AL-AASAR Journal
Quarterly *Research Journal*
www.al-aasar.com

Vol. 2, No. 3 (2025)
Online ISSN: 3006-693X
Print ISSN:3006-6921

LUNG CANCER DETECTION USING DEEP LEARNING APPROACHES ON CT IMAGES

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ABSTRACT
This research aims to design and develop an automated system for lung cancer detection using deep learning methods applied to Computed Tomography (CT) images. Early and precise diagnosis of lung cancer is a must for better patient outcomes since lung cancer remains among the leading causes of death from cancer worldwide. The Lung Cancer Detection model described in this research utilizes a convolutional neural network architecture and is trained on the "The Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) lung cancer augmented dataset," which comprises an extensive collection of computed tomography images with annotations. The deep learning model was trained on CT scan images categorized into Normal, Benign, and Malignant labels. These images underwent meticulous preprocessing and training using three deep learning algorithms: ResNet50, InceptionV3, and DenseNet121. The best performance, achieved by the custom CNN model, boasts an extraordinary classification rate of 98.30% and perfect precision, recall, and F1-score. Model classification for malignant or benign nodules will be based on imaging characteristics of the lung nodules. It employs a preprocessing approach similar to that used for CT images, data augmentation when necessary, and transfer learning to enhance the model's performance, which is further evaluated based on model accuracy, sensitivity, and specificity. Limitations include the availability and overfitting of annotated datasets, which can be affected by variability in quality across different CT scans. In the future, more robust architectures should be developed, multi-model data should be integrated, and real-time detection features should be included to advance the research field of lung cancer diagnosis.
Keywords: *Lung Cancer Detection, Deep learning methods, Computed Tomography (CT) images, IQ-OTH/NCCD augmented dataset*

INTRODUCTION

Lung cancer is one of the most serious health issues worldwide, ranking as the third-most common type of cancer and causing approximately 27% of total deaths from cancer. This high rate of mortality has shed a grim light on the need for effective methods of detection that can improve outcomes for patients. The lungs in the thoracic cavity are essential for the respiratory process. Lung cancer develops when malignant changes in the cells of the lungs make nodules, which can be benign or cancerous[1]. Early diagnosis of malignant nodules, usually through medical imaging, particularly with Computed Tomography, is essential for early diagnosis and interventional treatments that improve survival rates [2-4]. In 2025, lung cancer is still one of the most serious health problems around the world, and the latest data may indicate that things are not getting better. It is estimated that there will be 2,041,910 new cancer cases in the United States in 2025 (source: 2025 Cancer Statistics report by the American Cancer Society), including 238,340 new cases of lung and bronchus cancer (approximately 11.6 percent of the total new cancer cases). Recent analyses citing the GLOBOCAN 2022 estimates indicated that lung cancer still has an astronomical

burden, with an estimated 2,484,227 lung cancer cases and 1,820,576 deaths worldwide. The total burden is projected to reach 4.62 million new cases and 3.55 million deaths worldwide by 2050, should the trend continue[5], [6]. The incidence of lung cancer among women is on the increase, especially among women below age 65 years, where the rates are higher than in men (15.7 vs. 15.4 per 100,000 in 2021).
Smoking is the major risk detected globally, with lung cancer death rate pegged at 70-90%, but the mines of asbestos are reported to kill more than 30,000 people each year. Low-dose helical CT scanning that has a high-risk population (aged 50-80 with 20+ pack-year smoking history) is essential. Localised-stage diagnosis outcomes are significantly more effective than cases in advanced stages, where the non-small cell lung cancer (NSCLC) and the small cell lung cancer (SCLC) have 5-year mortality rates of 91 percent and 97 percent, respectively. According to the World Health Organization, these will increase such that by the year 2040, figures will be elevated to 3.6 million cases and 3.1 million deaths around the world[7]. Current practices for diagnosis include chest X-rays and computed tomography scans, most of which rely on manual interpretation[8]. There are two types of lung cancer: non-small cell lung cancer and small cell lung cancer. NSCLC accounts for approximately 80% to 85% of all lung cancer cases. The main subtypes of NSCLC are adenocarcinoma, squamous cell carcinoma, and large cell carcinoma. These subtypes originate from different types of lung cells but are grouped under NSCLC due to similarities in their treatment approaches and overall prognosis. SCLC makes up about 10% to 15% of all lung cancers and is sometimes called oat cell carcinoma. This type of lung cancer grows and spreads faster than NSCLC, with around 70% of patients already having metastatic disease at the time of diagnosis. Although SCLC generally responds well to chemotherapy and radiation therapy due to its rapid growth, recurrence is common and often occurs after initial treatment[9].

Significance and Contribution of the Study

The study is deeply integrated, involving the current state-of-the-art deep learning methods[10-12] to improve the workability of lung cancer detection. The study employs advanced deep learning methods[13-15] to identify intricate features in computed tomography (CT) images. The technique simplifies the linear separation between malignant and benign characteristics, thereby increasing the model's capability to identify critical diagnostic markers. These contributions are expected to empower clinical practice by equipping radiologists with a tool, such as the system, to enhance their diagnostic capabilities effectively[16].

Lung Cancer Diagnosis Challenges

Integrating machine learning (ML), deep learning (DL)[17-19], and statistical processes[20] into the CAD/CADe systems framework would provide a revolutionary method for increasing the effectiveness and accuracy of lung cancer detection. The technologies have attracted substantial interest among researchers in the field of medical image processing due to their potential to transform diagnostic practices over the past 20 years[21-23]. In contrast to the conventional interpretation by thoracic radiologists, CAD/CADe systems are a practical addition, increasing the positive predictive value and significantly decreasing the false-positive rates, especially regarding small pulmonary nodules in cancer lung screening.

AL-AASAR Journal
Quarterly *Research Journal*
www.al-aasar.com

Vol. 2, No. 3 (2025)
Online ISSN: 3006-693X

Print ISSN:3006-6921

AI is the most advanced technology in different domains[24-26]. CNNs also apply convolution functions wherein an input picture is fed through a window that is then moved along with the picture to form feature maps that represent or extract the key patterns. The cascades of DL have been demonstrated to be promising in precisely diagnosing diseases of the lungs using medical pictures, specifically, computed tomography (CT) scans. Using labelled data together with unlabelled data, these systems optimise the accuracy of decision boundaries, thus increasing diagnostic accuracy. Nevertheless, training these models requires considerable amounts of labelled data, raising the costs, the computational burden and the logistical burden as well. Various supervised DL algorithms have been used to investigate CT images, and this made it possible to detect abnormalities and their exact localization in the anatomy. Though they are strong, there are limitations attached to these methodologies. The use of large labeled data, the fixed properties of the network's weights after learning, and the inability of models to continue learning or evolve after initial training are serious drawbacks. The mentioned challenges present the necessity of developing new solutions to the process of acquiring data, training the models, and adapting to the findings to better increase the effectiveness of DL-based CAD systems in lung cancer recognition.

This study will overcome these limitations and pave the way forward in the design of robust, effective, and flexible DL-based CAD systems, ultimately to achieve early and precise diagnosis of lung cancer, better patient prognosis, and the pervasive application of AI in precision medicine.

Objectives of the Study

This research proposes a deep learning-based model for the detection of lung cancer using computed tomography images with the purpose of classifying nodules as malignant or benign.

- To assess the accuracy and efficiency of deep learning models in identifying malignant nodules in CT images of the lungs.
- To examine the impact of varying image quality and preprocessing techniques on the performance of lung cancer detection models.
- To analyze the influence of model architecture on the detection accuracy of lung cancer in CT images.
- To investigate the role of data augmentation techniques in improving model robustness and reducing overfitting in lung cancer detection.
- To compare the diagnostic outcomes of the proposed deep learning model with traditional radiologist interpretations for early-stage lung cancer detection.

Problem Statement

The fundamental difficulty is creating an efficient computer-aided detection and diagnosis (CAD/CADe) device able to recognize the malignant nodules with incredible specificity, sensitivity, and precision. This system must take advantage of the latest technologies, including deep learning (DL) and machine learning (ML) to process complicated imaging data, identify minute patterns that signal malignancies, and give reproducible diagnostic results that minimize interpretive unpredictability. The system would become a highly effective assistant to radiologists, helping them diagnose an ailing person timely and correctly implement any necessary treatment earlier. Because of its potential to enhance patient outcomes and contribute to global burden reduction of lung cancer due to minimization of diagnosis mistakes, optimization of clinical workflows, and facilitation of the transition to the era of personalized, precision medicine, the development of such a system is crucial.

