancer in a dataset into three classes: normal, benign, or malignant. a Computer-aided system introduced for detecting lung cancer. The models are trained with more than 1100 lung CT scan images. The dataset was collected in two Iraqi hospitals and development/analysis of the IQ-OTH/NCCD lung cancer Kaggle dataset. We provided a convolutional neural network technique with AlexNet architecture. several. The result showed that the model gives a high accuracy up to 93.5 %.

3. Research and thesis methodology

3.1. Used methodology

This chapter outlines the workflow of our study, which is depicted in Fig. 1. The workflow commences with data loading and culminates with the development and training of predictive models for lung cancer. Specifically, we will first detail the data loading process, followed by an explanation of the image enhancement techniques and data preprocessing steps employed. Additionally, we will describe the construction of our predictive models designed to diagnose Lung cancer disease (see Fig. 2).

3.2. Data loading

The dataset is obtained from Kaggle, a popular platform that hosts a diverse range of datasets for data science. It includes the "Chest CT-Scan Images Dataset," which is designed to aid research in medical imaging analysis, especially for lung diseases. Compiled by researcher Mohammad Hany, this dataset consists of 1000 CT scan images representing various types of lung cancer, available in both.png and.jpg formats. It is divided into three subsets: training, testing, and validation, and categorizes the images into four classes: Adenocarcinoma, Large cell carcinomas, Squamous cell carcinomas, and Normal cells. Visuals in the dataset provide examples of different lung cancers and a comparison with non-lung cancers.

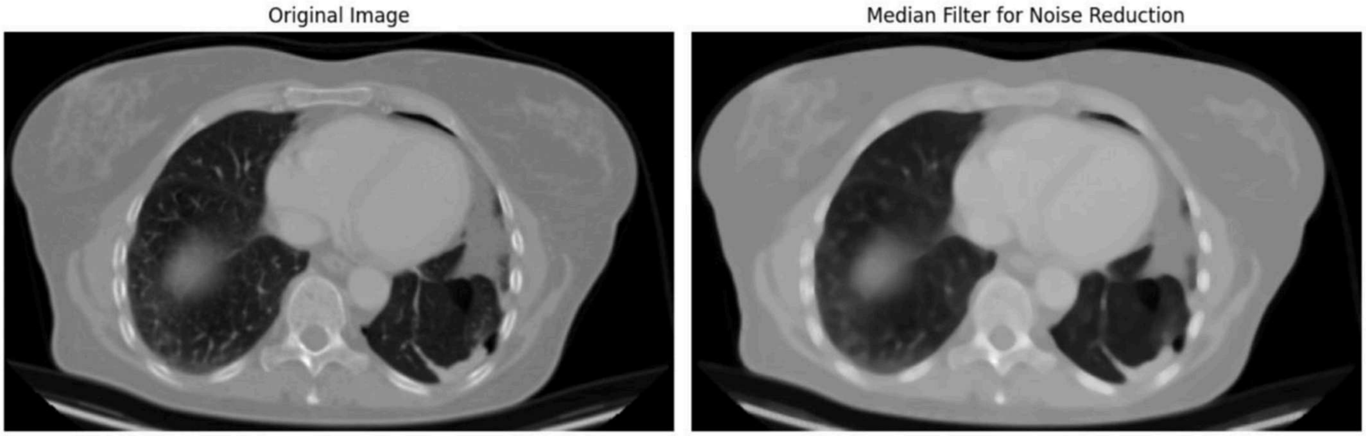

Fig. 4. CT scan image before and after applying the MF technique [49].

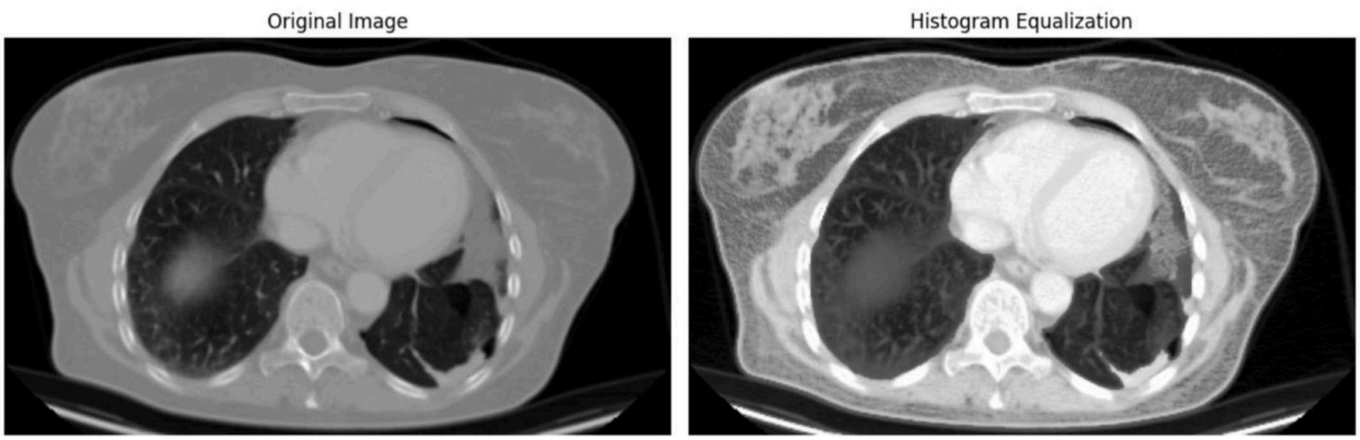

Fig. 5. CT scan image before and after applying the HE technique [49].

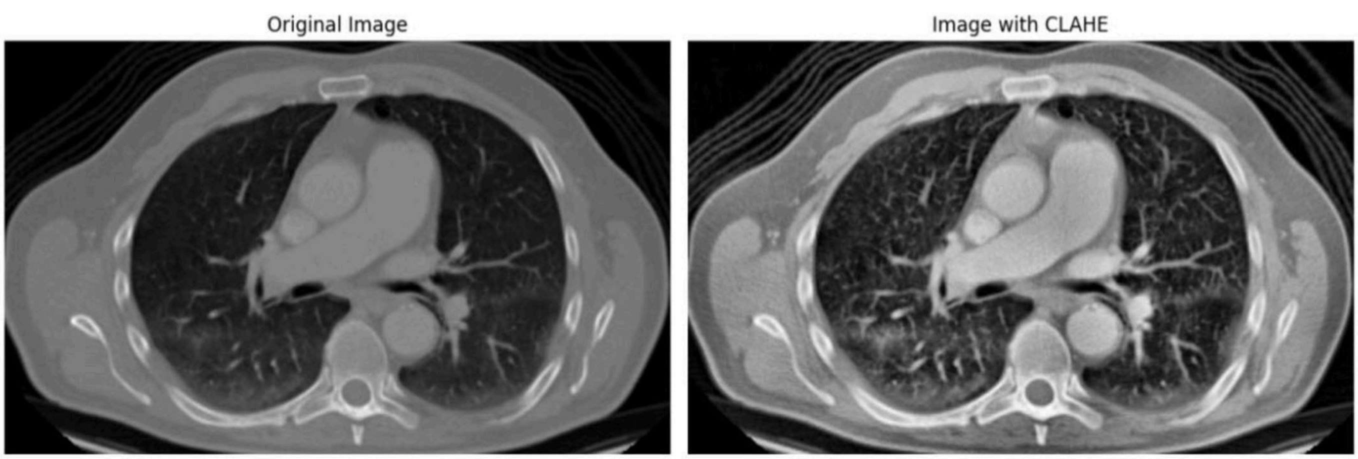

Fig. 6. CT scan image before and after applying the CLAHE technique [49].

3.3. Image enhancement techniques

CT images often suffer from degradation due to factors like noise, low contrast, and blurring, which compromise their clarity and representation of the subject. These issues are typically linked to low radiation doses and subpar enhancement algorithms. To improve CT image quality, various techniques can be employed to reduce noise, enhance contrast, and optimize overall image clarity. Critical to achieving the best results is the careful adjustment of these techniques based on the specific characteristics of the images and the desired enhancement level. Effective medical image enhancement, which includes methods such as histogram equalization (HE) and contrast-limited adaptive histogram equalization (CLAHE), is essential for helping physicians make accurate diagnoses by improving image visibility and providing more detailed information (see Fig. 3).

