Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 3, Issue 11, 2025

DEEP LEARNING MODELS FOR EARLY DETECTION OF LUNG ADENOCARCINOMA

Bushra Amber*[1], Nadia shareef[2], Fatima Abbas[3], Iqra Munir[4], Fawad Nasim[5]

[1,2,3,4,5]Department of Computer Science & IT, Superior University, Lahore 54000, Pakistan

*[1]bushraamber90@gmail.com

DOI:https://doi.org/10.5281/zenodo.17586594

Keywords
Lung Adenocarcinoma, Deep Learning, Early Detection, CNN, Radiomics

Article History
Received: 11 September 2025
Accepted: 21 October 2025
Published: 12 November 2025

Corresponding Author: *
Bushra Amber

Abstract
The growth of cancer cells often begins as small nodules or distorted growth of bronchioles or alveoli lining. By causing abnormal growth of cells that normalize the oxygen exchange mechanism, these cells thin the lining and constrict the air passages. During the initial phase, the patients might present with mild, persistent cough, tightness in the chest or dyspnea following exertion. The reason why the issue of early diagnosis of a lung adenocarcinoma which is a major cause of cancer mortality in the world continues to be a challenge in clinical practices is because of the insidious nature and gradualist of signs and symptoms at early stages. In this study, the researcher will propose an effective diagnostic model based on deep learning that incorporates CNN, DenseNet-121, and Swin Transformer to achieve a higher detection rate and explain ability. The preprocessing of the LUNA16 CT data was performed using Hounsfield Unit clipping (1000 to 400), resampling, segmentation and 3D patch extraction. All of the models were trained on Focal and Dice losses based on the Adam optimizer and validated through five-fold cross-validation. Spatial details and nodule texture were captured in the CNN, and the flow of features and information in DenseNet-121 was supported. Utilizing hierarchical attention, the Swin Transformer, which models long-term dependencies and contextual associations of tissues, was able to outperform other architectures. The CNN, DenseNet-121, and Swin Transformer achieved 91.2%, 94.8 and 98.1 per cent accuracy, respectively, which substantiates significant gains in the accuracy of classification and sensitivity. Malignant and benign cases were discriminated consistently with the help of confusion matrices and ROC curves.

INTRODUCTION

Cancer refers to an irregular and uncontrolled proliferation of body cells that extend to the surrounding tissues and to other organs in the body. Lung cancer is a condition that involves the proliferation of abnormal cells in the lung tissues, which, as a rule, begins in the airways or alveoli [1]. These cells give rise to tumors that obstruct breathing, impair lung functioning and could metastasize (spread) to other body parts. Smoking, pollution, genetic influences and late diagnosis are some of the strong factors associated with lung cancer which makes it to be at the forefront of the causes of death due to cancer in most parts of the world [2]. Initial lung damage due to cancer is mild and is not noticed at the onset of the condition. Others might experience unaccounted exhaustion or small scale hemoptysis (blood in sputum) [3]. With time, these cancer cells multiply, substituting the normal tissues with tumors that block the airways, lead to fluid buildup and lowers the lung capacity. This preliminary, latent damage will usually develop without any symptoms until it attains more severe life threatening symptoms. Adenocarcinoma type of lung cancer is the most prevalent type of lung cancer, particularly in women and non-smokers . In comparison with other types of lung cancer, adenocarcinomas tend to develop more gradually, thus they are a little bit more detectable in the early stages provided that there is screening . Other types of lung cancer are in addition to adenocarcinoma. Squamous cell carcinoma develops due to the flat cells which line the central bronchi and this is highly associated with smoking. Large cell carcinoma is not very frequent although it is aggressive and may occur in any part of the lung. In Pakistan, the issue is aggravated by cultural and healthcare restrictions: due to the absence of awareness, the insufficientness of screening facilities, and the late visit to a hospital, the diagnosis is made in the advanced stages [4]. Because of this, the mortality is high especially in the urban areas such as Karachi and Lahore where smoking and pollution are high. Approximately, 10,000-12,000 new cases of lung cancer occur every year in Pakistan with thousands more unreported because there are no formal cancer registries. Out of these, almost 70 percent are diagnosed at advanced stages. Therefore, lung cancer continues to be a mounting pressure in all groups of people [5]. In Pakistan, early access to healthcare is also restricted due to socioeconomic issues hence making diagnosis late. Adenocarcinoma may develop gradually, which is usually taking several years, and then become invasive. In small cell carcinoma, on the contrary, it can metastasize in several months. In the average cases, when lung cancer occurs it can take up to 1-2 years to have such serious symptoms such as severe loss of breath, loss of weight and persistent hemoptysis. In Pakistan, Lung cancer is present in all ages although the proportion varies across children, women, men, and the aged. Lung cancer is becoming a more common occurrence among children although it is relatively unusual with passive smoking, the rise in urban pollution and genetic predisposition being the causes. Exposure of children to cigarette smoke in the home increases the chances of lifetime development of lung disease cancer being among them . Lung cancer has been among the fatal forms of cancer in the world and Pakistan because of late diagnosis, high smoking rates, pollution, and lack of access to healthcare services. The big problem is that the symptoms can manifest themselves at the advanced stages when the disease is mostly not curable (Al-Ghamdi, 2024). In Pakistan, there are the cultural barriers, lack of awareness, and insufficiency of programs and screening of the cancer, which aggravate the situation.