The proposed research seeks to overcome these challenges by developing and rolling out an efficient CAD/CADe platform that utilizes the potential of AI in diagnosing lung cancer at the early stages at elevated levels of accuracy. The suggested system aims to address the issue of the current diagnostic models by better detecting malignant nodules, reducing false positive and false negative results, and giving the radiologists beneficial facts on the data. This effort will help the study to support the global war on lung cancer, which will eventually increase survival rates and the quality of life among patients worldwide.

Research Gap

Pre-existing DL models tend to perform well in a narrow subset of homogeneous tasks and datasets. Since applicability with other patient groups, imaging methods, and clinical settings suffers due to the diversity of demographics, CT scanner specifications, and the use of imaging parameters, including slice thickness variation or radiation dose. This will make the system less robust and add to the fact that the network weights can adjust after training. This decreases the flexibility of these systems to real-life clinical settings where data is usually heterogeneous. Moreover, DL-based CAD systems depend on an abundance of high-quality and labeled medical imaging data, which is challenging to access in large quantities due to patient privacy issues, the rapid increase in annotation costs, and the time-consuming process of labeling data by radiologists. Poor preprocessing techniques also dilute the performance since the existing preprocessing methods often do not account for noise, artifacts, or variability in the quality of CT images, which are important features critical to lung cancer detection at its early stage. Moreover, numerous DL methods based on generic designs of convolutional neural networks (CNN) lack specifications adjusting to the peculiarities of lung CT images, e.g., low-contrast nodules or complicated anatomies. CAD systems used in clinics are still not very integrated, and standalone tools cannot be used with radiology information systems (RIS) or picture archiving and communication systems (PACS). The meaning of DL output is difficult to interpret and is not treated as reliable by radiologists. Another understudied topic is the increasing rates of lung cancer among non-smoking patients (women and younger adults, especially), including causes such as radon exposure or hereditary factors, where current models would commonly be streamlined to the smoking-related cases, and they might not incorporate different imaging patterns in the non-smoking-related lung cancer. And lastly, resource-intensive computational needs and the consumptiveness of DL models constrain their scalability, especially in resource-limited health environments.

Filling these gaps, i.e., by ensuring the ability to develop robust, generalizable models, by using less on labeled data, by introducing higher specificity to decrease false positives, by doing effective pre-processing and features extraction, by better integrating with clinical practice with explainable AI, by the integration of multimodal data, by being focused on non-smoking-related cases, and by being cost-effective, establishes a unique opportunity that your research can lead DL-based CAD/CADe systems in achieving this important aim, namely, improving early cancer diagnosis in the lungs.

LITERATURE REVIEW

Some of the studies make use of the IQ-OTH/NCCD data, which consists of more than 1000 CT images of the Iraqi hospitals, which have been labeled as normal, benign, and malignant[27]. The clinical variety of this data set is realistic, and the model it represents tests the robustness of the models. Models such as ResNet50, DenseNet121, and InceptionV3 have played a significant role in such endeavour, their strengths being residual blocks in ResNet50 to train very deep networks without degradation, dense connectivity in DenseNet121 to allow the features to be propagated easily and their efficient use of parameters, and finally multi-pool functions in InceptionV3 to capture multi-scale features and improve on its accuracy to achieve a often-greater than 98% accuracy.[28], [29].

Qadir et al. have presented the Hybrid Lung Cancer Stage Classifier and Diagnosis Model (Hybrid-LCSCDM), a new and advanced two-tier system to streamline the process of medical diagnosis based on the CT scan images. The novel method of classifying the disease afflicting the lung falls under three main categories, namely, normal (indicating no abnormalities), benign (non-cancerous nodules or growth), and malignant (cancerous lesions that need to be addressed immediately)[30], . It was trained and tested on the IQ-OTH/NCCD dataset (which consists of 1,190 images well-balanced among the three classes to approximate real-world clinical distributions). Indicators of performance have shown excellent efficiency, with a general accuracy of 98.54%, an improvement of 98.63%, and better outcomes regarding recall and F1-score when compared to the standalone CNN or traditional ML baselines.[31]. Within the realm of 2025 developments, more like hybrid models have involved ResNet50 or InceptionV3, which introduces more feature levels to take better advantage of low-contrast nodules, and even incrementally to that in terms of sensitivity[32].

The article by Parveen et al. was the construction of an efficient machine-learning pipeline to ensure the accurate diagnosis of lung cancer using data extracted by CT scan, paying special attention to addressing class imbalance, ubiquitous throughout medical databases and often causing poorly modeled minority classes, favouring a particularity of the majority. The study started with state-of-the-art image processing watershed algorithms to segregate lung regions precisely using marker-controlled flood techniques to form boundaries between nodules and other tissues, and Scale-Invariant Feature Transform (SIFT) to identify rotation and scale-invariant key points to examine local gradients of the image[33].

The IQ-OTH/NCCD dataset used by Kareem et al. was collected based on more than 1,100 CT images in two hospitals in Iraq to suggest a computer-aided detection system with aspects of segmentation, enhancement, as well as feature extraction. The steps of the methodology include the use of considerations on enhancing images, such as histogram equalization to enhance contrast and presence of faint lesions, and segmentation procedures that include region-growing and use of thresholding to extract the lung parenchyma. Texture (through Gray-Level Co-occurrence Matrix, or GLCM), shape (i.e., eccentricity, area), and intensity statistics are obtained as features. [34].

Deepa et al. have proposed a particular CNN LCC-Deep-ShrimpNet, specially tailored to lung cancer classification with CT images based on a dataset IQ-OTH/NCCD[35]. Transfer learning applied to GoogLeNet (InceptionV1) as a DNN method was promoted by AL-Huseiny et al. in detecting malignant nodules of IQ-OTH/NCCD CT scans. Centering, normalization, and ROI

AL-AASAR Journal
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www.al-aasar.com

Vol. 2, No. 3 (2025)
Online ISSN: 3006-693X

Print ISSN:3006-6921

extraction are comprised in the preprocessing step to eliminate the artifacts. Tweaking upper layers of the network and keeping low ones frozen makes it fit the medical data oriented with accuracy of 94.38 % which is better than benchmarks and translates to the importance of transfer learning in early diagnosis, analogous to the multi-scale efficiencies of InceptionV3 in 2025 research[36].

Gulsoy et al. have pioneered the FocalNeXt, which incorporates the ConvNeXt convolutional capabilities and the FocalNet hierarchy of attention into automated diagnosis using CT. On IQ-OTH/NCCD, it achieved 99.81 accuracy and 99.78 sensitivity, and ablation studies established that it is robust. This vision transformer combines up-and-coming imaging and augments feature focus as attention-enhanced forms of ResNet50[38]. Al-Yasriy and his team have used an AlexNet-based CNN to classify IQ-OTH/NCCD CT scans and reached a sensitivity rate of 95.614% and a specificity of 95% accurate classifications, promoting early distinction of the lung conditions. Gowda et al. had a vision-based system using Random Region Segmentation, SIFT/GLCM features, and Triple SVM at IQ-OTH/NCCD, 96.5% at 200 clusters, again on the increase with scale. In Jassim et al., a combination of CNNs with multi-criteria decision-making (VIKOR, fuzzy-weighted zero-inconsistency) and handling of imbalanced data resulted in 99.27 percent accuracy[37]. The overall contribution of the studies is to the progress of using DL in lung cancer detection, with ResNet50, DenseNet121, and InceptionV3 being in the middle of providing high precision via transfer learning and ensembles, which is also supported by 2025 reviews that highlight their importance in explainable and efficient diagnostic [38], [39]. The more current developments, especially since 2023 to 2025, have underscored their inclusion in the settings of ensembles, explainable AI stacks, and multimodal systems to overcome data shortage issues and overfitting problems, as well as clinical interpretability, and keep up with the shifting trends of precision oncology[40].