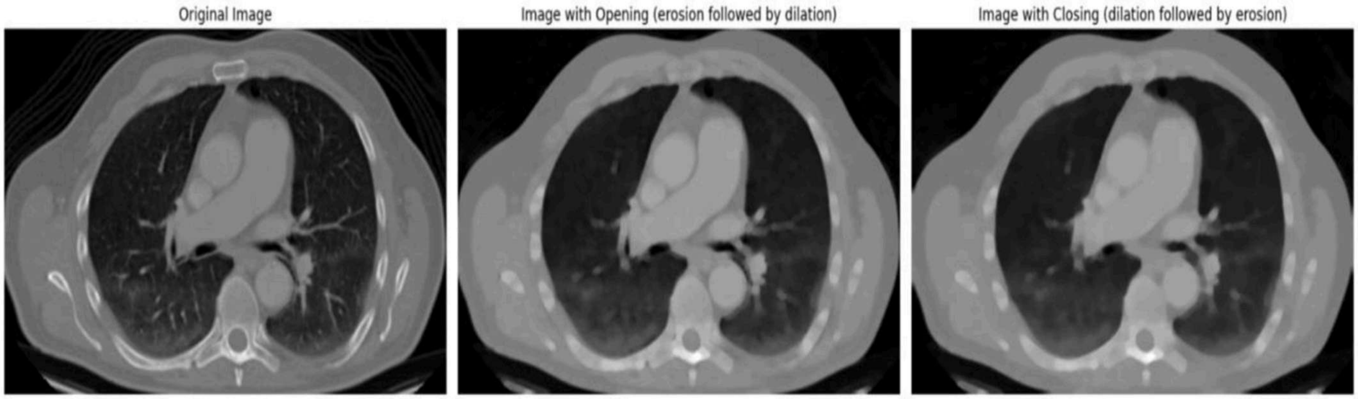

Fig. 7. CT scan image before and after applying the Dilation and Erosion techniques [49].

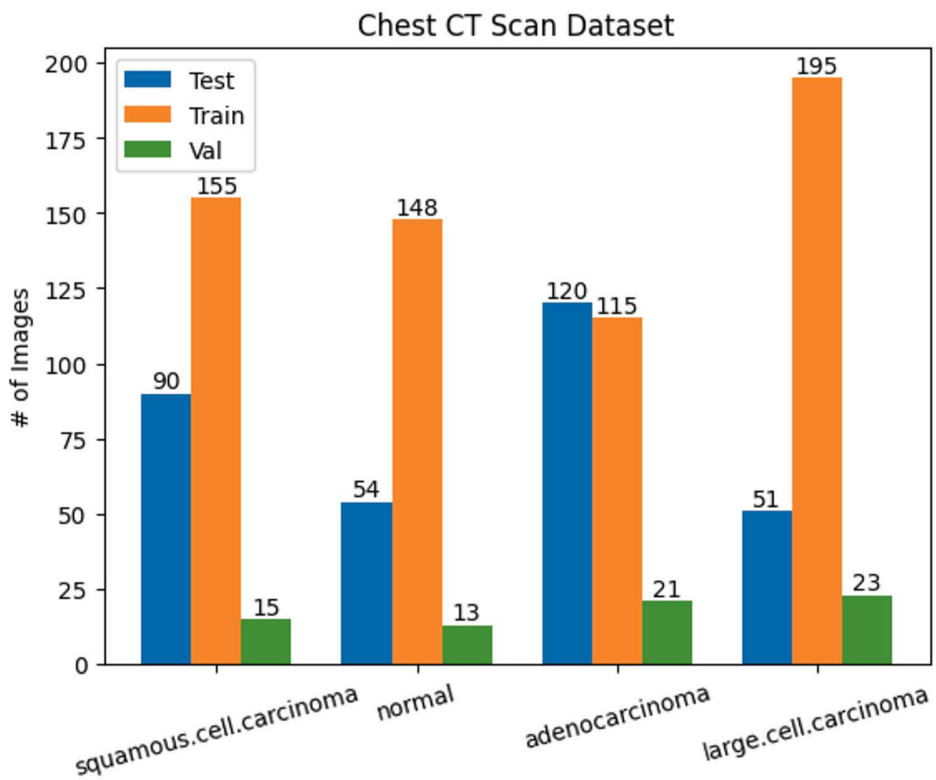

Fig. 8. Training, testing, and validating data distribution for each type [49].

3.3.1. Median Filter (MF)

The median filter is a noise reduction technique that replaces abnormal pixel values with a median value from surrounding pixels, effectively removing salt-and-pepper and Gaussian noise. It can be used as a preprocessing step for CT scan images to reduce noise and prepare the image for further enhancement, improving image quality [50]. Fig. 4 illustrates an example CT scan image from the dataset before and after applying the Median Filter technique.

3.3.2. Histogram Equalization (HE)

Histogram Equalization (HE) is a method used to enhance the contrast and brightness of an image, improving the visibility of structures and details [51]. It adjusts the distribution of pixel values to increase the dynamic range of the histogram [52]. HE is especially effective for low-contrast images, such as CT scans [51]. When applied after noise reduction, HE can significantly enhance the overall appearance of the image. Fig. 5 demonstrates a CT scan image from the dataset before and after applying the Histogram Equalization technique.

3.3.3. Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE (Contrast Limited Adaptive Histogram Equalization) is a technique that enhances image contrast and details by dividing the image into small regions. It can be used after Histogram Equalization to improve specific areas of an image. The CLAHE process involves 5 steps: histogram adjustment, mapping function application, and bilinear interpolation to remove block artifacts. By dividing the image into 64 blocks, each 8x8 pixels in size, CLAHE enhances contrast and details [53]. It also limits contrast amplification in homogeneous regions to prevent noise amplification [50,54]. Fig. 6 illustrates an example of a CT scan image from the dataset before and after applying the CLAHE technique.

3.3.4. Morphological Operators (MO)

Morphological operations can be used to further enhance image

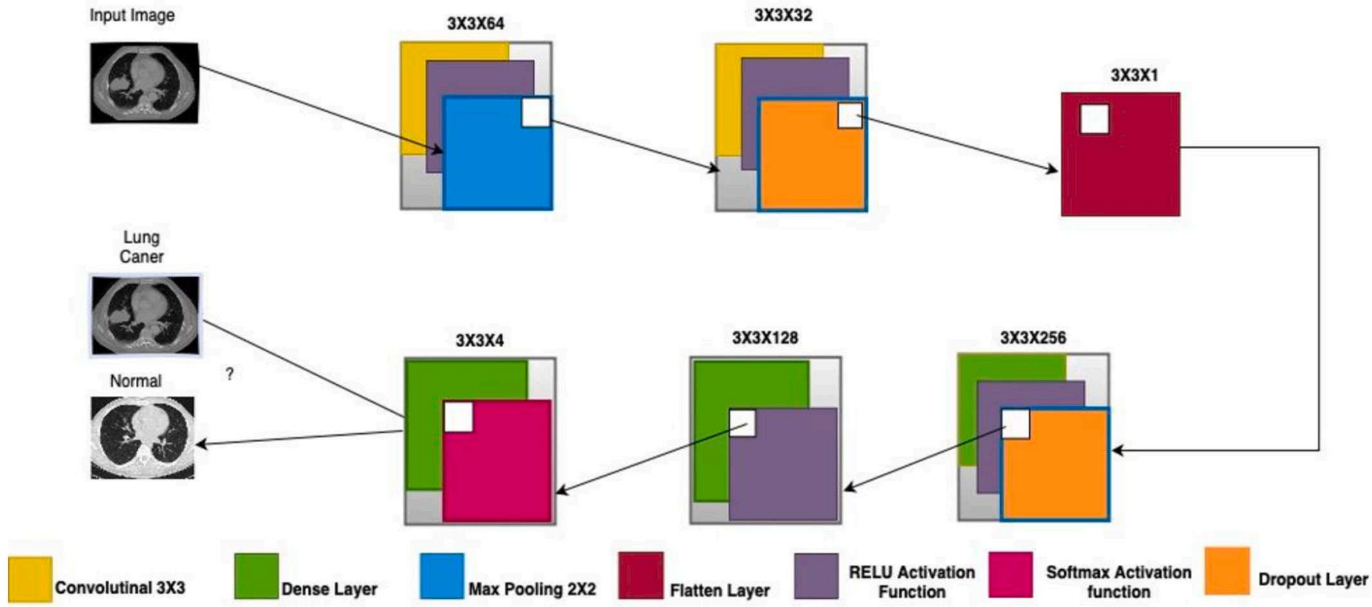

Fig. 9. Enhanced CNN model architecture of lung cancer prediction.

details and contrast, particularly after applying CLAHE [55]. Dilation increases the visibility of features and fills in small gaps, while Erosion removes small objects and islands, allowing only substantive features to remain. These filters are effective in edge detection, refining the enhancement process by combining dilation and erosion [56]. This technique is commonly used in medical imaging to sharpen photos by finding edges using gradient-based operators and applying morphological filters. Fig. 7 illustrates an example of a CT scan image from the dataset before and after applying the Dilation and Erosion techniques.