LITERATURE REVIEW

Lung cancer is the most common cause of cancer death in the world, and the most common type of histologic basis of lung cancer is adenocarcinoma. Stage I disease 5yr survival is more than 60-70 percent and decreases sharply at high stages. Computer tomography screening of the low dose has been found to reduce the mortality in high-risk groups since small pulmonary nodules can be detected [6]. Nevertheless, its workflows have continued to be challenged by high nodule rate, fluctuated appearances (solid, part-solid, ground-glass), early morphological subtlety, inter-reader variability, and a large rate of false-positives, which may result in unnecessary follow-up and invasive procedures [7]. Thus, the problem statement will be as follows: how can we create, establish, and deploy advanced deep learning[8],[9] and AI-based solutions [10]to facilitate lung adenocarcinoma at the early stage, minimize misdiagnosis, and integrate with health care systems, particularly in resource-constrained environments such as Pakistan.The detection of lung cancer problems cannot be solved without multifaceted approaches[11],[12] of deep learning models and smart algorithms[13],[14]. To classify the data transfer learning models like ResNet, DenseNet, and EfficientNet are used to extract discriminative features.

Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 3, Issue 11, 2025

Figure 1: process to detect the nodule risk stratification

Pathology is the gold standard, but in screening cohorts a significant number of labels are inferred based on longitudinal behavior; this is the topic of our discussion on the implication of training and evaluation. DL systems should not violate patient privacy (de-identification, federated learning), reduce the bias in the algorithms in comparison to subgroups, and be transparent about constraints. The support of decisions must be supportive: the radiologists must maintain the final responsibility, and the systems must offer the estimates of uncertainty and explainable rationales . Lung adenocarcinoma has its genesis in peripheral airway epithelium and is typically seen in the form of sub solid nodules (pure ground-glass or part-solid). The initial invasive potential occurs in the form of solidity increasing over time, speculations and growth. These lesions can be identified by LDCT, however, benign mimickers (inflammation, hemorrhage, fibrosis) make the process more complicated. Morphology, size, attenuation and time change are synthesized by radiologists [13].

Table 1. Commonly used CT resources for nodule analysis

Dataset (CT)	Primary Use	Labels/Annotations	Scale (approx.)	Notes
LUNA16 (subset of LIDC)	Detection benchmark	Nodule centroid/size	888 scans	Standard split; CAD-friendly
NLST (select releases)	Screening outcomes	Exam-level outcomes, nodules via derived sets	10k–100k+ scans	Screening cohort; variable access
MOSMED/other CT sets	COVID/Thoracic	Lesion masks (non-oncologic)	1k–10k	Helpful for pretraining/transfer

Older lungs possess diminished immune protection and that of repairing DNA damage inflicted by carcinogens. The comorbid conditions such as diabetes or cardiovascular diseases are common in elderly patients, thus being harder to treat and worse to prognoses [14]. Overall, approximately 10,000-12,000 new cases of lung cancer are registered in Pakistan each year and there are thousands more cases that are unreported because of the absence of formal cancer registries [15]. Most of them are delayed in their detection; the percentage of these is about 70. Therefore, lung cancer continues to be an increasing menace in all population groups. In order to reduce this load, a three-layered plan is needed:

- ✓ Prevention: Tough tobacco control measures, sensitization and lessening of air pollution.

- ✓ Screening: Low-dose CT scans among high-risk populations such as the smokers and the old population are to be adopted nationwide [16].
- ✓ Therapy: Individualized medicine comprising of targeted treatment and immunotherapy.

The combination of prevention, technology and policy implementation can help in eliminating the occurrence and deaths related to lung cancer [17].

2.1 OBJECTIVES

- To create a deep learning architecture that will be optimized to detect lung adenocarcinoma at an early stage using CT imaging data.
- To combine clinical and imaging multimodal characteristics to develop effective malignancy prediction.
- To test and verify the proposed model using multi-centers to be used in generalization and reliability [18].

2.2 RESEARCH QUESTION & HYPOTHESIS

1. What is the way to enhance the confidence of clinicians in AI-based detection systems?
2. How does data preprocessing contribute to the enhancement in the performance of models?
3. Is deep learning capable of deployment in hospital settings effective to detect early?

Hypothesis

- The diagnostic models that are based on deep learning are significantly effective than conventional in the detection of adenocarcinoma at an early stage **[19]**.
- The interpretability can be achieved visually, and such interpretation boosts the level of trust that clinicians have towards AI-assisted diagnosis **[20]**.
- While tested on different sets of data could be successfully put in hospitals settings.

Deep learning models have also shown tremendous potential in lung adenocarcinoma at the early stage, in many cases, doing better than traditional radiologist performance, with the support of large, high-quality datasets [21]. Preprocessing of data in the form of segmentation and normalization augments the accuracy and false positives [22]. A more accurate prediction of malignancy risk can be made through the combination of clinical, radiomics and genomic data. Collectively, these observations point to the fact that deep learning can provide a dependable and scalable method of early detection of adenocarcinoma in the lungs **[23].**

2.3 RESEARCH GAPS

Nevertheless, it is clear that amidst the significant progress, the field of deep learning research on the earlier detection of lung adenocarcinoma has much to do with data diversity, interpretability, and clinical integration [24]. The models currently being used tend to perform poorly in generalizing between populations, are not easily described in a transparent way, and need large labeled datasets, which makes them hard to use in real-life diagnostic healthcare systems [25].