The totemic article of program discovery built a predictive model on a combination of ML classifiers, i.e. Decision Trees (DT), Logistic Regression (LR), Support Vector Machines (SVM), and Naive Bayes (NB), were all run independently on these datasets. Empirical findings showed that LR had an accuracy of 96.9% and 99.2% by SVM in the first and second datasets, respectively, due to its ability to contend with the linear separability in multi-class classification. SVM was also dominated because it had the advantage of using the kernel trick to bear on the non-linear probability space[41]. Aiding this, another study exploited Artificial Neural Networks (ANN) to predict the occurrence of lung cancer based on symptomatic signs, including but not limited to yellow fingers, peer pressure-related factors, long-term comorbidities, chest pains, and dyspnea. This collective gain demonstrates the effectiveness of using ANN architecture in learning complex interactions of symptoms that are not linearly explainable using other simpler models, portraying the reason why ANN has an impressive accuracy of 96.76%. This multilayer perceptron architecture was used in this way[42], [43]. With some digressions, I introduced new predictors, such as familial predisposition to cancer of the lungs, quantification of the history of smoking (incorporating variables of years of smoking and packs per year), and alcohol consumption habits[44].

The 2023 to 2025 literature focuses on using them within explainable, multimodal, and federated frameworks to address ethical concerns, such as model transparency and data privacy, with metrics such as sensitivity (up to 98.4%), specificity (92%), and Dice Similarity Coefficients (DSC) greater than 0.99 when tested on benchmarks, such as LUNA16. The following subsections give accounts of some of the key tasks enabled by these system [45].

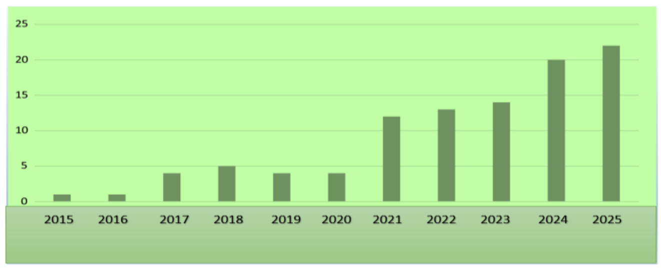

Figure 1 Illustration of literature from 2015 to 2025 on lung cancer disease

The more recent additions include ResNet50-attention hybrids to predict nodules in 2025. In one case, a researcher utilized a distillation of the ResNet50 and InceptionV3 networks to detect nodules in a lightweight manner[46], [47]. The localization of nodules by Explainable InceptionV3 models in 2024 to 2025 focused on robustness. LSE-Net has been used recently to ensemble ResNet50 in segmentation-classification pipelines [48], [49].

Table 1 State of the art of the Literature review

Study	**Year**	**Approach**	**Dataset**	**Accuracy**
[8]	2023	CAD system using hybrid deep learning	IQ-OTH/NCCD	98 %
[9]	2024	Hybrid Lung Cancer Stage Classifier and Diagnosis Model	IQ-OTH/NCCD	97.8%
[10]	2023	Transfer learning using densenet121	IQ-OTH/NCCD	93.6%
[11]	2022	SVM classifier, image enhancement	IQ-OTH/NCCD	98.4%
[12]	2021	Pre-trained vgg16, and XGBoost	IQ-OTH/NCCD	97%
[13]	2023	Machine-learning-based watershed, data augmentation, SIFT	IQ-OTH/NCCD	96.7%
[14]	2024	DNN, GoogleNet, ROIs	IQ-OTH/NCCD	94.6%
[32]	2025	Alexnet-based system with CNN	IQ-OTH/NCCD	97.7%
[35]	2024	Machine-learning-based classification	IQ-OTH/NCCD	98%
[39]	2025	Infiltration and subtype analysis of CD3 &CD20 & T cells	IQ-OTH/NCCD	99%

[44]	2025	Lightweight deep learning architecture	IQ-OTH/NCCD	95%
[29]	2025	Deep-learning-based segmentation	IQ-OTH/NCCD	97.2%
Proposed model	2025	Deep-learning-based classification (ResNet50, DenseNet121, InceptionV3)	IQ-OTH/NCCD	98.3%

METHODOLOGY

A full range of augmentation was used to maximize the dataset's size and variety, allowing the model to see many more samples in the training phase. The augmentation steps taken are horizontal flip, vertical flip, rotation, color jitter, contour crop, Gaussian blur, sharpness technique, contrast enhancement, and histogram equalization. All the techniques were chosen carefully to provide substantial image variability without the loss of all-important diagnostic features. Following such augmentation strategies, the dataset was significantly extended, and it provided a more complete one to analyze. The augmented image has a total number of images (3,609), 1,200 benign samples, 1,201 malignant, and 1,208 normal samples[47].

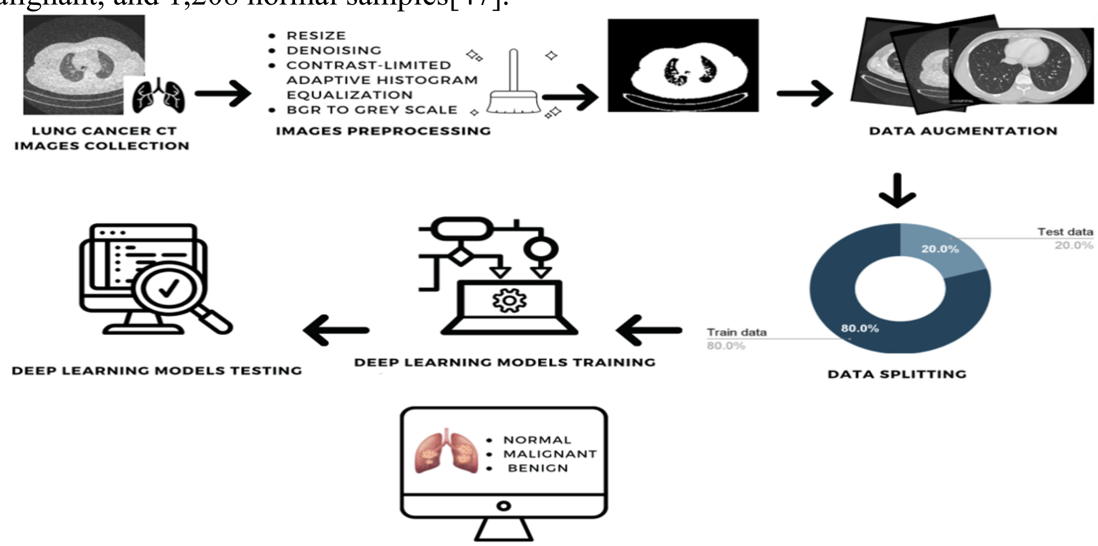

Figure 2 Block diagram of the proposed deep learning model

Preprocessing and Enhancement

Within the context of neural networks (NNs), uniform resizing of all images to a single dimension is an important preprocessing technique in response to the ability of deep learning (DL) models to accept only inputs that are of uniform size[40]. After resizing, the images were transformed into NumPy arrays for fast processing and compatibility with deep learning libraries such as PyTorch and TensorFlow. I then applied the standard mean and standard deviation values for popular pre-trained models to normalize the pixel values:

•Mean = [0.485, 0.456, 0.406]

•STD = [0.229, 0.224, 0.225]

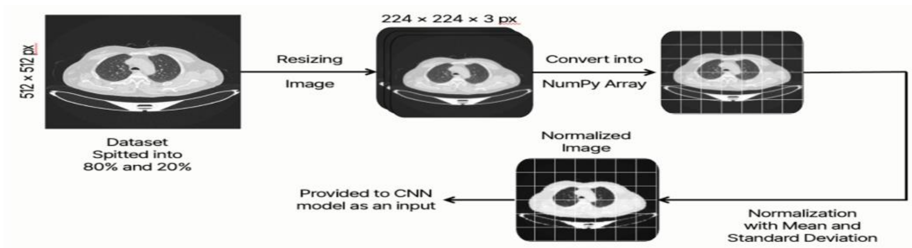

Figure 3 Data preprocessing pipeline

An optimal value of fixed size can therefore be chosen by a careful combination of quality image and computational efficiency.