3.4. Data pre-processing

3.4.1. Data augmentation

The data augmentation technique enhances the volume and complexity of training data for lung cancer detection using CT scan images. It aims to fine-tune model parameters, reduce the gap between training and validation sets, and lower validation error, especially when dealing with small datasets and variability in image acquisition. This study applies several augmentation strategies:

- Resizing: Adjusting CT scan images to a fixed size of 224x224 pixels to improve computational efficiency.
- Shear Range: Implementing a 20 % shear transformation to improve the model's robustness to angled lesions.
- Horizontal Flip: Flipping images horizontally to help the model recognize lesions from different orientations.
- Vertical Flip: Flipping images vertically for improved recognition of lung lesions.
- Rescale: Normalizing pixel values to a range of 0–1 to enhance the model's learning of robust features and minimize overfitting.

These strategies increase training data diversity and enhance model generalizability, leading to better performance on unseen data, which is critical for accurate lung cancer diagnosis and treatment.

3.5. Models building

This section details the development of models for predicting lung cancer from the provided datasets. An Enhanced Convolutional Neural Network (CNN) was created and developed, alongside the use of pre-trained models such as ConvNeXtSmall, Vgg16, ResNet50, InceptionV3, and EfficientNetB0. The dataset of 1000 CT scans was randomly shuffled and divided into varying-sized training, testing, and validation sets, with the distribution depicted in Fig. 8.

3.5.1. Enhanced CNN model architecture

One kind of neural network model that is especially well suited for image classification tasks and analysis of visual imagery is the convolutional neural network (CNN). It has demonstrated greater proficiency in a range of tasks, such as object recognition, picture classification, and medical image analysis, which may be used to identify lung cancer in CT scan images, among other things (83,84).

This research introduces a multi-class lung abnormality classifier using a customized Convolutional Neural Network (CNN) architecture, comprising a total of eight layers.

1. Layer 1: A convolutional layer with 64 filters (3x3) and ReLU activation extracts features from input images with a shape of (224, 224, 3), followed by a max-pooling layer (2x2) to reduce spatial dimensions.
2. Layer 2: Another convolutional layer featuring 32 filters (3x3) with ReLU activation, succeeded by another max-pooling layer (2x2) for further dimensionality reduction.
3. Layer 3: A similar convolutional layer with 32 filters (3x3) and ReLU activation, followed by a dropout layer with a rate of 0.4 to combat overfitting.
4. Layer 4: A dropout layer helps further mitigate overfitting.
5. Layer 5: The output from the convolutional layers is flattened into a 1D array for the dense layers.
6. Layer 6: A dense layer with 256 neurons and ReLU activation connects the previous layers and extracts more features, followed by another dropout layer (0.4) to prevent overfitting.
7. Layer 7: A dense layer with 128 neurons and ReLU activation.
8. Layer 8: The final dense layer, consisting of 4 neurons with a SoftMax activation function, produces a probability distribution over the output classes. The model architecture is visualized in Fig. 9.

3.5.2. ConvNeXtSmall model architecture

Facebook AI Research (FAIR) unveiled ConvNeXt, a kind of neural network architecture, in 2022 [58]. It is a next-generation convolutional neural network design that has been more and more well-liked in the last few years, especially for computer vision applications like object

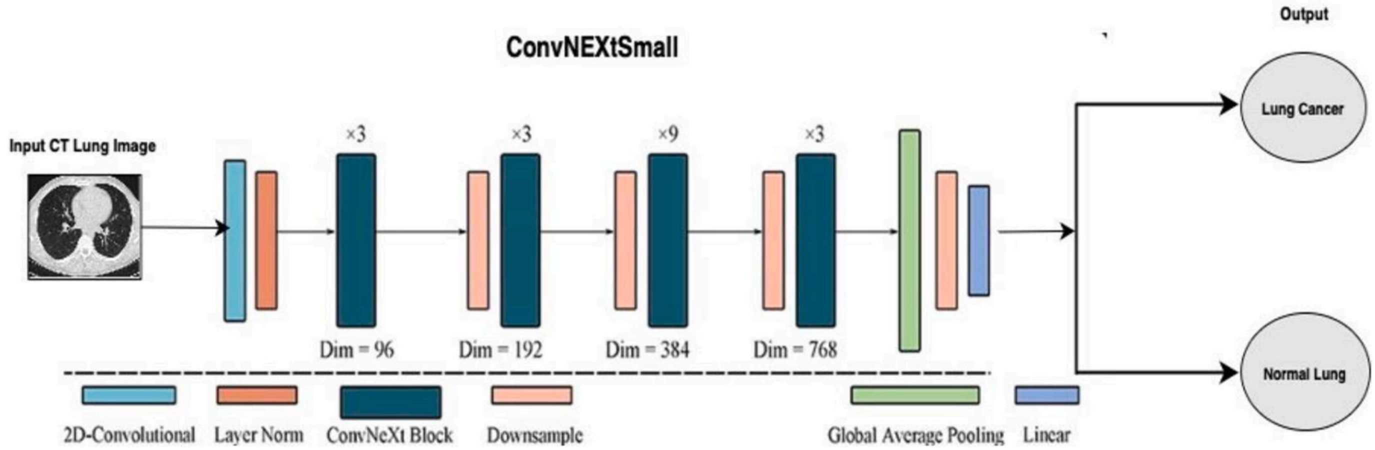

Fig. 10. ConvNeXtSmall model architecture of lung cancer prediction [60].

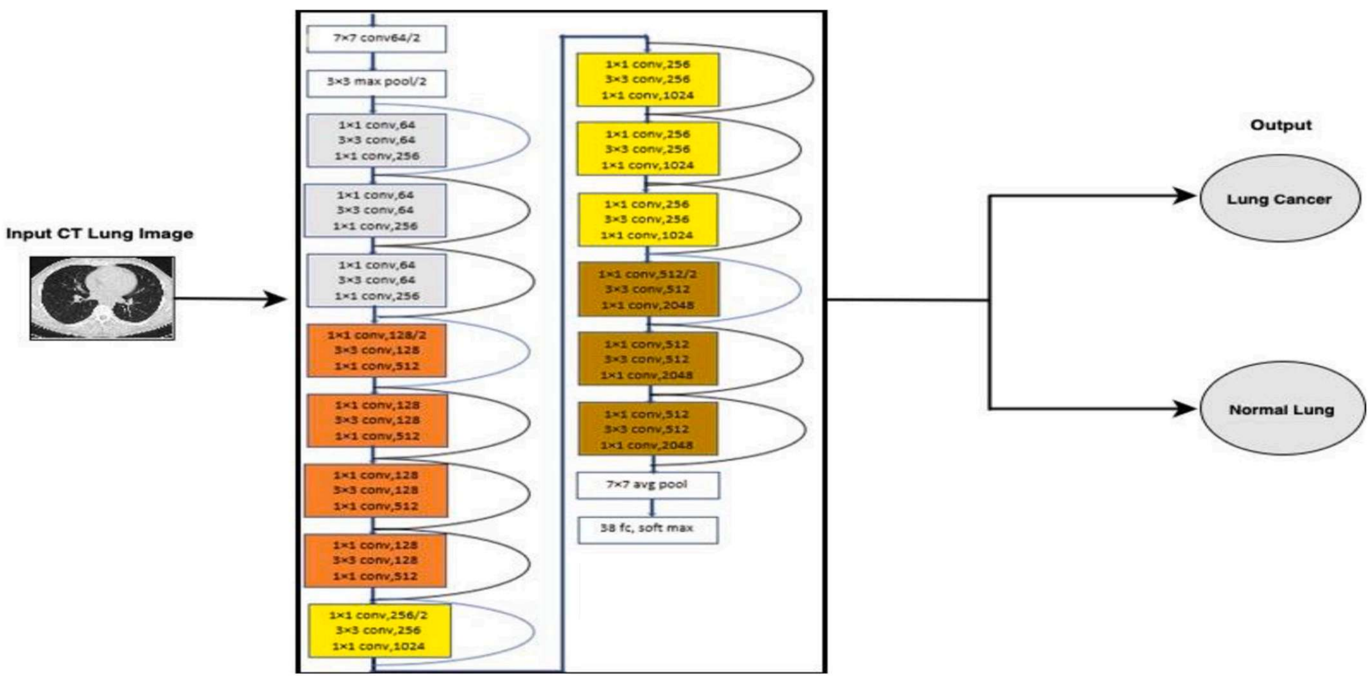

Fig. 11. ResNet50 model architecture of Lung cancer prediction [64].