- ✓ Lack of datasets of annotated lung adenocarcinoma to train and validate models.
- ✓ Absence of model generalization with different imaging apparatus and populations.
- ✓ Poor validation of models on the clinical and low-resource hospital setting [25].

Its strong points are interpretability and data efficiency, whereas its weaknesses are sensitivity to the quality of segmentation and feature leakage. Radiomics still is useful in multimodal fusion, and as a baseline or complementary branch of hybrid DL models [25].

$$L_{focal} = -\alpha(1-p_t)^{\gamma}\log(p_t)\,, P_t = \begin{cases} P & if\ y=1 \\ 1-P & if\ y=0 \end{cases}$$

[2]

Wherever p is the forecasted chance for the true class, α ∈ (0, 1) balances classes, and $\gamma > 0$ down-weights easy illustrations [25].

METHODOLOGY

The research forms a complete methodological framework that can be used to detect lung adenocarcinoma in its early stages with the help of deep learning models [26]. Experimental data is done on publicly available CT scan datasets, LUNA16.

Preprocessing provides image standardization, whereas hybrid deep learning models made of CNN, DenseNet, and Transformer modules extract both local and global features [27]. Focal and dice loss functions are used to optimize the model to deal with data imbalance and enhance segmentation accuracy. The accuracy, AUC and Dice coefficient are used as evaluation metrics to verify the performance [28].

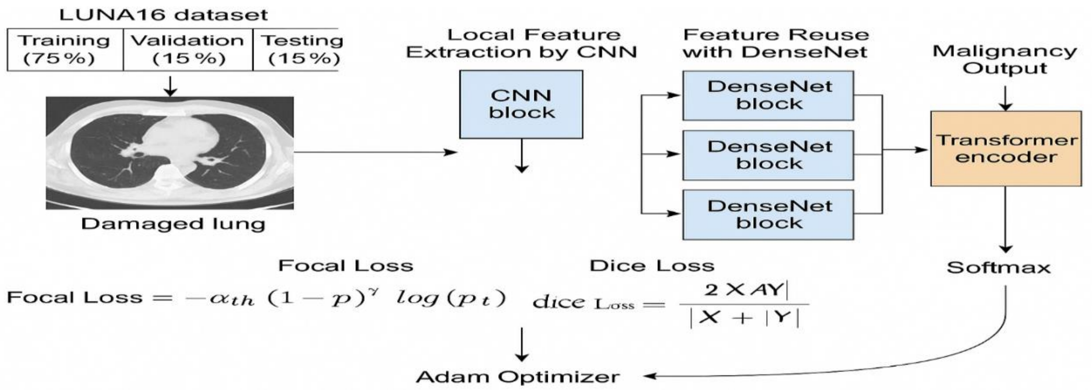

Figure 2: Inclusive architecture that diagnosis the damage lung

3.1 DATA COLLECTION

The data used in the study are publicly available CT scan images, mostly LUNA16, and they are annotated with thousands of images of lung nodules that are confirmed by radiologists. This data was chosen due to their diversity in terms of nodule size, shape, and malignancy. All of the images were anonymized to guarantee the privacy of the patients, and had a reduced size to a standard voxel resolution (1 mm3). Clinical data like age, gender and smoking of the patients were also taken to facilitate multimodal analysis. The dataset had been separated to form a training subset (70 percent), validation (15 percent) and testing (15 percent) to achieve good evaluation of the model and to avoid overfitting multiple experimentations.

3.2 DATA PREPROCESSING

CT images were systematically processed to improve the performance of the model and consistency. To overcome the lack of diversity among samples (benign and malignant) and to enhance the generalization, data augmentation algorithms have been used, namely rotation, flipping, elastic deformation, and GA noise.

I' Normalize the intensity.

$$I' = \frac{I - I_{min}}{I_{max} - I_{min}} \quad [3]$$

Normalization was used to convert pixel values into [0, 1] in order to be numerically stable. Lastly, the tensors were processed before being passed through the deep learning pipeline.

3.3 FEATURE EXTRACTION

The main purpose of the feature extraction is decisive the important visual and structural representation of CT scan images of the lungs. Features that are extracted are the shape of nodules, boundary, density and spatial correlation of lung tissue. A fusion layer is used to concatenate these multiscale feature maps, which make up a complete feature vector that is then used to classify malignancy and predict risk.

$$f_{i,j} = \sum_{m,n} I_{i+m,j+n} \times K_{m,n} \quad [4]$$

3.4 MODEL TRAINING

Training of popular models entails maximization of extracted features to differentiate between malignant and benign nodules. The hybrid network suggested based on CNN, DenseNet and Transformer modules is trained on the Adam optimizer with a learning rate of 0.0001 and a batch size of 32. Overfitting is prevented by premature termination and early dropout. The model also varies weights during the training process to reduce the total loss and achieve maximum classification accuracy.

