International Journal of Interpreting Enigma Engineers (IJIEE)
https://ejournal.svgacademy.org/index.php/ijiee/
https://doi.org/10.62674/ijiee.2025.v2i04.001
eISSN: 3048-6300
OPEN ACCESS


# LUNG CANCER PREDICTION USING FEED FORWARD NEURAL NETWORK FOR CHEST SCAN IMAGES

**Dr. K. Reddy Madhavi[1], Madhusudhan Gurramkonda[2], P.Sumanaswini[1], N. Vishnu Vardhan Reddy[1], S. Abhiteja[1], M. Jyothi[1], B.Balu Amareswar[1]**

**Original Article**

[1]Mohan Babu University (Erstwhile Sree Vidyanikethan Engineering College), Tirupati, India.
[2]Head of AI, Data Engineering and Analytics, Amazon.com , Seattle, U.S.A

**Corresponding Author's Email: [1]kreddymadhavi@gmail.com, [1]psumanaswini1@gmail.com, [1]neelamvishnu23@gmail.com, [1]abhisamudrala21@gmail.com , [1]mekalajyothi30@gmail.com , [1]balubejagam@gmail.com, [2]gurramkonda.madhu@gmail.com*

## Abstract

*Abstract*—Lung cancer is the leading cause of cancer related death in the world, and increased patient outcomes would lead to improvements in its diagnosis and detection at an early stage. Machine learning (ML) has emerged as a useful instrument in lung cancer diagnosis because it can offer superior diagnosis and aid in treatment decisions. Large clinical data sets, including patient demographics, medical histories, and genetic markers, can be analyzed by ML algorithms to find patterns and associations that can be used to estimate the risk of lung cancer. Numerous machine learning (ML) algorithms, such as logistic regression, support vector machines (SVMs), random forests, and deep learning models, have been used to predict lung cancer. Every method has advantages and disadvantages, and the best one to choose will rely on the particulars of the dataset as well as the intended result. Research has exhibited the effectiveness of machine learning (ML) in the prognosis of lung cancer, with a notable degree of accuracy in recognizing benign and malignant nodules on chest CT scans. This study utilizes deep learning techniques the Xception convolutional neural network model, to precisely classify different forms of lung cancer. To enhance the datasets diversity and boost our models training efficacy we apply data augmentation methods despite the encouraging outcomes, there are difficulties with using ML to predict lung cancer.However, it also comes with several challenges and shortcomings such as the need to select well-chosen and quality data, data bias issues, and the multifaceted decision-making that elaborate machine learning models entail.

***Index Terms—Classification of Lung Cancer, Analysis of Med- ical Images, Advanced Learning Techniques, Xception Model Application, Convolutional Neural Networks, Imaging using Chest CT Scans, the use of Artificial Intelligence in Healthcare.***

## Introduction

The sphere of diagnostics is changing, and artificial intelligence and the use of advanced methods of deep learning are introduced. Within the field of oncology with regard to diagnosing lung cancer, accurate and categorization of types of cancer through CT scanning of the chest is a significant advancement in the field. This research paper addresses the challenge of classifying lung cancer using the model of Xception network to distinguish different types of lung cancer and normal lung tissue with high precision.

Lung cancer is one of the reasons of cancer related deaths in the world and therefore efforts should be made in developing early detection and classification methods. The traditional techniques of diagnosis which largely depend on the experience of radiologists face challenges because of the complexity and variety of lung cancer pattern in radiographic analysis. Moreover, the processing of medical imaging volumes generated in settings is an extra challenge that could lead to time losses and possible diagnosis mistakes.

To address this need, our study dwells on the concept of intelligence, i.e. deep learning, as a solution to optimizing and possibly revolutionizing the process of lung cancer diagnosis. In image recognition, an analysis of chest CT scans can be done with the use of the Xception models expertise. It is a procedure that does not aim to make the process of diagnosing cancer subtypes more accurate but rather speed up the process in order to improve patient outcomes.

The basis of an examination of the conditions of lung cancer testing, its challenges, and the possibilities of deep learning lies here to ensure that the challenges are addressed. We give a summary of our research, the dataset utilized, structure and model approach taken in training and evaluating the model. It is not our intention to put forward a solution to the classification of lung cancer, but also add to the broader story of using advanced technology in health-care. By applying the extensive potential of deep learning, this study aims at providing answers to the future of testing by combining technology with experience to provide better patient care and outcomes.

We discuss more in depth in our approach intricacies where we discuss the aspects of the model and data preparation and enhancement processes and give a comprehensive analysis of the model performance quality. This introduction provides a background to understanding the contribution of our work to the issues and technological advancement.

## Related Work

### *A. Traditional Diagnostic Methods*

In history, the diagnosis of lung cancer has significantly relied on imaging (chest X rays and CT scans) analyzed by radiologists. These techniques are successful but subject to influence by some factors such as inconsistency. The possibility of errors especially, during early stages of the disease.