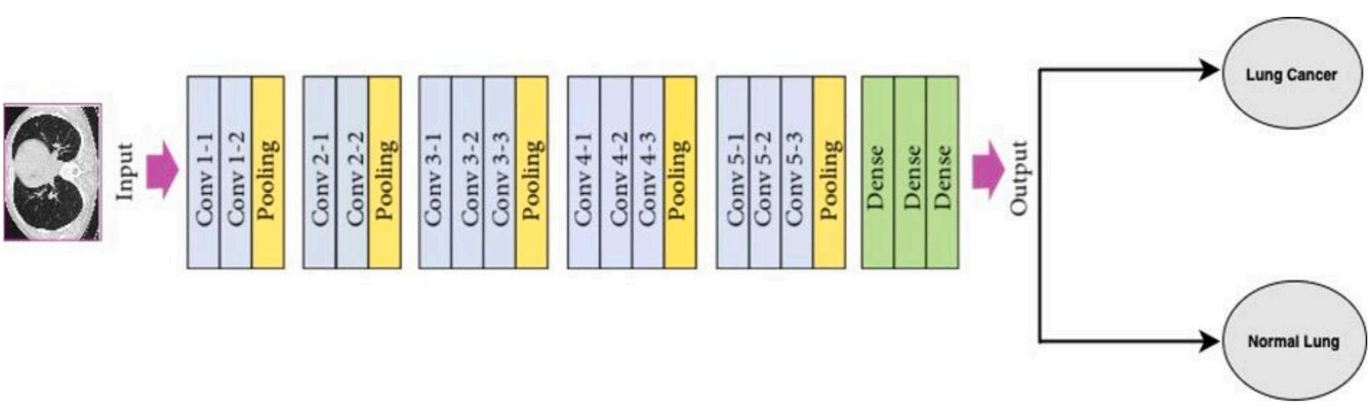

Fig. 12. VGG16 model architecture of Lung Cancer prediction [67].

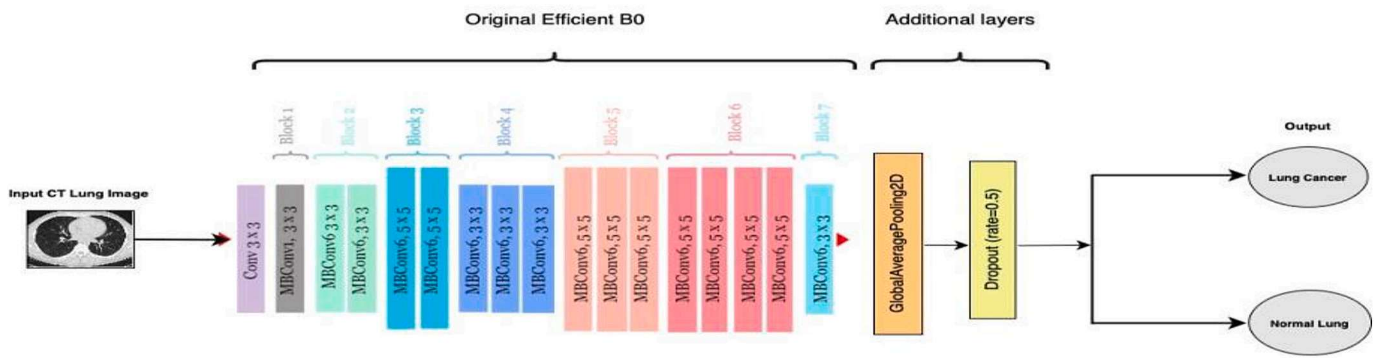

Fig. 13. EfficientNetB0 Modified model architecture of Lung Cancer prediction [70].

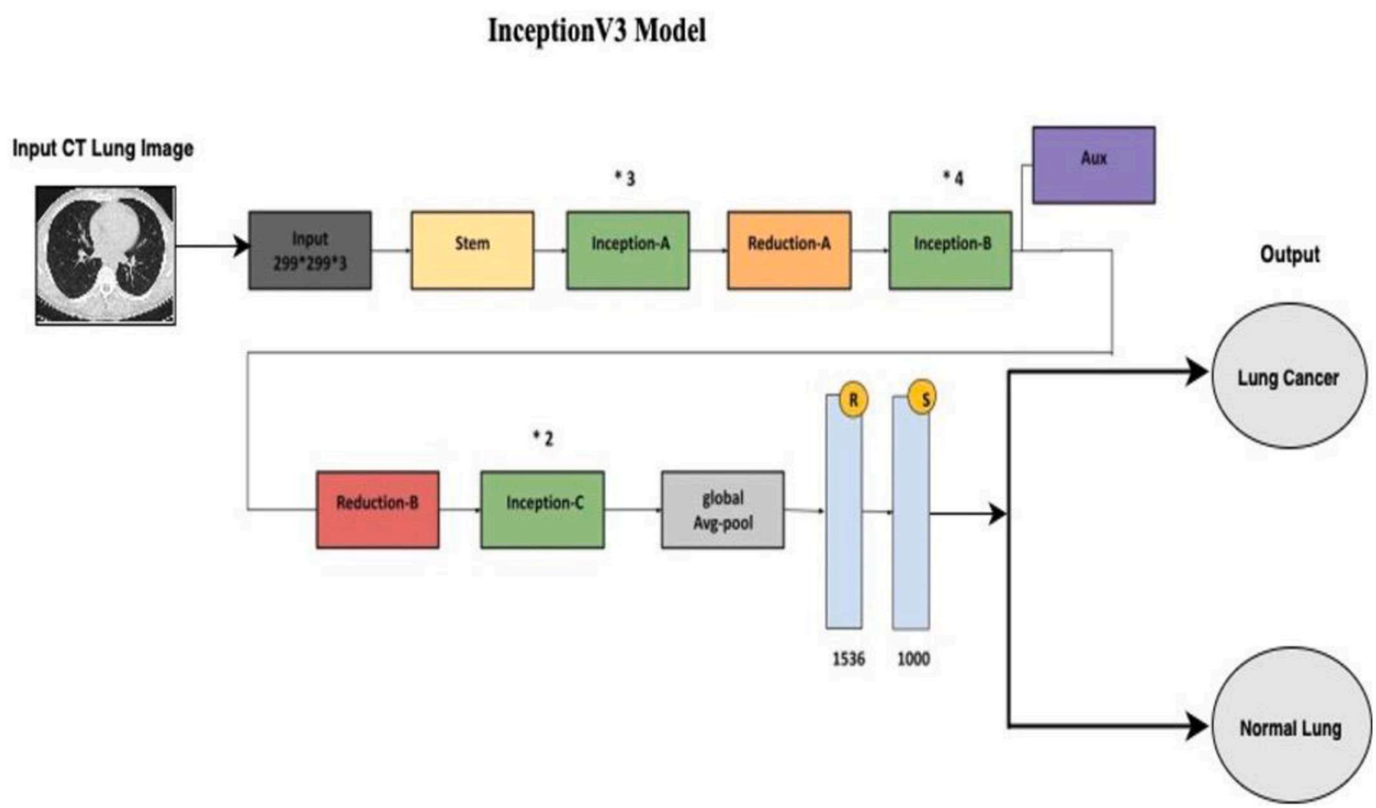

Fig. 14. InceptionV3 model architecture of Lung Cancer prediction [74].

Table 1
The Percentages and Number of images in the training, testing, and validating dataset.

Dataset	Number of Images	Splitting percentage
Training set	613	70 %
Testing set	315	20 %
Validating set	72	10 %

identification and picture categorization [59].

ConvNeXtSmall is a pre-trained model utilized for predicting lung cancer from CT scan images. Introduced in 2022, it is a smaller and more efficient variant of the ConvNeXt architecture, featuring a convolutional neural network (CNN) with 50 layers, including depth-wise separable convolutions and channel shuffle capabilities for effective feature extraction. The model includes a pooling layer to reduce spatial dimensions and two fully connected (FC) layers for classification, outputting values between 0 and 4 to indicate lung cancer classification.

In this study, the ConvNeXtSmall model served as the base, enhanced with additional layers, including dropout layers, batch normalization, and dense layers with ReLU activation. The model was compiled using the Adam optimizer and categorical cross-entropy loss function, and it was trained for 150 epochs. The model architecture is illustrated in Fig. 10.