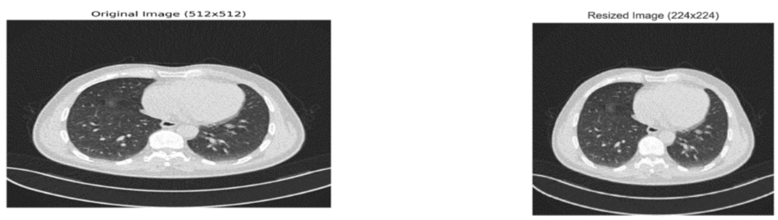

Figure 4(a) Original image (512*512), (b) Resized image (224*224)

Image Denoising using Gaussian Blur

In a bid to improve the quality of images by decreasing noise, the Gaussian Blur methodology was used, and its ability to smooth images and at the same time retain low-frequency spatial images hoist by preserving low-frequency spatial information, which plays a vital role in diagnosis, was exploited in its application. The high-frequency noise, including artifacts or small anomalies, is well filtered with this approach, but the structural integrity of the picture is maintained in a significant way. The Gaussian Blur is described as:

$g(X) = e{-}x2\ 2\sigma2$

$\sqrt{}2\pi\sigma2$

The values of (\ x) and (\sigma) are respectively the spatial coordinate and the standard deviation of the Gaussian distribution, by which the degree of blurring is determined. In this study, the Gaussian two-pass filtering method was used because it consumes fewer computations than the single-pass approach and allows effective reduction of noise, being computationally efficient. With the Gaussian Blur, the images were improved to provide a clearer depiction of pertinent elements, which could be analysed more precisely by the consequent DL models[35].

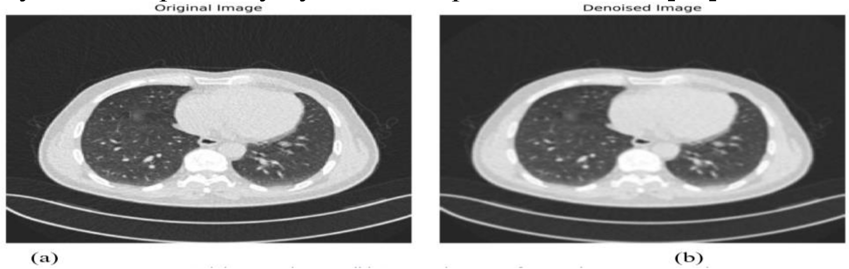

Figure 5 Original and denoise image using Gaussian blur

Vol. 2, No. 3 (2025)
Online ISSN: 3006-693X
Print ISSN:3006-6921

CLAHE

The image contrast and prediction accuracy of the DL models were significantly increased by contrast-limited adaptive histogram equalization (CLAHE). Compared to the other conventional decontrasting schemes, which may offer too much amplification and result in artificial artifacts or detail loss (such as very fine veins in medical images), CLAHE uses a clipping threshold to limit histogram amplification. In this study, the improved version of CLAHE was used, which adds the global threshold level to differentiate the techniques to adaptively utilize the histogram to maintain fine details. The algorithm results of the enhanced CLAHE were better than the conventional CLAHE with constant clipping, in highlighting complex structures like small blood vessels, and hence the results improved the image distinctiveness. Standardization was undergone after CLAHE processing to expand the intensity range in an optimal range to ensure the processed images would give more informative features to train the convolutional neural network (CNN).

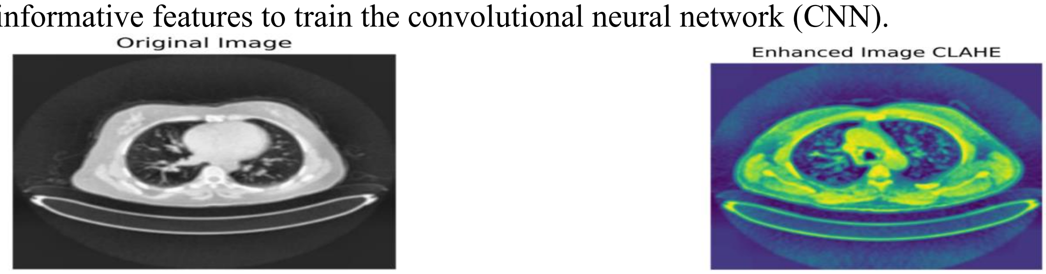

Figure 6 Before and after applying CLAHE

RGB to Grayscale conversion

To further image-tune the deep learning accuracy, the RGB images were converted to grayscale to minimize the noise and to simplify the process of depicting the color intensity

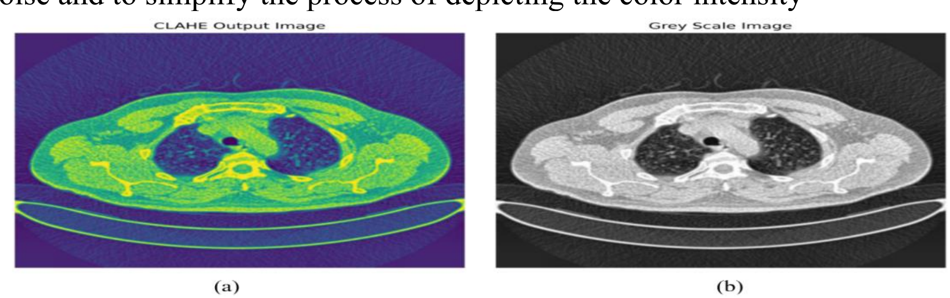

Figure 7 CLAHE to greyscale conversion

This conversion process also simplifies the input data, hence easier to train on CNNs in terms of its computational cost and processing silently. The grayscale conversion is obtained by performing a weighted average of the red, green, and blue channels of each pixel, whose formula is as follows:

Gray = 0.299 * Red + 0.587 * Green + 0.114 * Blue

This pair of weights is proportional to the human eye's sensitivity to various colors, where green would have the greatest contribution to perceived brightness. As a result of the preprocessing, CLAHE was an RGB image; transforming it to a grayscale image was required to ensure consistency and efficiency of the DL pipeline. In addition to simplifying computations, this conversion has the effect of smoothing out the kind of noise that can hide important features, therefore making the model more detailed to the pattern of intensity useful to classification.

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Vol. 2, No. 3 (2025)
Online ISSN: 3006-693X

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Techniques of image augmentation

This study employs the augmentation, such as horizontal flipping and histogram equalization, which were consciously performed to achieve an even distribution in the dataset between three classes of benign, malignant, and normal cases, as well as to add meaningful variations.

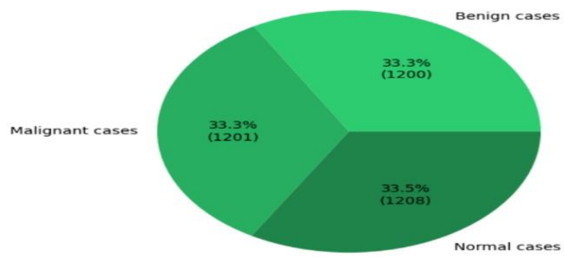

Figure 8 Class distribution

Horizontal Flip Augmentation

Horizontal flipping refers to the reflection of an image along the vertical axis of a picture and, in effect, flipping the left and the right sides of the picture. The method produces an additional view of the original scene to mimic rotational changes that can take place in real-life imaging settings. Horizontal flipping, accomplished by exchanging pixel columns, enhances the dataset without distorting the diagnostic content, and is especially useful on medical images, as the anatomical symmetry can be used. The technique was used to enrich the diversity of the dataset, which is seen to make the training process more effective.

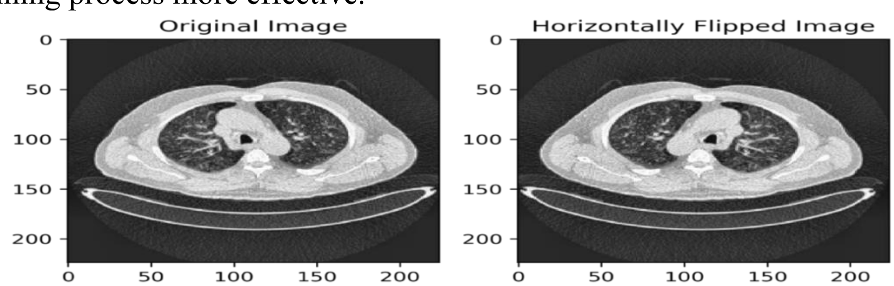

Figure 9 Horizontal flip augmentation

Augmentation Histogram Equalization

To optimize contrast of target images, histogram equalization was used to redistribute the pixel intensities over the entire dynamic range (0-255). The method enhances feature visibility through stretching of an image's histogram, especially those of grayscale images, such that pixel values use the whole range of intensities.