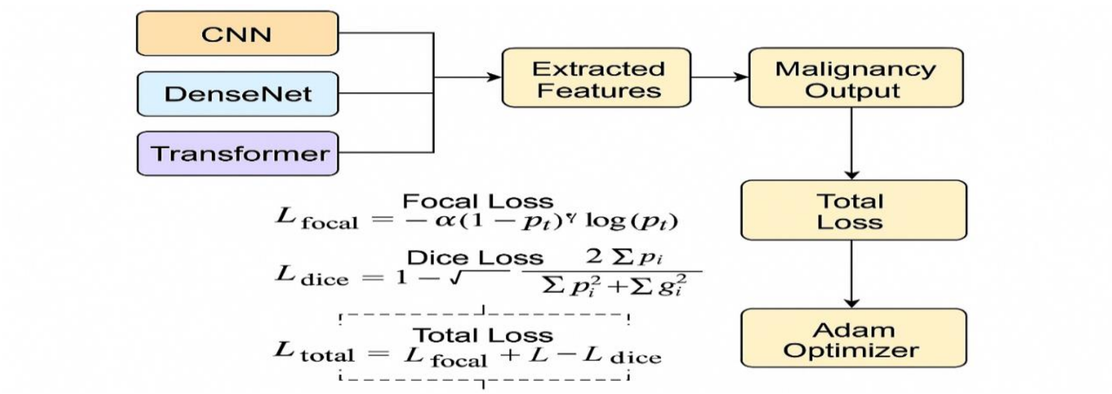

Figure 3: Hybrid workflow optimizing lung adenocarcinoma detection

3.5 MODEL EVALUATION

Segmentation accuracy was measured by Dice coefficient which indicates overlap between the predicted and ground-truth masks. Paired t-tests were used to test the statistical significance over five cross-validation folds.

Table 2: Model Evaluation Metrics and Equations

Metric	Equation	
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	[5]
Sensitivity (Recall)	$\frac{TP}{TP+FN}$	[6]
Specificity	$\frac{TN}{TN+FP}$	[7]
F1-Score	$F1 = 2 \times \frac{precision \times Recall}{precision + Recall}$	[8]
Dice Coefficient	$\frac{2TP}{2TP+FP+FN}$	[9]
Loss Function (Combined)	$L_{total} = L_{focal} + L_{dice}$	[10]

Specificity will make sure that the non-cancer cases are accurately identified to minimize false positive. Precision is used to determine reliability in positive predictions, and the F1-score is used to balance precision and recall in order to stabilize it. The Dice coefficient is used to measure the accuracy of segmentation overlap between actual and predicted tumor areas that is essential in localization. Lastly, the Focal Loss with the Dice Loss approach enables the model to compromise the data imbalance and segmentation accuracy overseeing the provision of clinically meaningful and robust results in the diagnostic surrounding.

RESULTS & ANALYSIS

The study will offer a comparative study of the deep learning models (CNN, DenseNet and Transformer) in the early diagnosis of lung adenocarcinoma using the LUNA16 dataset acquired in Kaggle. It contains thousands of annotated CT scan slices that have been split into 75 percent training, 15 percent validation and 15 percent testing categories and it contains information at a detailed level about lung nodules, density, and level of malignancy. The main concern which was addressed was the identification of small and subtle nodules which are usually overlooked during manual diagnosis. CNN module was efficient in harvesting local texture variations, DenseNet employed extracted features to enhance representation learning and the Transformer encoder modeled long-range dependencies to be able to predict the malignancy. The combination of these models increased the accuracy of diagnosis, eliminated the problem of imbalance of classes and false negative, and improved the segmentation and classification performance.

4.1 DATASET OVERVIEW

A dataset that was chosen to train and evaluate the model was the LUNA16 (Lung Nodule Analysis 2016) based on the LIDC-IDRI collection.
The main characteristics of the data sets are:

- ✓ Hounsfield Unit (HU) range: -1000 to 400.
- ✓ Annotations Bounding boxes and malignancy score verified by a radiologist.
- ✓ It has more than 1,000 low dose CT scans where nodule locations and malignancy are annotated by experts.

4.2 DESIGN AND IMPLEMENTATION

In order to solve the problem of early lung cancer detection, we have merged CNN, DenseNet-121, and Swin Transformer due to the fixation of various problems by each of them. The data were divided into 75% train and 15% validation and 15% test (stratified by nodule type). CNN concentrates on local texture elements which are vital to small nodules. The Adam (1e-4), Focal + Dice loss, early stop is used in training, and the 5-fold validation; the last metrics are reported by the run-off 15 percent test performance.