3.5.3. ResNet50 model architecture

In 2015, Microsoft Research introduced the Residual Neural Network (ResNet) architecture to solve the issue of disappearing gradients in deep neural networks [61]. ResNet50 is a specific variation of the ResNet architecture that uses shortcut connections called residual connections [62]. Therefore, a ResNet model with 50 layers is referred to as ResNet50 [63].

The ResNet50 model was employed as a pre-trained model for predicting lung cancer in this study due to its efficiency in extracting high-quality image features. It contains fifty convolutional layers, one pooling

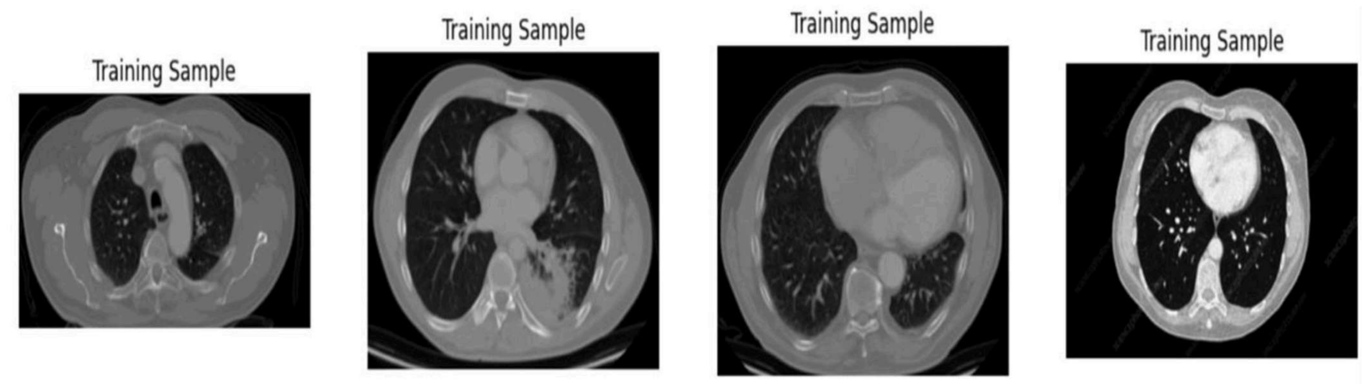

Fig. 15. Sample of CT scan images from the training dataset.

Fig. 16. Sample of CT scan images from the testing dataset [49].

Table 2
Training hyperparameters and loss function for training.

Hyperparameter	Value
Optimizer	Adam
Loss function	categorical_crossentropy
Metrics	accuracy, precision, recall
Early Stopping	True
Patience	20
Number of epochs	150
Batch size	(default: 32)

Table 3
Confusion Matrix [57].

	Predictive Class Positives	Predictive Class Negative
Actual Class Positives	True Positive (TP)	False Negative (FN)
Actual Class Negative	False Positive (FP)	True Negative (TN)

Table 4
The average of the Performance Measures results for the models.

Models	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Enhanced CNN	99.2 %	98.0 %	98.4 %	100 %
ConvNeXt	86.7 %	89.5 %	88.0 %	87 %
VGG16	99.1 %	98.4 %	99.6 %	99 %
ResNet50	93.1 %	76.4 %	85.2 %	94.5 %
IneseptionV3	48.5 %	93.2 %	77.1 %	76.9 %
EfficientNetB0	99.5 %	99.2 %	99.6 %	97.9 %

layer, and two fully connected (FC) layers. The pooling layer helps summarize features, reduce parameters, speed up computation, and mitigate overfitting, while the convolutional layers focus on feature extraction. The FC layers perform classification based on the extracted features.

In the initial training phase, 70 % of the lung scans were used to train the original ResNet50 model, and its performance was evaluated on the remaining 30 %. The model was built using the binary cross-entropy loss function and the Adam optimizer and trained for 150 iterations. During classification, filters are applied to the images, and the SoftMax layer generates output values between 0 and 1 to indicate the likelihood of lung cancer presence. As illustrated in Fig. 11 the trained model effectively identifies lung cancer in CT scan images by analyzing the input data and producing classification results.

3.5.4. VGG16 model architecture

The VGG16 model, which consists of 16 trainable weight layers—13 convolutional layers and 3 fully connected layers—is renowned for its simplicity and efficacy. Little 3x3 filters with a stride of 1 and a padding of 1 are used in the convolutional layers of the VGG16 architecture [65, 66].

VGG16 is a widely used deep learning model known for its strong performance in image recognition, particularly beneficial for small datasets and understanding network architecture. Its deep convolutional neural network design enables effective pattern recognition in medical images, such as CT scans and chest X-rays, making it suitable for identifying features indicative of lung cancer, like nodules or tumors. In this study, the VGG16 model was employed as a pre-trained model for predicting lung cancer from CT scan images. Modifications included freezing the initial layers and focusing on the prediction layers. The architecture comprises five convolutional blocks with convolutional and pooling layers, followed by dense layers, including ReLU, dropout, and a

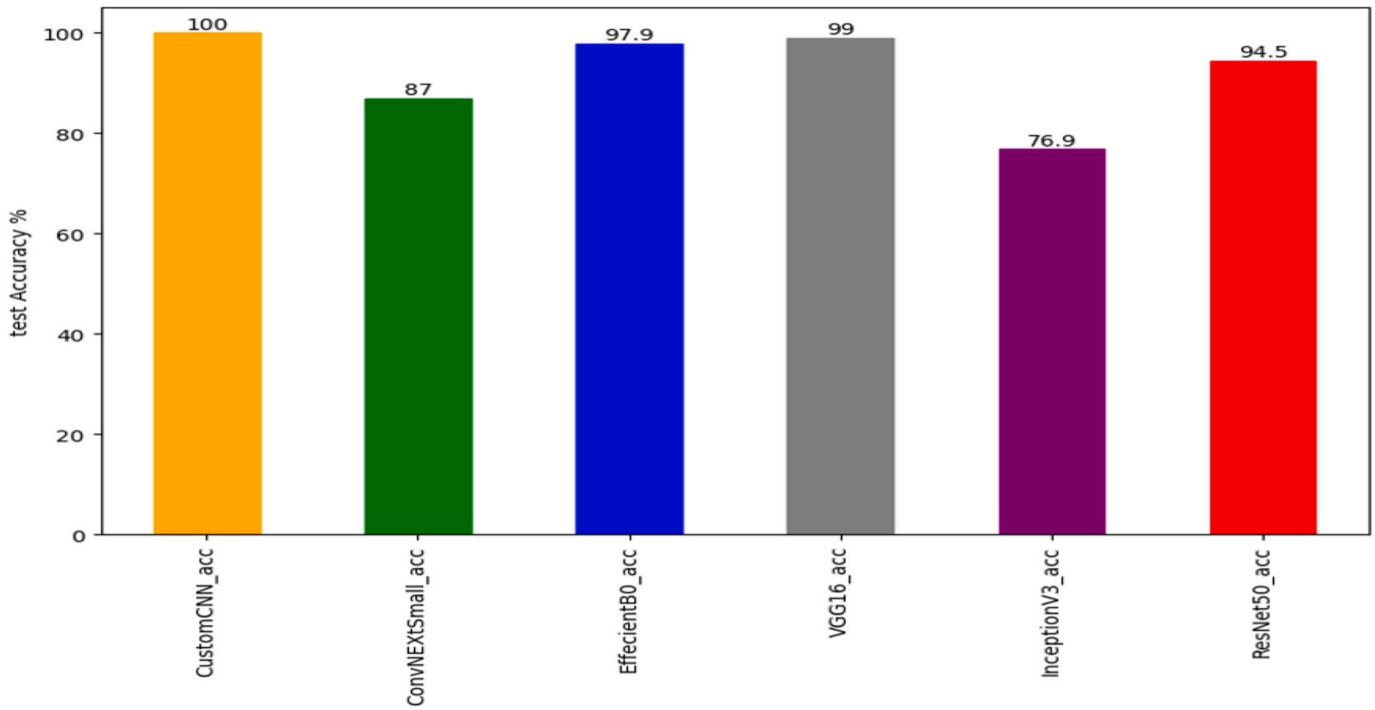

Fig. 17. Comparison of Performance Accuracy for all models.