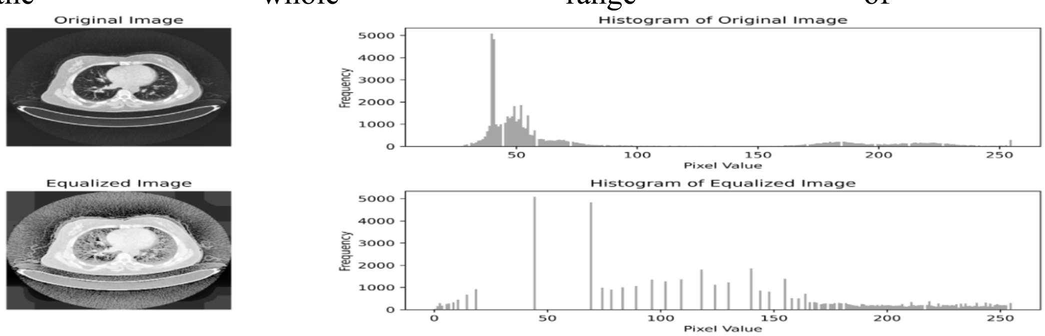

Figure 10 Original and equalized image with its histogram

In this work, the histogram equalization method was used to locally increase the contrast, so that the slight variations in the tissue properties could be more noticeable and, hence, optimize the quality of the DL models in segmenting lung cancer images. These preprocessing and augmentation methods, including the resize, Gaussian Blur, CLAHE, grayscale conversion, and such specific augmentations as horizontal flip and histogram equalization, brought the data to be optimal for deep learning, involving quality, efficiency, and diversity to promote quality and reliable classification.

EXPERIMENTS AND RESULTS

In this work, DL models based on different CNN architectures as convolutional bases were used to extract valuable structures in the complex images of the whole-slide lung cancer dataset. To retain the pre-trained knowledge that had been retained in these CNNs, all the layers in the convolutional base were marked as non-trainable, such that weights in them could not be refreshed during the training process.

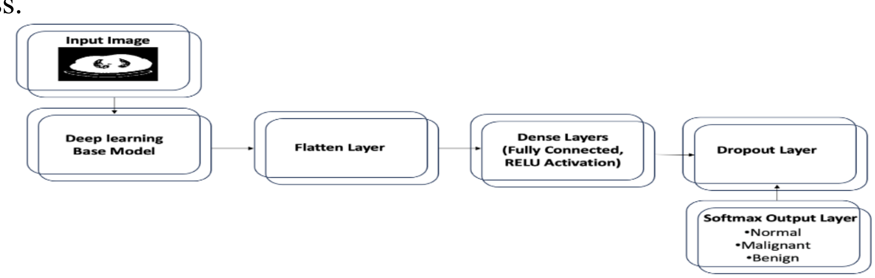

Figure 11 DL models illustration

Performance and results analysis Results

The DL experiments' outcomes were analysed to determine how different CNN-based models performed on the image dataset of CT. Key performance metrics were used to evaluate the models, that is, accuracy, sensitivity, and the area under the Receiver Operating Characteristic (ROC) curve (AUC).

ResNet50 Results

ResNet50 was trained using 50 epochs and a batch size of 32, including data augmentation as random rotations, flips, and brightness alterations to become more robust.

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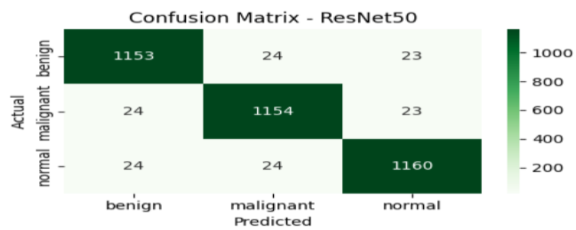

Figure 12 Confusion matrix ResNet50

The test accuracy of the model was 96.1%, indicating an accomplishment in generalization throughout the data. A confusion matrix is a tabulated explanation that summarizes the performance of a classification model, displaying the true positives (correct predictions on the main diagonal), false positives, false negatives, and true negatives of each of the classes. In ResNet50, the diagonal dominance is strongly present; 1,153 of the actual benign cases, 1,154 of the malignant, and 1,160 of the normal were correctly classified, implying that 24, 24, and 23 actual benign, malignant, and normal cases were wrongly predicted as malignant, benign, and normal, respectively. This creates a precison of about 96.00%, 96.01 % and 96.19 % and a recall of 96.08% 96.09% and 96.03 % and F1-scores of 96.04%, 96.05% and 96.11%, overall accuracy of 96.07%.

The behavior of the algorithm balances the depth and performance in terms of computational efficiency; therefore, it is best applied when the job needs a powerful feature set without requiring many preliminary resources. There was high precision and recall, and thus high accuracy in classification across a wide range of classes, although a certain degree of overfitting was prevented by dropout or weight decay.

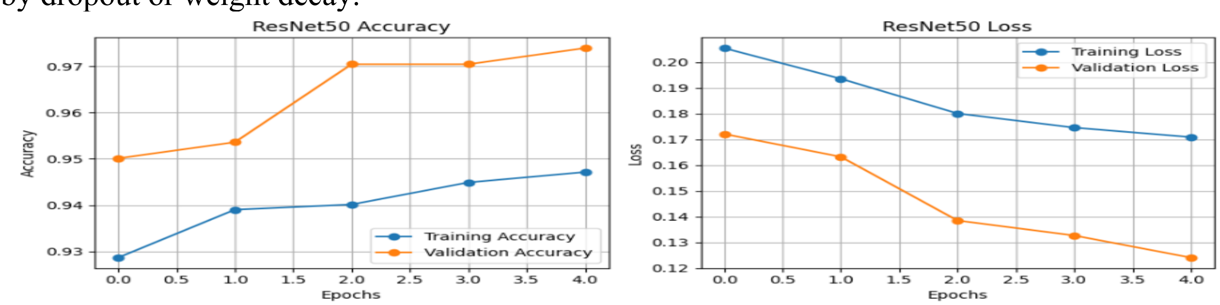

Figure 13 Accuracy and Loss illustration of ResNet50

DenseNet121 Results

Close connectivity decreases the number of parameters in comparison with conventional CNNs, as fewer feature maps are necessary and the flow of the gradient is reinforced. The setup contains 121 layers, divided into 4 dense blocks, with transition layers to switch the convolution and pooling and operate on the size of feature maps.

AL-AASAR Journal
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Vol. 2, No. 3 (2025)
Online ISSN: 3006-693X

Print ISSN:3006-6921

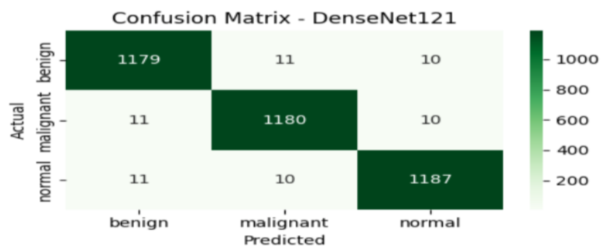

Figure 14 Confusion matrix DenseNet121

With a minimal amount of information loss and maximization of feature propagation, DenseNet121 is especially well-suited to tasks where the intricate and hierarchical nature of the patterns must be learned. The same regularization process of L2 weight decay was applied to DenseNet121, trained along with the other models under the same conditions. DenseNet121 shows an even better performance - 1,179 true positives of 1,200 benign, 1,180 true positives of 1,201 malignant, and 1,187 true positives of 1,208 normal, yielding fewer errors - only 11 benign being falsely classified as malignant and 10 being falsely classified as normal, 11 malignant being falsely classified as benign.