### *B. Machine Learning in Lung Cancer Detection*

Medical imaging various machine learning methods were used to improve the detection of lung cancer. Algorithms such as Support Vector Machine (SVM) were first used and Random Forest are used for classifying lung nodules as Benign or Malignant based on feature extraction from imaging data. However, these methods required great feature engineering and were limited by the quality and diversity of the dataset used.

### *C. Deep Learning for Enhanced Accuracy*

In the recent past, researchers have begun to discover more sophisticated deep learning models to classify lung cancer. The Xception model enables depth wise separable convolutions, which preserve the balance between the model complexity and performance. The imaging data should be separated between different cancer subtypes and normal tissues in lung cancer classification, and the Xception model offers tremendous capabilities to do so.

### *D. Adopting Advanced Architectures Xception Model*

Recently researchers have started finding more advanced deep learning architectures for lung cancer classification. The Xception model supports depth wise separable convolutions, that maintains the balance between performance and model complexity. In lung cancer classification the imaging data has to be differentiated among various cancer subtypes and normal tissues, the Xception model provides great ability to achieve this.

### *E. Comparative Analysis and Limitations of Existing Work*

Past works have utilized machine learning in detecting lung cancer but they have drawbacks such as quality dependency, problems in results interpretation and overfitting. Altogether, despite the fact that machine learning and deep learning have made significant progress in lung cancer detection there is still room to improve. Future studies need to be based on improving the diagnostic properties of models such as Xception. This project attempts to address these voids though the Xception model, to classify lung cancer.

## Literature Survey

In the emerging domain of medical imaging analysis, recent studies have established progress and a variety of approaches. Azizi and colleagues (2021) made advancements in classifying images using self-supervised machine models [2].

At the same time, Matsoukas et al. (2022) studied the factors that make transfer learning effective and improve the accuracy of the medical imaging field and feature reuse is one of them among the others [5].

Investigating further, Sahoo et al. (2022) conducted a comparative analysis of medical images to look deeper into the advantages of transfer learning based deep learning models [8].

Salehi et al. (2023) presented an examination in medical imaging of how convolutional neural networks (CNNs) and transfer learning methods are used in medical imaging, and also discussed the challenges and future aspects for these technologies [9].

Mahmud and Hong's (2022) research on semantic image segmentation using CNN techniques helps further understanding of image-based diagnostics [4]. Similarly, Nemade and Sonavane (2019) focused on the importance of image segmentation for annotation through networks [6].

Gamara and colleagues, in 2022, made improvements in the field of lung cancer by enhancing chest X-ray images using CLAHE and Wiener filters, an image processing technique, which helps in pre-processing for deep learning tasks [3].

Zafeiriou et al. (2023) provided a new idea in the field of machine learning through ensemble methods, the research provided techniques to enhance the interpretability of medical image analysis systems [13].

Looking forward to 2024, Wang and team plan to introduce an innovative framework for deep learning diagnosis, using fully and semi- supervised reciprocal learning methods that helps to focus on both accuracy and interpretability [10].

Prasanna et al. (2022) extensively researched the application of deep learning for detecting non-small cell lung cancer using histopathological images, marking a significant impact on oncological imaging [7].

Wang and Xing (2021) analyzed deep learning applications in radiology and pathology for lung cancer detection [11], while Al-Shouka and Alheeti (2023) concentrated on using transfer learning for intelligent lung cancer detection [1]. Finally, Yuvarani and colleagues (2023) demonstrated how analyzing lung CT scans will enhance the diagnostic accuracy in the deep learning techniques in the field of lung cancer classification[12]

These studies show how deep learning and transfer learning plays an important role in healthcare using artificial intelligence and provide a detailed idea in medical image analysis. [14-16]

## System Model

In this research the Xception model is used for classifying lung cancer and the system architecture as follows

*A. Data Preparation and Preprocessing*

- **Dataset Acquisition:** The dataset consists of lung CT scans that includes a total four types of lung cancers, Adenocarcinoma, Large cell carcinoma, Squamous cell and normal cases. Each CT scan is labeled with the type of lung cancer. Marked as normal.

- **Image Preprocessing:** The images go through prepro- cessing steps such as normalization to a scale resizing to meet the input requirements of the Xception model (299×299 pixels) and using techniques, like rotation and zoom to enhance the datasets diversity.