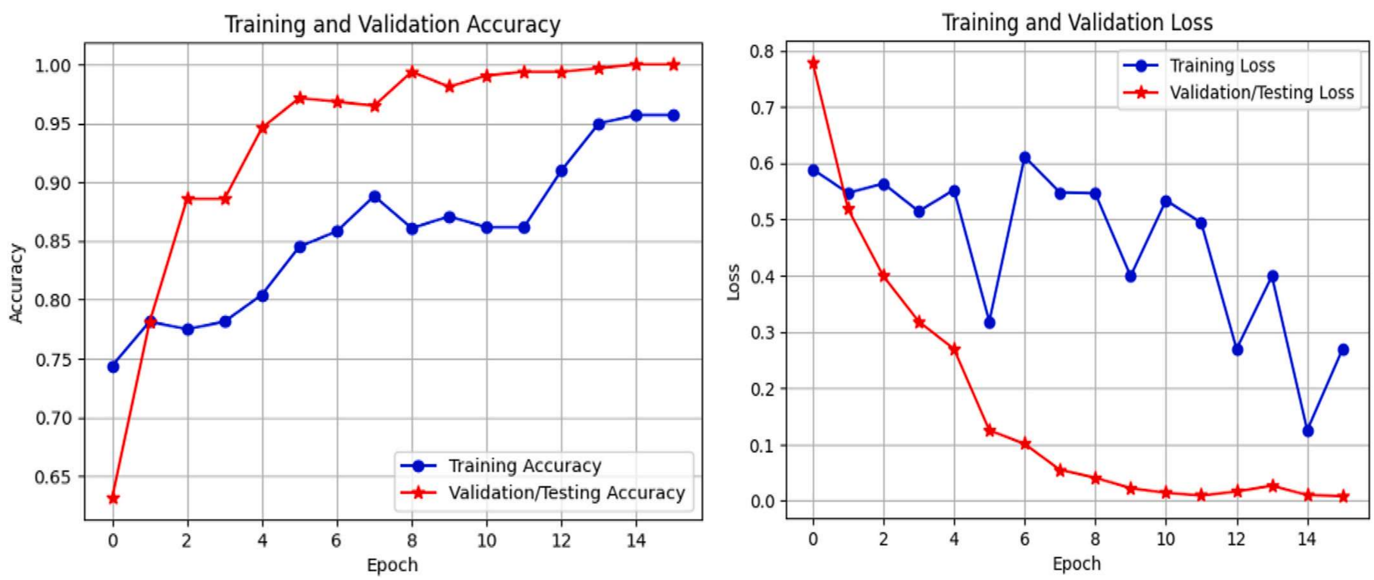

Fig. 18. The Enhanced CNN model Accuracy and Loss during training and testing.

final SoftMax layer for cancer probability prediction.

The model was trained on a dataset of lung CT images, using 70 % for training and 30 % for validation, with the Adam optimizer and categorical cross-entropy loss function. Early stopping was implemented with a patience of 20 epochs to avoid overfitting. Model performance was evaluated using accuracy, precision, recall, and loss metrics, with the architecture depicted in Fig. 12.

3.5.5. EfficientNetB0 model architecture

Compared to other state-of-the-art convolutional neural network (CNN) architectures, EfficientNet has distinguished itself as a top-performing CNN design due to its exceptional capacity to produce high accuracy with notably lower processing requirements and parameter counts [68]. Because of this special quality, it's a desirable choice in situations when computing power is scarce, like in embedded systems or mobile devices [69].

The EfficientNetB0 model was utilized as a pre-trained base for lung cancer classification due to its high accuracy and computational efficiency in image tasks. Modifications included adding GlobalAveragePooling2D and Dropout layers to address overfitting and enhance model robustness. The model was trained on 70 % of a lung CT-scan image dataset and evaluated on the remaining 30 %, using the Adam optimizer and categorical cross-entropy loss function. Designed for 224x224x3 input images, it employs multiple convolutional layers with a 3x3 receptive field for feature extraction and was trained for 100 epochs., with its architecture detailed in Fig. 13.

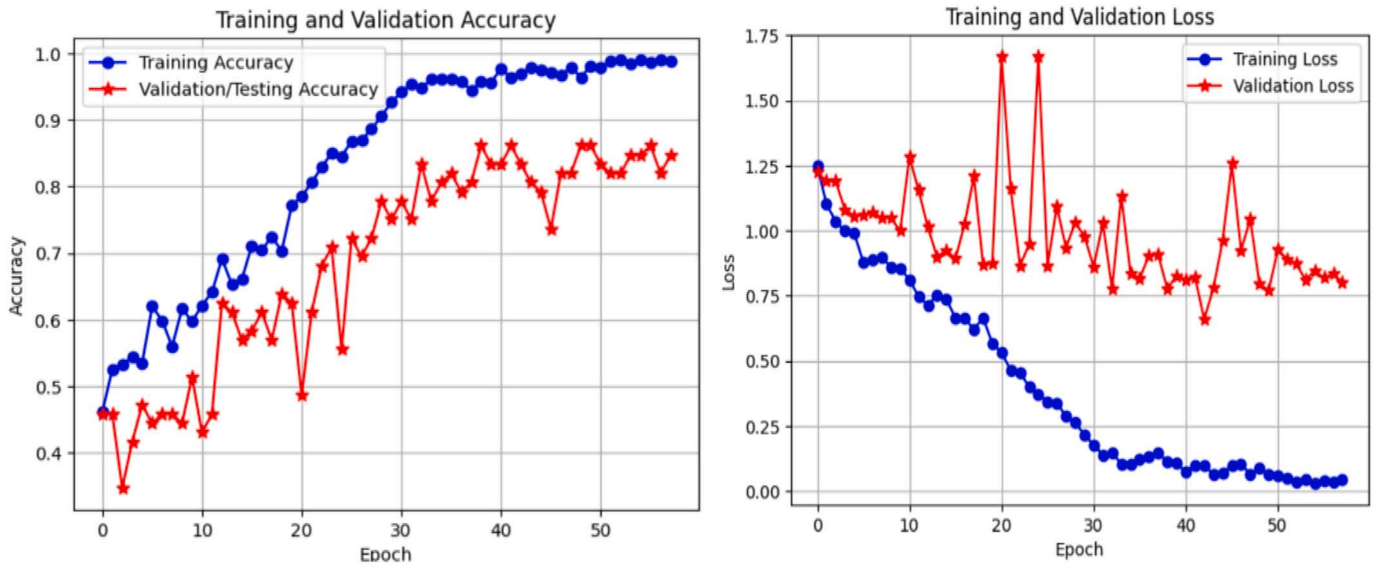

Fig. 19. The ConvNeXtSmall model Accuracy and Loss during training and testing.

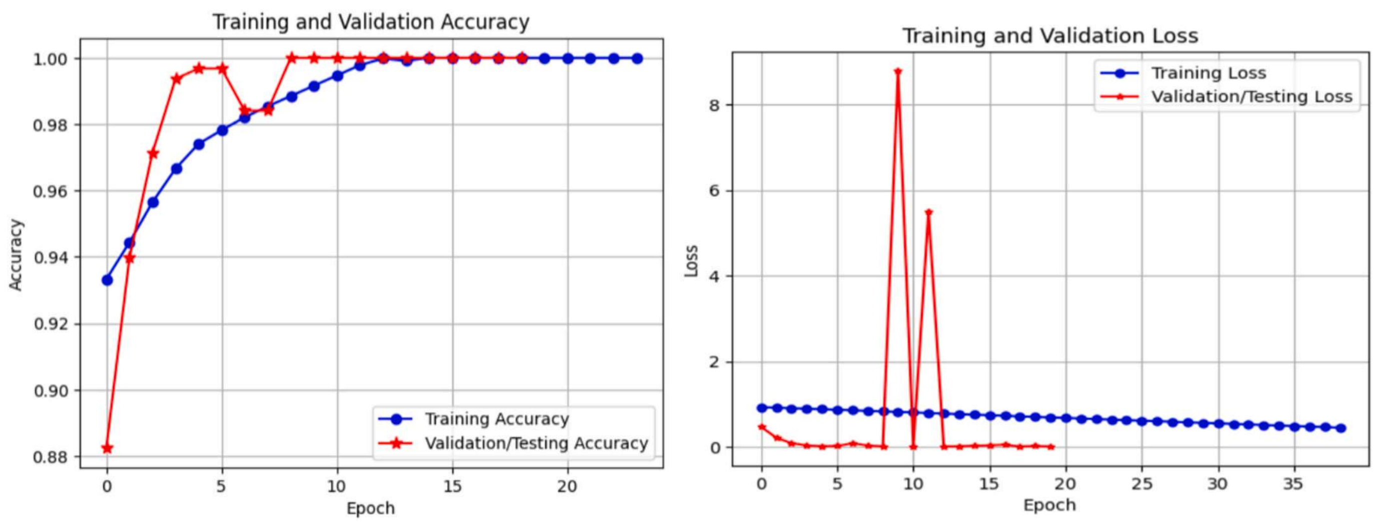

Fig. 20. The VGG16 model Accuracy and Loss during training and testing.