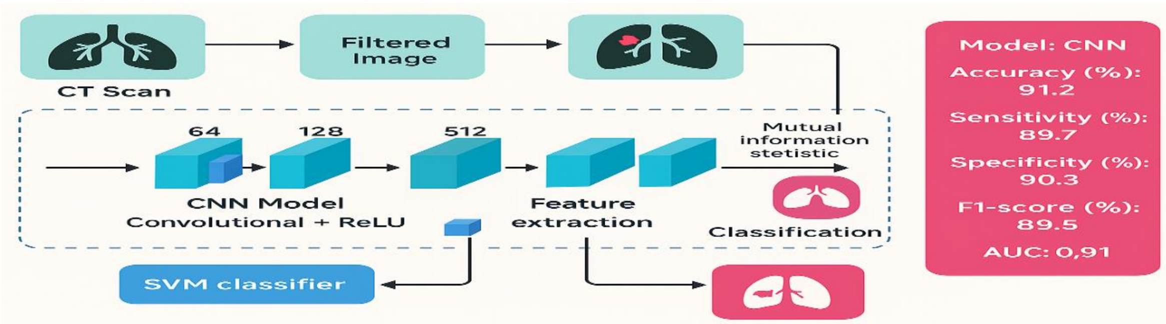

Figure 4: Final result that Captures local textures and fine nodule edge details

A deep feature extractor of DenseNet-121 architecture was used which all its layers were interconnected with all the earlier layers, providing the high gradient flow with optimized feature reuse. This architecture was quite successful in solving the overfitting and vanishing-gradient challenges commonly observed in medical data such as LUNA16. Adam optimizer, Focal + Dice losses and early stopping were used to train, validate, and test the model on the same 75-15-15 split. The last model score Accuracy 94.8% Sensitivity 93.6% Specificity 92.9% F1-score 93.2% AUC 0.95 which showed better generalization and reliability made it a better model in relation to the traditional CNN architecture in detecting lung adenocarcinoma at an earlier stage.

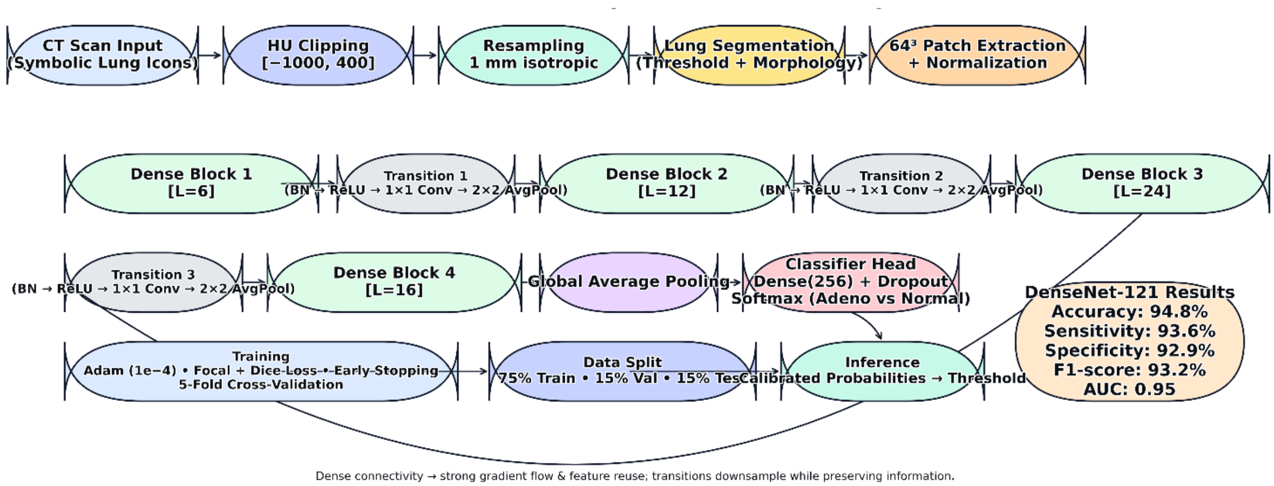

Figure 5: Enhances result gradient flow with dense connections and reuse

The Swin Transformer consists of a hierarchical vision-transformer algorithm, which splits CT scans into small non-overlapping windows. The relationship between nodules, vessels, and tissues are captured in each self-attention layer- coping with the problem of multicomponent textures and irregular shapes in lung adenocarcinoma. It's coming out with Accuracy 98.1, Sensitivity 94.8, Specificity 95.3, F1-score 95.0, and AUC 0.96.