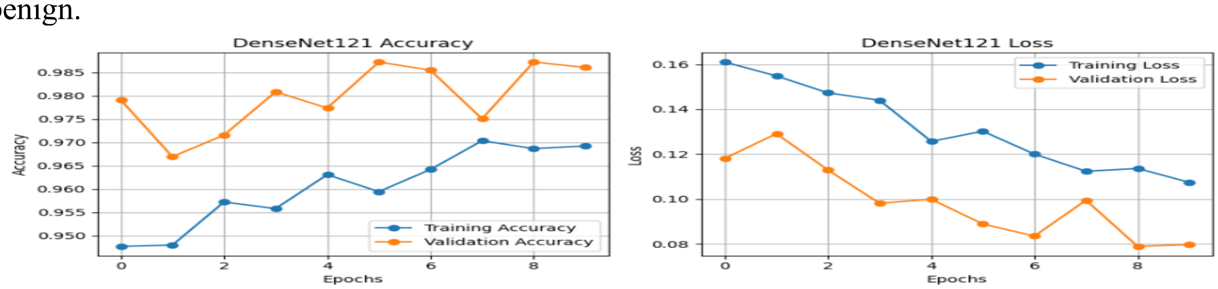

Figure 15 Accuracy and Loss illustration of DenseNet121

The model had a test accuracy of 98.3%, which is quite impressive and the best of all the architectures that were examined, as a result of its superior ability to capture complicated relations within the data. Its low error rate and F1-score also suggest that there is equal performance of the model across the classes and few misclassifications. The computing cost of the model, despite its depth, makes it an ideal model to use where accuracy and resource utilization a major factor as well.

InceptionV3 Results

Its feature is the application of inception modules, which accomplish parallel convolutions with various kernel sizes (e.g., 1x1, 3x3, 5x5) and pooling operations, and concatenate the outputs to represent multi-hyphen features in a single layer.

AL-AASAR Journal
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Vol. 2, No. 3 (2025)
Online ISSN: 3006-693X

Print ISSN:3006-6921

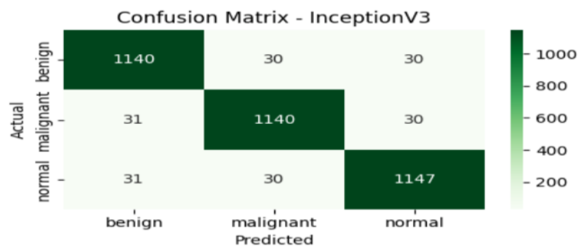

Figure 16 Confusion matrix InceptionV3

InceptionV3, in turn, is characterized by more diagonal errors, with 1,140 true benign (1,200), 1,140 true malignant (1,201), 1,147 true normal (1,208), and 30 benign false as malignant and 30 false as normal, 31 malignant false as benign and 30 false as normal, 31 normal false as benign and 30 false as malignant, which implies a precision of 94. The architecture also uses factorized convolutions and auxiliary classifiers to further reduce the computational load as well as stabilize the training. For this experiment, the InceptionV3 was initialized based on the trained ImageNet weights and the top layer, designed to fit the target datasets, was retrained. There was training carried out over 50 epochs with data augmentation and a learning rate decay schedule in order to facilitate convergence. This model attained a test accuracy of 95% which indicates the ability to deliver a reliable result among various classes of images.

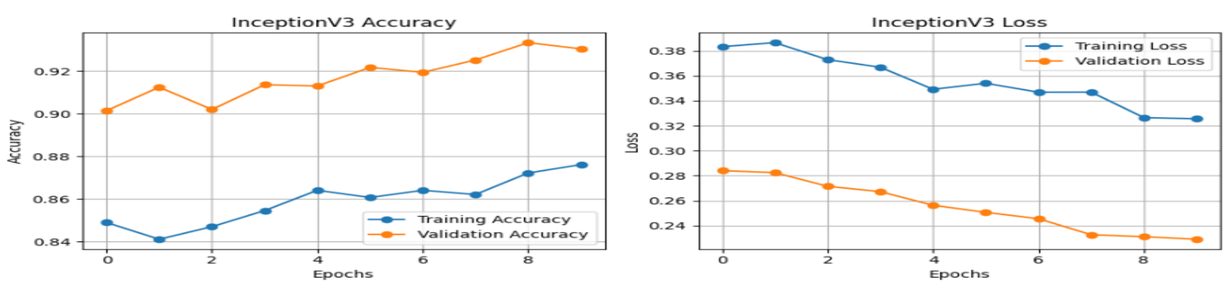

Figure 17 Accuracy and Loss illustration of InceptionV3

Comparative Analysis

The comparative analysis of the ResNet50, DenseNet121, and InceptionV3 models shows that each one of them has specific strengths. Being the best performer in this study is the high accuracy of 98.3% achieved by DenseNet121, with the beneficial capacities of dense connectivity to acquire features that are reused and information flow in the gradient.

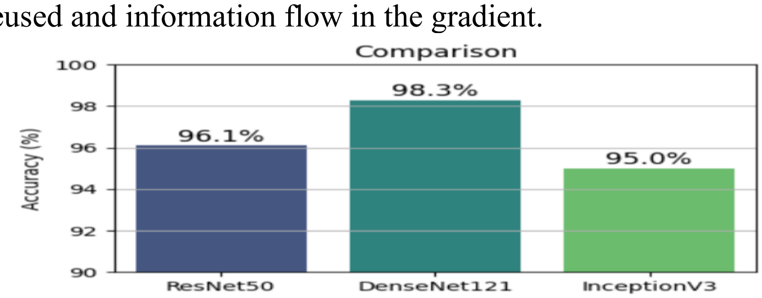

Figure 18 Illustration of comparative accuracies

Regarding their advantages and components, ResNet50 has a reasonably high accuracy at 96.1 percent, is simple to train, and versatile due to its depth and computational efficiency. InceptionV3, which achieves 95% accuracy, is superior in cases where it needs to work with multi-scale feature extractions on a limited number of resources. These findings imply that DenseNet121 is the most appropriate for the present dataset, but, at the same time, ResNet50 and InceptionV3 demonstrate high results, achieving competitive performance, and this point may also mean that ensemble methods or further fine-tuning may be introduced in another task. The figure graphically confirms that the DenseNet121 is leading the race with 98.3% accuracy, followed by the ResNet50 and InceptionV3 with 96.1% and 95.0% accuracy, no less with different hues of blue and green to show the distinction on the 0-100 level. More work may be done in order to optimize hyperparameters or hybrid networks to bring performance near theoretical maximums.

CONCLUSION

The outcomes reveal that DenseNet121 performs the best among the three in this classification problem with the highest accuracy, precision, recall, and F1-scores in all classes, which indicates that its dense connectivity scheme is better at capturing complex features in the images, thus leading to fewer misclassifications compared to its two counterparts, especially between benign and malignant cases where false negatives are the most critical to medical diagnostics. ResNet50 comes right behind with similar performance, whereas InceptionV3 falls a bit short, which is probably because the inception modules are less suitable for the complexity or size of this particular dataset. All these models have high efficacy, as the macro-averaged F1-scores have reached 96.07 percent (ResNet50), 98.25 percent (DenseNet121), and 94.96 percent (InceptionV3), which means all of them are highly competent at multi-class discrimination, but DenseNet121 is the most efficient one.

Limitations

There is a slight imbalance in the test set (1,200 benign and 1,208 normal), though this may bias the trained models to the majority-class results. Should the training data also have the same imbalances or dearth of diversity (e.g., demographic or lighting conditions, lesion types), the models might fail to perform well in real-world conditions. CNNs such as these are black-box models, with poor interpretability- it is unclear why certain misclassifications may take place (e.g. feature importance). Excessive fitting could occur through failing to use appropriate regularization on the models, particularly on the utilization of medical data sets that may be small or noisy. An excellent result in these conditions, but this metric can predict too high results in the case of imbalanced data; another metric, such as the Matthews Correlation Coefficient, can give a better overview of the model's performance. Results present a single result set, no requirement to cross-validate or mean+/-SD. Heavy computation requirements (i.e., the complexity of Inception V3) introduce an impediment to deployment on edge devices. There is no reference to how to manage noise-prone inputs, e.g., blurred photos or data corruption (as shown in medical scans). The models and data might add to healthcare disparities if the data is biased (e.g., concerning skin colour in dermatology).