3.5.6. InceptionV3 model architecture

For a variety of computer vision applications, such as object detection, in computer vision, the Inception V3 model has shown to be an invaluable resource, especially when it comes to the interpretation of medical images [71,72]. It is a valuable option for several applications, such as object recognition, segmentation, and image captioning, due to its capacity to extract characteristics from images [73].

The InceptionV3 model was used as a pre-trained framework to predict lung cancer from medical images. The initial layers were frozen to retain pre-trained knowledge while focusing on the prediction layers. InceptionV3 features 92 layers, including convolutional, pooling, and concatenation operations, with a final SoftMax layer that provides a probability score for classification as lung cancer or normal lung. The model was trained on 70 % of the dataset and evaluated on the remaining 30 %, utilizing the Adam optimizer and categorical cross-entropy loss function over 150 epochs. Early stopping was implemented to halt training if validation loss plateaued for 20 consecutive epochs. The trained model successfully classified CT scan images of lung cancer patients, as illustrated in Fig. 14.

4. Experiments and results

To achieve the study's objectives, two experiments were conducted to detect lung cancer from chest CT scan images. The first involved creating an Enhanced Convolutional Neural Network (CNN) from scratch, while the second used five pre-trained models—ConvNeXtSmall, VGG16, ResNet50, InceptionV3, and EfficientNetB0—optimized for the dataset. Model performance was then evaluated using a testing dataset. The experiments were coded in Python, known for its readability and versatility, and executed on the Kaggle platform, which offers a diverse range of datasets for research purposes.

4.1. Experiment dataset

The dataset was categorized into four classes: adenocarcinoma (338 images), large cell carcinoma (187 images), squamous cell carcinoma (260 images), and normal (215 images). The dataset was divided as follows: 70 % for training, 20 % for testing, and 10 % for validation as shown in Table 1. Additionally, Fig. 15 presents samples from the

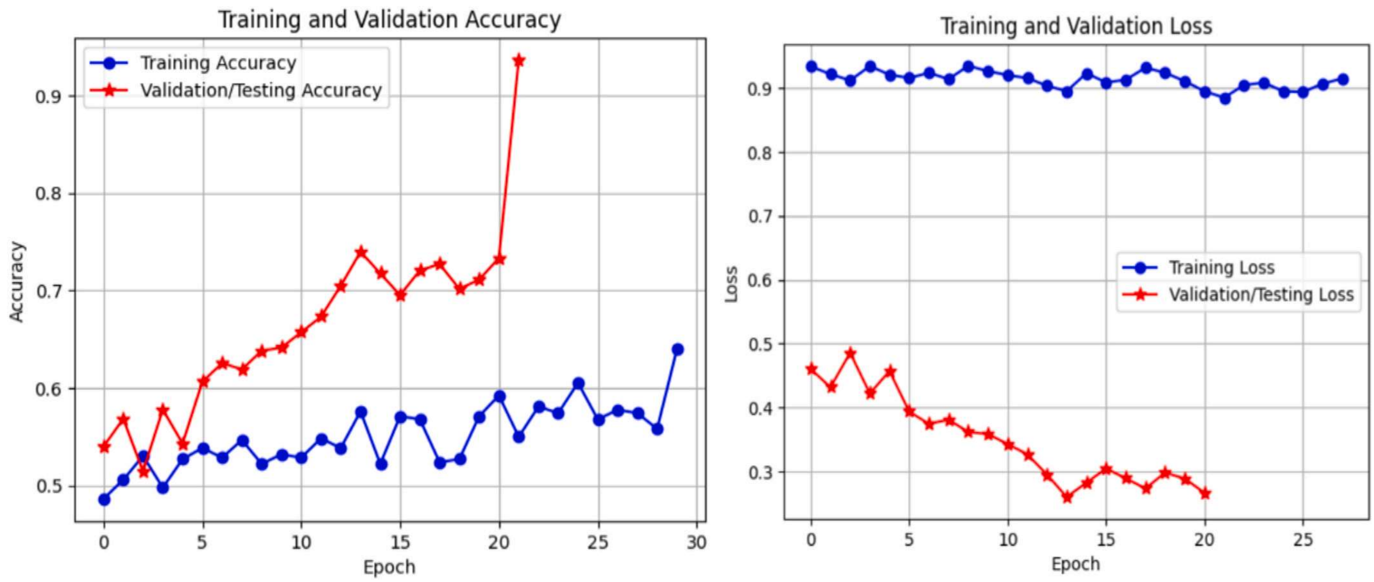

Fig. 21. The ResNet50 model Accuracy and Loss during training and testing.

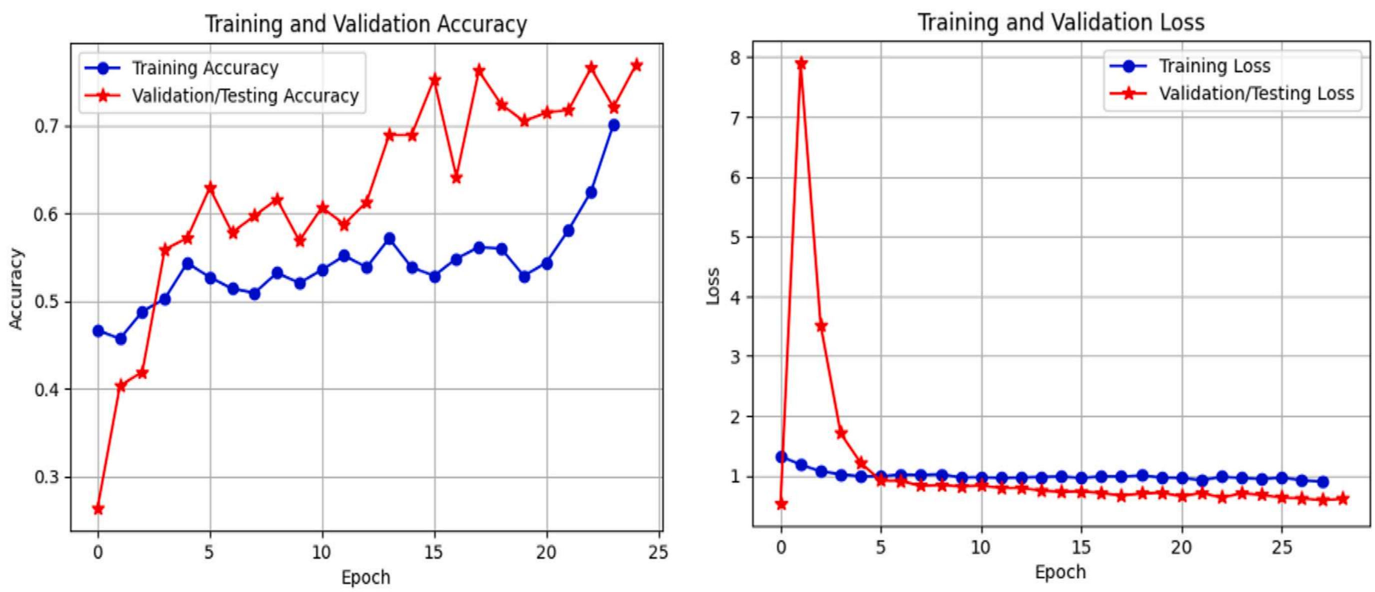

Fig. 22. The InceptionV3 model Accuracy and Loss during training and testing.

training dataset, while Fig. 16 shows samples from the testing dataset.

4.2. Hyperparameters

A specific set of hyperparameters was selected to optimize model performance. The training was conducted over 150 epochs with early stopping to prevent overfitting, monitoring validation loss, and stopping if no improvement was observed after 20 epochs. While the default input size was 224x224 for most models, the ConvNeXt model utilized an increased size of 256x256 to assess performance benefits. The Adam optimizer with a standard learning rate facilitated stable training. Metrics such as categorical_crossentropy loss, accuracy, precision, and recall were used to evaluate model effectiveness. These hyperparameters were essential in achieving high-quality results. Table 2 presents the training hyperparameters and loss functions utilized.

4.3. Performance evaluation metrics

The performance of our models was evaluated using a confusion matrix, which is effective for assessing classification accuracy. Our study focused on four classes: adenocarcinoma, large-cell carcinoma, squamous cell carcinoma, and normal lung tissue. The confusion matrix summarizes predictions, providing counts for True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). TP counts correct predictions for any of the cancer types or normal tissue, while TN indicates accurate non-cancer predictions. FP and FN represent incorrect predictions for the respective classes. Table 3 presents the confusion matrix for our study.