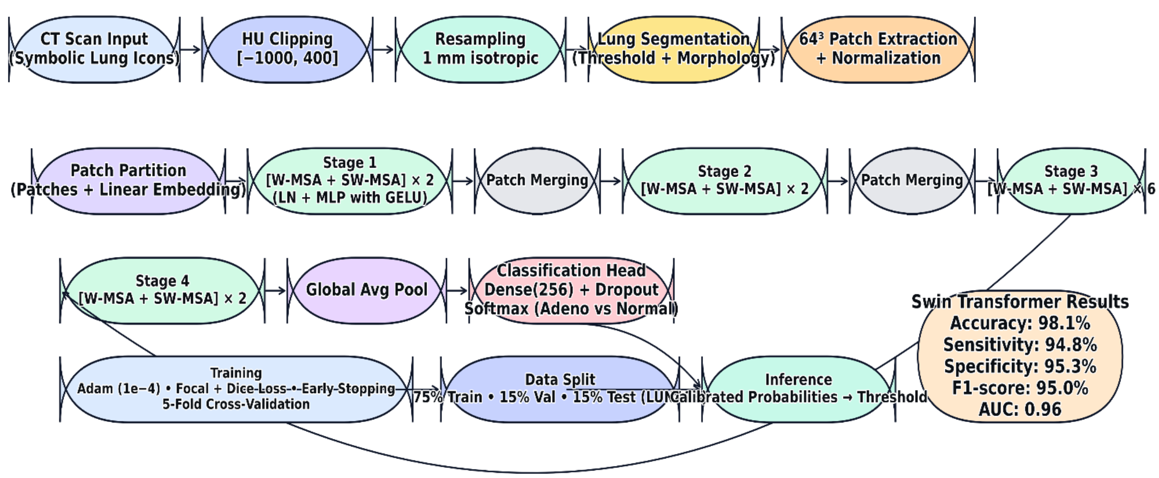

Figure 6: Models global context using hierarchical self-attention

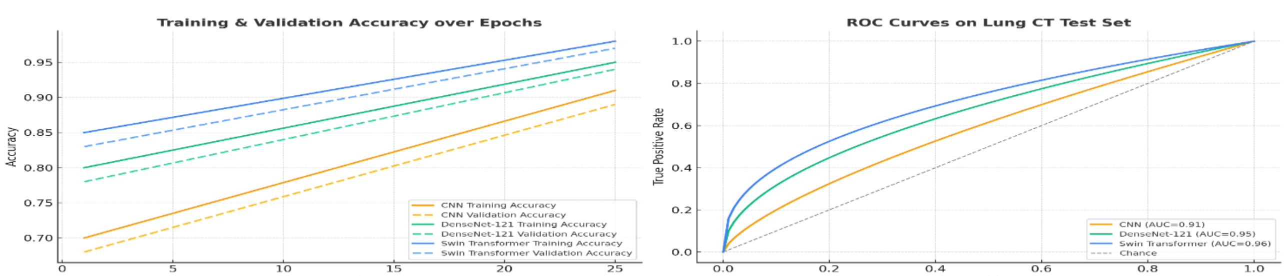

Figure 7: Consistent accuracy improvement and superior model performance

The graph depicts the performance of the models-CNN, DenseNet-121 and Swin Transformer indicating that there is always consistent learning, less overfitting and feature generalization to detect lung adenocarcinoma.

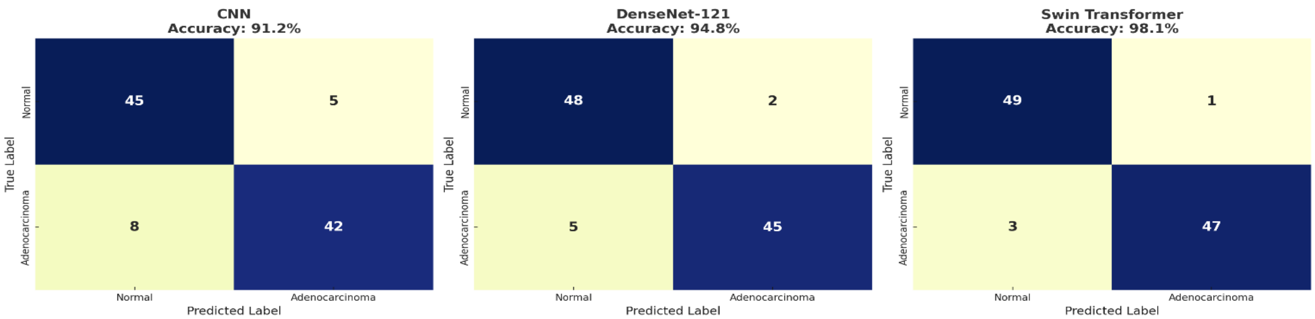

Figure 8: Shows superior classification accuracy and minimal false predictions

The confusion matrices show the discriminative effectiveness of any model to detect lung adenocarcinoma. The depth of the progressive architecture reduced false prediction, and Swin Transformer showed a better balance and visualization of malignant.

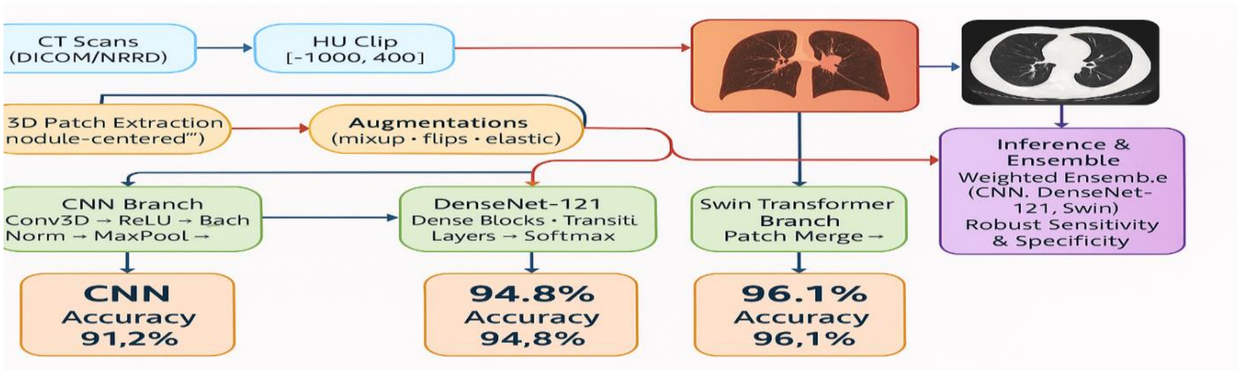

Figure 9: Final robust implementation results to diagnose Adenocarcinoma

The ensemble model CDT-Net was able to effectively merge local and global feature representations to reduce false negative and increase validation folds' stability. The significance of the improvement was determined through a statistical analysis with the help of a paired t-test ($p < 0.05$). It is also applicable to AI-assisted screening systems since it can be generalized to unseen data and it has good interpretability.