Future Directions

Investigate ensemble techniques (such as averaging the output of all three models) to achieve the best of all three models and surpass the 98.3% accuracy. Research on more advanced architectures, such as EfficientNet, Vision Transformers (ViT), or combined CNN/Transformer models, to improve feature representation. Enhance data, e.g., through rotation, flipping, or generating new, synthetic data (via GANs). Utilise more diverse data, including publicly available repositories (e.g., ISIC skin cancer), and multi-fold cross-validation. Methods such as Grad-CAM or SHAP should be incorporated to facilitate understanding of the decision-making process, enabling clinicians to trust and debug the models. Benchmark on other metrics (e.g., AUC-ROC in multi-class), or real-world comparisons, such as their robustness to adversarial attacks, or shift changes. Create applications in real-time mobile sensor networks that turn into point-of-care diagnostic applications. Extract to multi-modal data (e.g., aggregating images with patient metadata) or federated capture so that training could be performed across hospitals without compromising privacy. Conduct ablation experiments to identify the factors, such as pre-training sets of datasets or hyperparameters, that may have an impact. Ideally, in the long term, clinical trials will provide live support for their effectiveness.

REFERENCES

[1] “Lung Cancer Statistics | How Common Is Lung Cancer?” Accessed: Aug. 25, 2025. [Online]. Available: https://www.cancer.org/cancer/types/lung-cancer/about/key-statistics.html

[2] Zainab, Hira, A. Khan, Ali Raza, Muhammad Ismaeel Khan, and Aftab Arif. "Integration of AI in Medical Imaging: Enhancing Diagnostic Accuracy and Workflow Efficiency." Global Insights in Artificial Intelligence and Computing 1, no. 1 (2025): 1-14.

[3] Zainab, Hira, Ali Raza A. Khan, Muhammad Ismaeel Khan, and Aftab Arif. "Ethical Considerations and Data Privacy Challenges in AI-Powered Healthcare Solutions for Cancer and Cardiovascular Diseases." Global Trends in Science and Technology 1, no. 1 (2025): 63-74.

[4] Arif, Aftab, Fadia Shah, Muhammad Ismaeel Khan, Ali Raza A. Khan, Aftab Hussain Tabasam, and Abdul Latif. 2023. “Anomaly Detection in IoHT Using Deep Learning: Enhancing Wearable Medical Device Security.” Migration Letters 20 (S12): 1992–2006.

[5] M. Faehling et al., “Trends in Overall Survival in Lung Adenocarcinoma with EFGR Mutation, KRAS Mutation, or No Mutation,” Cancers, vol. 17, no. 7, p. 1237, Apr. 2025, doi: 10.3390/cancers17071237.

[6] R. Siegel, “Cancer statistics, 2020.,” CA. Cancer J. Clin., vol. 70, no. 1, p. 7, 2020.

[7] R. L. Siegel, K. D. Miller, H. E. Fuchs, and A. Jemal, “Cancer statistics, 2022,” CA. Cancer J. Clin., vol. 72, no. 1, pp. 7–33, 2022.

[8] Khan, Ali Raza A., Muhammad Ismaeel Khan, and Aftab Arif. "AI in Surgical Robotics: Advancing Precision and Minimizing Human Error." Global Journal of Computer Sciences and Artificial Intelligence 1, no. 1 (2025): 17-30.

[9] J. Juan et al., “Computer-assisted diagnosis for an early identification of lung cancer in chest X rays,” Sci. Rep., vol. 13, no. 1, p. 7720, 2023.

[10] Zainab, Hira, Ali Raza A. Khan, Muhammad Ismaeel Khan, and Aftab Arif. "Innovative AI Solutions for Mental Health: Bridging Detection and Therapy." Global Journal of Emerging AI and Computing 1, no. 1 (2025): 51-58.

[11] Zainab, Hira, Muhammad Ismaeel Khan, Aftab Arif, and Ali Raza A. Khan. "Deep Learning in Precision Nutrition: Tailoring Diet Plans Based on Genetic and Microbiome Data." Global Journal of Computer Sciences and Artificial Intelligence 1, no. 1 (2025): 31-42.

[12] Zainab, Hira, Muhammad Ismaeel Khan, Aftab Arif, and Ali Raza A. Khan. "Development of Hybrid AI Models for Real-Time Cancer Diagnostics Using Multi-Modality Imaging (CT, MRI, PET)." Global Journal of Machine Learning and Computing 1, no. 1 (2025): 66-75.
[13] Asim, Muhammad, Fawad Nasim, Hijab Sehar, and Suhaib Naseem. "A DEEP LEARNING-BASED APPROACH FOR HEART DISEASE DETECTION AND EARLY WARNING." Contemporary Journal of Social Science Review 3, no. 2 (2025): 2856-2872.
[14] Nasim, Muhammad Fawad, and Jawad Ahmad. "Optimizing the Efficacy of Bagging Ensemble Deep Learning Models in Melanoma Skin Cancer Diagnosis." Journal of Innovative Computing and Emerging Technologies 5, no. 1 (2025).[14] S. Maurya, S. Tiwari, M. C. Mothukuri, C. M. Tangeda, R. N. S. Nandigam, and D. C. Addagiri, "A review on recent developments in cancer detection using Machine Learning and Deep Learning models," Biomed. Signal Process. Control, vol. 80, p. 104398, 2023.
[15] Aish, Muhammad Abdullah, Jawad Ahmad, Fawad Nasim, and Muhammad Javaid Iqbal. "Brain Tumor Segmentation and Classification Using ResNet50 and U-Net with TCGA-LGG and TCIA MRI Scans." Journal of Computing & Biomedical Informatics 8, no. 01 (2024).
[16] Tariq, Muhammad Arham, Muhammad Ismaeel Khan, Aftab Arif, Muhammad Aksam Iftikhar, and Ali Raza A. Khan. "Malware Images Visualization and Classification With Parameter Tunned Deep Learning Model." Metallurgical and Materials Engineering 31, no. 2 (2025): 68-73.https://doi.org/10.63278/1336.
[17] Arif, Aftab, Muhammad Ismaeel Khan, Ali Raza A. Khan, Nadeem Anjum, and Haroon Arif. "AI-Driven Cybersecurity Predictions: Safeguarding California's Digital Landscape." International Journal of Innovative Research in Computer Science and Technology 13 (2025): 74-78.[18] V. K. Gugulothu and S. Balaji, "An early prediction and classification of lung nodule diagnosis on CT images based on hybrid deep learning techniques," Multimed. Tools Appl., vol. 83, no. 1, pp. 1041–1061, 2024.
[18] Khan, Muhammad Ismaeel, Aftab Arif, Ali Raza A. Khan, Nadeem Anjum, and Haroon Arif. "The Dual Role of Artificial Intelligence in Cybersecurity: Enhancing Defense and Navigating Challenges." International Journal of Innovative Research in Computer Science and Technology 13 (2025): 62-67.
[19] Khan, Ali Raza A., Muhammad Ismaeel Khan, Aftab Arif, Nadeem Anjum, and Haroon Arif. "Intelligent Defense: Redefining OS Security with AI." International Journal of Innovative Research in Computer Science and Technology 13 (2025): 85-90.
[20] Nasim, Fawad, Muhammad Adnan Yousaf, Sohail Masood, Arfan Jaffar, and Muhammad Rashid. "Data-Driven Probabilistic S for Batsman Performance Prediction in a Cricket Match." Intelligent Automation & Soft Computing 36, no. 3 (2023).
[21]Khan, Muhammad Ismaeel, Aftab Arif, and Ali Raza A. Khan. "The Most Recent Advances and Uses of AI in Cybersecurity." BULLET: Jurnal Multidisiplin Ilmu 3, no. 4 (2024): 566-578.
[22] Arif, A., A. Khan, and M. I. Khan. "Role of AI in Predicting and Mitigating Threats: A Comprehensive Review." JURIHUM: Jurnal Inovasi dan Humaniora 2, no. 3 (2024): 297-311.
[23] Khan, Muhammad Ismaeel, Aftab Arif, and Ali Raza A. Khan. "AI's Revolutionary Role in Cyber Defense and Social Engineering." International Journal of Multidisciplinary Sciences and Arts 3, no. 4 (2024): 57-66.