We used four key metrics—accuracy, precision, recall, and F1-score—to evaluate the performance of our classification model for predicting four classes: adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal tissue. These metrics are defined as follows:

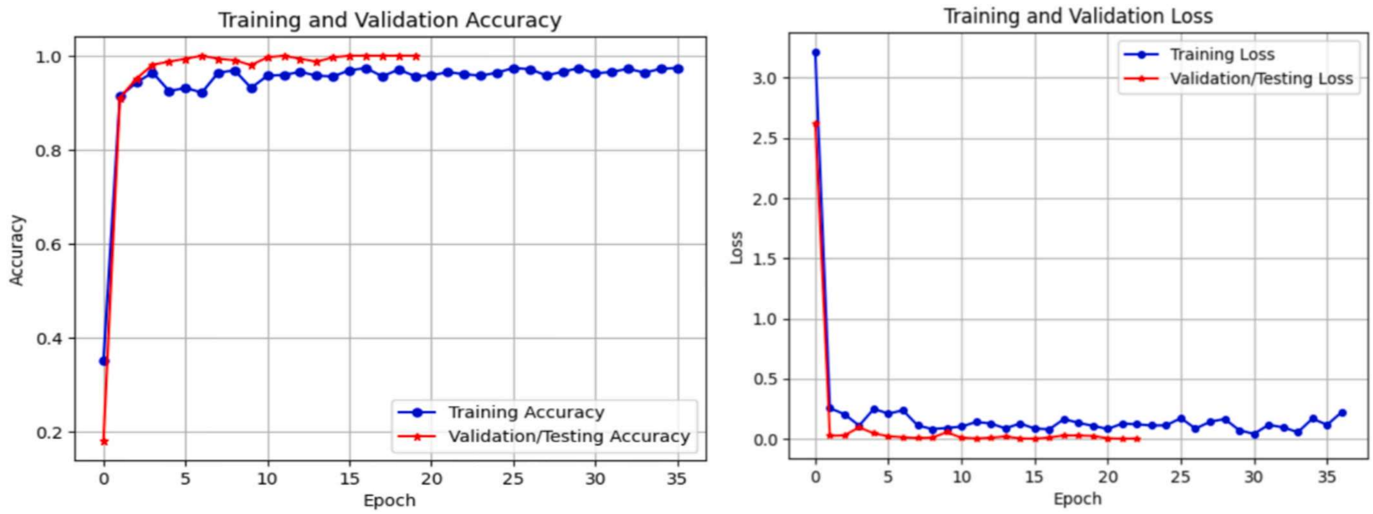

Fig. 23. The EfficientNetB0 model Accuracy and Loss during training and testing.

1. Accuracy: measures the proportion of correctly classified instances (Equation (1)).
2. Recall: indicates the proportion of true positive predictions among actual positive cases (Equation (2)).
3. Precision: represents the proportion of true positive predictions among all positive predictions (Equation (3)).
4. F1-Score: is the harmonic mean of precision and recall, providing a balanced assessment (Equation (4)).

$$Accuracy = TP/(TP + FP) \tag{1}$$

$$Recall = TP/(TP + FN) \tag{2}$$

$$Precision = TP/(TP + FP) \tag{3}$$

$$F1\text{-}Score = (2 * Precision * Recall / (Precision + Recall)) \tag{4}$$

These metrics offer a comprehensive evaluation of the model's predictive capabilities. Collectively, they evaluate the model's reliability and effectiveness in clinical applications where accurate diagnosis is essential.

4.4. Models results

After training our models on the training dataset. we tested it using the testing and validation datasets, which comprised 30 % of the images. We evaluated the performance of our models using accuracy, recall, precision, and F1-score metrics. As well as we calculate the accuracy, recall, precision, and F1-score metrics for the whole model.

Table 4 compares the performance of several models for lung cancer diagnosis based on metrics such as Precision, Recall, F1-Score, and Accuracy. The Enhanced CNN model excels with 100 % accuracy, 99.2 % precision, 98.0 % recall, and an F1-score of 98.4 %, indicating its strong ability to accurately detect cases while minimizing errors. VGG16 follows closely, achieving 99 % accuracy and high scores in precision and F1-score. EfficientNetB0 also performs well, with the highest precision (99.5 %) and strong recall. ResNet50 shows moderate results, especially with lower recall, while ConvNeXt has a balanced but lower overall performance. Lastly, InceptionV3 ranks the lowest, with significantly low precision and accuracy. Overall, Enhanced CNN is highlighted as the most effective model for lung cancer diagnosis. Fig. 17 illustrates a Comparison of the Performance accuracy of our Models. The findings suggest that all the models developed in this study exhibited promising results. Notably, the Enhanced CNN model demonstrated exceptional performance, achieving an accuracy of 100 %, which surpassed the pre-trained traditional deep learning models. In comparison, the VGG16 and EfficientNetB0 models achieved accuracies of 99 % and 97.9 %, respectively, representing the highest accuracy among pre-trained models. These results indicate that these models can be relied upon to predict lung cancer disease accurately.

Fig. 18 presents the accuracy and loss curves for the proposed CNN model during testing and validation. The model achieved an impressive accuracy of 100 %, with a gradual decrease in loss throughout the training and testing phases, indicating strong performance. The loss metric, which measures the difference between predicted and actual values, is essential for assessing the model's fit to the data and guiding potential improvements.Fig. 19 shows the accuracy and loss curves during the training and validation phases of our ConvNeXtSmall model. The final model achieved a high accuracy of 86 %, and the model loss decreased gradually during the training and testing process, indicating a very good performance. Fig. 20 shows the accuracy and loss curves during the training and validation phases of our VGG16 model. The final model achieved a high accuracy of 99 %, and the model loss decreased gradually during the training and testing process, indicating a high performance. Fig. 21 shows the accuracy and loss curves during the training and validation phases of our ResNet50 model. The final model achieved a high accuracy of 94.5 %, and the model loss decreased gradually during the training and testing process, indicating a strong performance. Fig. 22 shows the accuracy and loss curves during the training and validation phases of our InceptionV3 model. The final model achieved a good accuracy of 76.9 %, and the model loss decreased gradually during the training and testing process, indicating a good performance. Fig. 23 shows the accuracy and loss curves during the training and validation phases of our EfficientNetB0 model. The final model achieved a good accuracy of 76.9 %, and the model loss decreased gradually during the training and testing process, indicating a high performance.

5. Conclusion

In the last century, lung cancer has emerged as a major global health concern, contributing to 13–14 % of cancer diagnoses and presenting a significant challenge due to its rapid progression and high mortality rates, particularly in advanced stages. Early detection is crucial, as survival rates can increase dramatically with timely diagnosis. However, current challenges such as poor image quality, physician stress, inadequate information, and ineffective communication often hinder early detection, leading to escalated medical costs and further deterioration of patient health.

In this study, we aimed to address these issues by developing advanced models for the automatic classification and prediction of lung cancer from chest CT scan images. Utilizing a dataset of 1000 CT scans sourced from Kaggle, we achieved a training-test split of 70 % and 30 %, respectively, with balanced representation across various cancer types (Adenocarcinoma, Large Cell Carcinoma, Squamous Cell Carcinoma, and Normal). Our customized Convolutional Neural Network (CNN) model achieved an unprecedented 100 % testing accuracy, outperforming existing models, and marking a significant advancement in lung cancer detection research, particularly through the application of innovative enhancement techniques and the implementation of ConvNeXt.

Our findings underscore the importance of artificial intelligence techniques in medical imaging, particularly in enhancing the early detection of lung cancer. Despite facing challenges such as limited high-quality data and technical constraints, our research contributes valuable insights into improved methodologies for lung cancer classification and prediction. By bridging existing gaps in the field, this study represents a pivotal step toward more effective diagnostic tools that can assist healthcare professionals in combating lung cancer in its early stages. Thus, we hope our findings will foster further research and development, ultimately leading to improved patient outcomes and survival rates.

CRediT authorship contribution statement

Mohammad Q. Shatnawi: Supervision, Resources, Project administration, Conceptualization. **Qusai Abuein:** Writing – review & editing, Project administration, Methodology. **Romesaa Al-Quraan:** Writing – original draft, Software, Investigation, Data curation.

Declaration of competing interest

All authors declare that they have no known competing financial interests, personal relationships, or affiliations that could have influenced the work presented in this research.

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