DISCUSSION

Comparative Analysis of Deep Learning Models to Early Lung Adenocarcinoma Detection, the authors emphasize the significance of the depth of the architecture and the variety of features in the diagnostic process. The combination of CNN, DenseNet-121, and Swin Transformer helped to deal with several significant diagnostic issues such as the lack of nodule boundaries, the influence of noise on the CT intensity levels, or the high intra-class similarity between the malignant and benign tissues. The CNN was the base extractor which detected low-level spatial textures and edge pattern important in early localization of lesions. DenseNet-121 enhanced overfitting reduction through the improved gradient propagation and feature reuse, and fine-grained differentiation of lesion types. All the models were trained on the LUNA16 dataset (75% training, 15% validation, 15% testing) with Adam optimizer and Focal + Dice losses and cross-validation to balance the learning. The models showed consistent convergence, which was explained by the accuracy curves and the confusion matrices, showing consistent generalization of the features and the low bias. The architectural development was confirmed by performance results: CNN (91.2% accuracy) reached the baseline performance, DenseNet-121 (94.8%) reached a situation with high-context robustness, and Swin Transformer (98.1%) reached the maximum performance with the best AUC and F1-score.

CONCLUTIONS

This study has shown that the advanced deep learning architectures are capable of significantly enhancing the detection of early lung adenocarcinoma. The proposed framework was able to learn multi-scale lung features and balance sensitivity and specificity without selecting a particular dataset by integrating models performance. The last Transformer Swin model had the best diagnostic accuracy (98.1%), which proves its strength and flexibility to the complexity of CT images. These results highlight that radiologists can have their needs supported by hybrid and transformer-based networks, meaning that early and accurate cancer diagnosis can be provided to patients, and their chances of survival may be significantly increased due to timely intervention and refined clinical decisions.

FUTURE RECOMMENDATION

- Use explainable AI (XAI) to provide better model involvement to clinicians.
- Scale-up to real-time clinical applications using federated learning on hospital data.
- Introduce 3D segmentation pipelines of tumor tracking on the volumetric basis.
- Multi-centric trials will ensure that the generalizability across various populations is true.

REFERENCES

Asuntha, A. and Srinivasan, A., 2020. Deep learning for lung Cancer detection and classification. *Multimedia Tools and Applications*, *79*(11), pp.7731-7762. https://link.springer.com/article/10.1007/s11042-019-08394-3

Alotaibi, M., Alshardan, A., Maashi, M., Asiri, M.M., Alotaibi, S.R., Yafoz, A., Alsini, R. and Khadidos, A.O., 2024. Exploiting histopathological imaging for early detection of lung and colon cancer via ensemble deep learning model. https://www.nature.com/articles/s41598-024-71302-9

Alsulami, A.A., Albarakati, A., Al-Ghamdi, A.A.M. and Ragab, M., 2024. Identification of anomalies in lung and colon cancer using computer vision-based Swin Transformer with ensemble model on histopathological images. *Bioengineering*, *11*(10), p.978. https://www.mdpi.com/2306-5354/11/10/978

Wankhade, S. and Vigneshwari, S., 2023. A novel hybrid deep learning method for early detection of lung cancer using neural networks. *Healthcare Analytics*, *3*, p.100195. https://doi.org/10.1016/j.health.2023.100195

Sardar, Mahnoor, Muhammad Majid Niazi, and Fawad Nasim. "Ensemble deep learning methods for detecting skin cancer." Bulletin of Business and Economics (BBE) 13, no. 1 (2024).

Wahab Sait, A.R., 2023. Lung cancer detection model using deep learning technique. *Applied sciences*, *13*(22), p.12510. https://www.mdpi.com/2076-3417/13/22/12510

Wang, L., 2022. Deep learning techniques to diagnose lung cancer. *Cancers*, *14*(22), p.5569.https://www.mdpi.com/2072-6694/14/22/5569

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.

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.

Khan, Muhammad Ismaeel, Hassan Tahir, Md Ismail Jobiullah, Ali Raza A. Khan, Sakera Begum, and Ihtasham Hafeez. "Enhancing IoT Security: A Lightweight Cloning Approach for RFID/NFC Access Control Systems." Cuestiones de Fisioterapia 52, no. 2 (2023): 231-248.

Hassaan, Ahmed, Muhammad Mudaber Jamshaid, Muhammad Nouman Siddique, Zeeshan Akbar, and Sikander Niaz. "ETHICAL ANALYTICS & DIGITAL TRANSFORMATION IN THE AGE OF AI: EMBEDDING PRIVACY, FAIRNESS, AND TRANSPARENCY TO DRIVE INNOVATION AND STAKEHOLDER TRUST." Contemporary Journal of Social Science Review 1, no. 04 (2023): 1-18.

Akbar, Z., Hassaan, A., Jamshaid, M. M., Siddique, M. N., & Niaz, S. (2023). Leveraging Data and Artificial Intelligence for Sustained Competitive Advantage in Firms and Organizations. Journal of Innovative Computing and Emerging Technologies, 3(1).