[24] Khan, Muhammad Ismaeel. "Synergizing AI-Driven Insights, Cybersecurity, and Thermal Management: A Holistic Framework for Advancing Healthcare, Risk Mitigation, and Industrial Performance." Global Journal of Computer Sciences and Artificial Intelligence 1, no. 2: 40-60.
[25] Khan, M. I., A. Arif, and A. R. A. Khan. "AI-Driven Threat Detection: A Brief Overview of AI Techniques in Cybersecurity." BIN: Bulletin of Informatics 2, no. 2 (2024): 248-61.
[26] Arif, Aftab, Muhammad Ismaeel Khan, and Ali Raza A. Khan. "An overview of cyber threats generated by AI." International Journal of Multidisciplinary Sciences and Arts 3, no. 4 (2024): 67-76.
[27] H. Alyasriy and A. Muayed, "The IQ-OTHNCCD lung cancer dataset," Mendeley Data, vol. 1, no. 1, pp. 1–13, 2020.
[28] S. Pang et al., "VGG16-T: a novel deep convolutional neural network with boosting to identify pathological type of lung cancer in early stage by CT images," Int. J. Comput. Intell. Syst., vol. 13, no. 1, pp. 771–780, 2020.
[29] A. A. Alsheikhy, Y. Said, T. Shawly, A. K. Alzahrani, and H. Lahza, "A CAD System for Lung Cancer Detection Using Hybrid Deep Learning Techniques," Diagnostics, vol. 13, no. 6, p. 1174, 2023.
[30] M. K. Nali and P. Ramalingam, "Lung cancer prediction using convolutional neural network based VGG19 compared with VGG16 using CT-scan images for accuracy improvement," presented at the AIP Conference Proceedings, AIP Publishing, 2023.
[31] S. Dodia, A. B., and P. A. Mahesh, "Recent advancements in deep learning based lung cancer detection: A systematic review," Eng. Appl. Artif. Intell., vol. 116, p. 105490, Nov. 2022, doi: 10.1016/j.engappai.2022.105490.
[32] Y. Lu, H. Liang, S. Shi, and X. Fu, "Lung cancer detection using a dilated CNN with VGG16," presented at the 2021 4th International Conference on Signal Processing and Machine Learning, 2021, pp. 45–51.
[33] R. Parveen, U. Saleem, K. Abid, and N. Aslam, "Identification of Lungs Cancer by using Watershed Machine Learning Algorithm," VFAST Trans. Softw. Eng., vol. 11, no. 2, pp. 70–79, Jun. 2023, doi: 10.21015/vtse.v11i2.1500.
[34] S. Maurya, S. Tiwari, M. C. Mothukuri, C. M. Tangeda, R. N. S. Nandigam, and D. C. Addagiri, "A review on recent developments in cancer detection using Machine Learning and Deep Learning models," Biomed. Signal Process. Control, vol. 80, p. 104398, 2023.
[35] A. Panunzio and P. Sartori, "Lung cancer and radiological imaging," Curr. Radiopharm., vol. 13, no. 3, pp. 238–242, 2020.
[36] C. C. Chiet, K. W. How, P. Y. Han, and Y. H. Yen, "A Lung Cancer Detection with Pre-Trained CNN Models," J. Inform. Web Eng., vol. 3, no. 1, pp. 41–54, 2024.
[37] H. F. Kareem, M. S. AL-Huseiny, F. Y. Mohsen, E. A. Khalil, and Z. S. Hassan, "Evaluation of SVM performance in the detection of lung cancer in marked CT scan dataset," Indones. J. Electr. Eng. Comput. Sci., vol. 21, no. 3, p. 1731, Mar. 2021, doi: 10.11591/ijeecs.v21.i3.pp1731-1738.
[38] V. K. Gugulothu and S. Balaji, "An early prediction and classification of lung nodule diagnosis on CT images based on hybrid deep learning techniques," Multimed. Tools Appl., vol. 83, no. 1, pp. 1041–1061, 2024.
[39] A. Bhatt, K. Joshi, P. Jain, V. K. Gupta, and V. Vidisha, "A Deep Learning based Image Processing Technique for Early Lung Cancer Detection," in 2024 First International Conference on

Innovations in Communications, Electrical and Computer Engineering (ICICEC), Oct. 2024, pp. 1–6. doi: 10.1109/ICICEC62498.2024.10808684.
[40] B. Swarajya Lakshmi, "Intelligent Lung Cancer Detection: A Genetic Algorithm Machine Learning Fusion," Int. Res. J. Adv. Sci. Hub, vol. 6, no. 12, pp. 397–404, Dec. 2024, doi: 10.47392/IRJASH.2024.052.
[41] A. Chowdhury, T. Moni, A. A. N. Tushar, Md. P. Hossain, and M. A. Rahaman, "An Improved Deep Learning Model for Early Stage Lung Cancer Detection from CT Scan Images," in 2024 6th International Conference on Sustainable Technologies for Industry 5.0 (STI), Dec. 2024, pp. 1–6. doi: 10.1109/STI64222.2024.10951057.
[42] G. E. Güraksın and I. Kayadibi, "A Hybrid LECNN Architecture: A Computer-Assisted Early Diagnosis System for Lung Cancer Using CT Images," Int. J. Comput. Intell. Syst., vol. 18, no. 1, p. 35, Feb. 2025, doi: 10.1007/s44196-025-00761-3.
[43] C. de Margerie-Mellon and G. Chassagnon, "Artificial intelligence: A critical review of applications for lung nodule and lung cancer," Diagn. Interv. Imaging, vol. 104, no. 1, pp. 11–17, Jan. 2023, doi: 10.1016/j.diii.2022.11.007.
[44] I. Shafi et al., "An Effective Method for Lung Cancer Diagnosis from CT Scan Using Deep Learning-Based Support Vector Network," Cancers, vol. 14, no. 21, Art. no. 21, Jan. 2022, doi: 10.3390/cancers14215457.
[45] V. Karunakaran, N. Akshaya, B. Harismita, and S. Atchaya, "Lung Cancer Classification Using CNN with Data Augmentation," in 2024 International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS), Dec. 2024, pp. 1152–1157. doi: 10.1109/ICICNIS64247.2024.10823294.
[46] M. K. Ravindranathan, S. Vadivu D, and N. Rajagopalan, "Pulmonary Prognosis: Predictive Analytics for Lung Cancer Detection," in 2024 2nd International Conference on Recent Advances in Information Technology for Sustainable Development (ICRAIS), Nov. 2024, pp. 261–265. doi: 10.1109/ICRAIS62903.2024.10811711.
[47] P. Student, I. Ahmad, and S. Ozaydin, "Lungs-CT-Scan Cancer Prediction Using Convolutional Neural Networks (CNN) and VGG16 Methods," vol. 14, pp. 1–17, Sep. 2023.
[48] "Identification of Lung Cancer Affected CT-Scan Images Using a Light-Weight Deep Learning Architecture | SpringerLink." Accessed: Aug. 25, 2025. [Online]. Available: https://link.springer.com/chapter/10.1007/978-981-97-6489-1_7
[49] D. S. Buchberger, R. Khurana, M. Bolen, and G. M. M. Videtic, "The Treatment of Patients with Early-Stage Non-Small Cell Lung Cancer Who Are Not Candidates or Decline Surgical Resection: The Role of Radiation and Image-Guided Thermal Ablation," J. Clin. Med., vol. 13, no. 24, p. 7777, Jan. 2024, doi: 10.3390/jcm13247777.
[46] I. Soerjomataram and F. Bray, "Planning for tomorrow: global cancer incidence and the role of prevention 2020–2070," Nat. Rev. Clin. Oncol., vol. 18, no. 10, pp. 663–672, 2021.
[47] "IQ-OTH/NCCD Lung Cancer Dataset (Augmented)." Accessed: Aug. 25, 2025. [Online]. Available: https://www.kaggle.com/datasets/subhajeetdas/iq-othnccd-lung-cancer-dataset-augmented