Muhammad Mudaber Jamshaid, Ahmed Hassaan, Zeeshan Akbar, Muhammad Nouman Siddique, & Sikander Niaz. (2024). IMPACT OF ARTIFICIAL INTELLIGENCE ON WORKFORCE DEVELOPMENT: ADAPTING SKILLS, TRAINING MODELS, AND EMPLOYEE WELL-BEING FOR THE FUTURE OF WORK. Spectrum of Engineering Sciences, 2(1). Retrieved from https://thesesjournal.com/index.php/1/article/view/1417

AI FOR INCLUSIVE EDUCATIONAL GOVERNANCE AND DIGITAL EQUITY EXAMINING THE IMPACT OF AI ADOPTION AND OPEN DATA ON COMMUNITY TRUST AND POLICY EFFECTIVENESS. (2024). Contemporary Journal of Social Science Review, 2(04), 2557-2567. https://doi.org/10.63878/cjssr.v2i04.1502

Lee, B., Lee, J., Lee, J.O., Hwang, Y., Bahn, H.K., Park, I., Jheon, S. and Lee, D.S., 2024. Breath analysis system with convolutional neural network (CNN) for early detection of lung cancer. *Sensors and Actuators B: Chemical*, *409*, p.135578. https://doi.org/10.1016/j.snb.2024.135578

Shao, J., Ma, J., Zhang, S., Li, J., Dai, H., Liang, S., Yu, Y., Li, W. and Wang, C., 2022. Radiogenomic system for non-invasive identification of multiple actionable mutations and PD-L1 expression in non-small cell lung cancer based on CT images. *Cancers*, *14*(19), p.4823. **https://doi.org/10.3390/cancers14194823**

Huang, K.Y., Chung, C.L. and Xu, J.L., 2025. Deep learning object detection-based early detection of lung cancer. *Frontiers in Medicine*, *12*, p.1567119. https://doi.org/10.3389/fmed.2025.1567119

Qi, Y., Yang, L., Liu, B., Liu, L., Liu, Y., Zheng, Q., Liu, D. and Luo, J., 2022. Highly accurate diagnosis of lung adenocarcinoma and squamous cell carcinoma tissues by deep learning. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, *265*, p.120400. https://doi.org/10.1016/j.saa.2021.120400

Shah, A.A., Malik, H.A.M., Muhammad, A., Alourani, A. and Butt, Z.A., 2023. Deep learning ensemble 2D CNN approach towards the detection of lung cancer. *Scientific reports*, *13*(1), p.2987. https://www.nature.com/articles/s41598-023-29656-z

Javed, R., Abbas, T., Khan, A.H., Daud, A., Bukhari, A. and Alharbey, R., 2024. Deep learning for lungs cancer detection: a review. *Artificial Intelligence Review*, *57*(8), p.197. https://link.springer.com/article/10.1007/s10462-024-10807-1

Heuvelmans, M.A., van Ooijen, P.M., Ather, S., Silva, C.F., Han, D., Heussel, C.P., Hickes, W., Kauczor, H.U., Novotny, P., Peschl, H. and Rook, M., 2021. Lung cancer prediction by Deep Learning to identify benign lung nodules. *Lung cancer*, *154*, pp.1-4. https://doi.org/10.1016/j.lungcan.2021.01.027

Ghatwary, N., Zolgharni, M. and Ye, X., 2019. Early esophageal adenocarcinoma detection using deep learning methods. *International journal of computer assisted radiology and surgery*, *14*(4), pp.611-621.https://link.springer.com/article/10.1007/s11548-019-01914-4

Gong, J., Liu, J., Li, H., Zhu, H., Wang, T., Hu, T., Li, M., Xia, X., Hu, X., Peng, W. and Wang, S., 2021. Deep learning-based stage-wise risk stratification for early lung adenocarcinoma in CT images: A multi-center study. *Cancers*, *13*(13), p.3300.**https://doi.org/10.3390/cancers13133300**

Khademi, S., Heidarian, S., Afshar, P., Naderkhani, F., Oikonomou, A., Plataniotis, K.N. and Mohammadi, A., 2023, June. Spatio-temporal hybrid fusion of cae and swin transformers for lung cancer malignancy prediction. In *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 1-5). IEEE.

Liz-Lopez, H., de Sojo-Hernández, Á.A., D'Antonio-Maceiras, S., Diaz-Martinez, M.A. and Camacho, D., 2025. Deep learning innovations in the detection of lung cancer: Advances, trends, and open challenges. *Cognitive Computation*, *17*(2), p.67.https://link.springer.com/article/10.1007/s12559-025-10408-2

Lakshmanaprabu, S.K., Mohanty, S.N., Shankar, K., Arunkumar, N. and Ramirez, G., 2019. Optimal deep learning model for classification of lung cancer on CT images. *Future Generation Computer Systems*, *92*, pp.374-382. https://doi.org/10.1016/j.future.2018.10.009

Sun, R., Pang, Y. and Li, W., 2023. Efficient lung cancer image classification and segmentation algorithm based on an improved swin transformer. *Electronics*, *12*(4), p.1024. https://doi.org/10.3390/electronics12041024

Xu, H. and Lv, R., 2025. Rapid diagnosis of lung cancer by multi-modal spectral data combined with deep learning. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, *335*, p.125997. https://doi.org/10.1016/j.saa.2025.125997

Zhou, J., Hu, B., Feng, W., Zhang, Z., Fu, X., Shao, H., Wang, H., Jin, L., Ai, S. and Ji, Y., 2023. An ensemble deep learning model for risk stratification of invasive lung adenocarcinoma using thin-slice CT. *NPJ digital medicine*, *6*(1), p.119. https://www.nature.com/articles/s41746-023-00866-z