*B. Model Architecture – Xception*

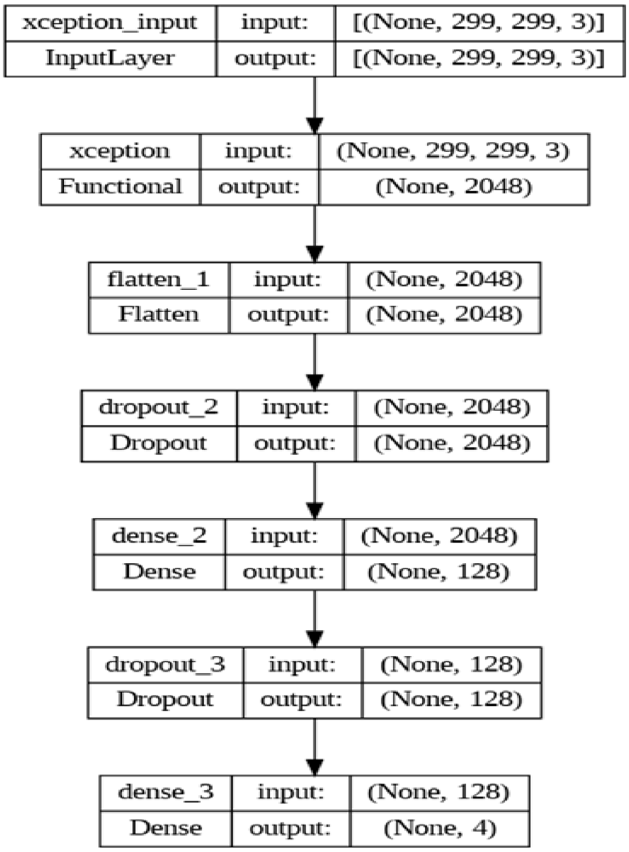



Figure. 1. Flowchart of the deep learning model used

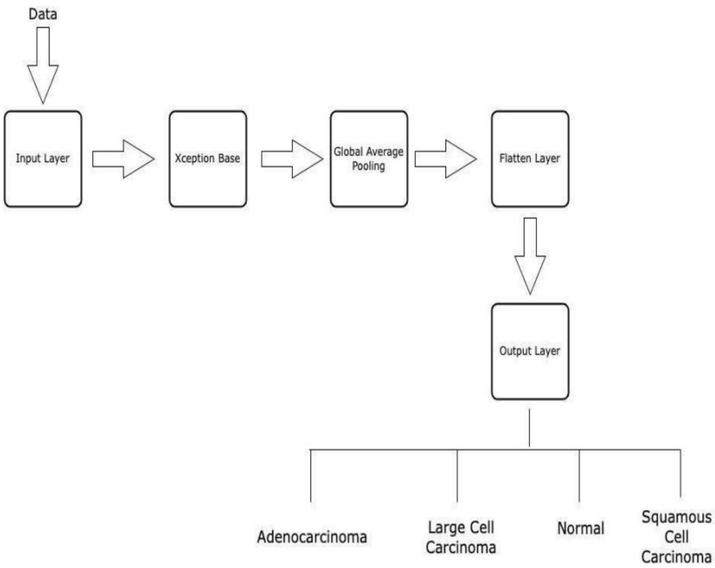



Figure. 2. Xception Model of Architecture applied in the study..

- **Input Layer*:*** Input of processed CT scan images in standard format.
- **Base Model**: It is made of blocks of convolutions with depthwise convolutions in order to extract complex patterns and features.
- **Global Average Pooling:** This segment builds information on the feature maps that are useful in reducing their sizes.

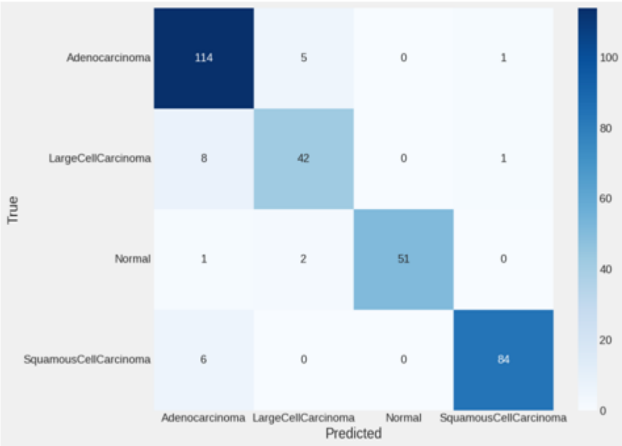
- **Fully Connected Layers:**Additional dense layers are connected with the aim of categorization with intention of interpreting association, between features and target categories.

- **Output Layer:** It is used to generate a likelihood distribution of types of lung cancer and a category, given a scan with the use of a softmax activation function.

*C. Training and Evaluation*

- **Loss Function:** The system uses cross entropy that is useful in solving multi classes classification problems.
- **Optimizer:** Adamax optimizer is used and the learning rate is adjusted to 0.001 to optimize model parameters..

- **Evaluation Metrics:**Accuracy, Precision, Recall, and F1-score are the evaluation metrics used in evaluating the performance of the model at training and validation stages.




Fiureg. 3. Confusion matrix

- **Training Process** Training Processes mini batches of data and updates parameters with loss gradients.

- **Validation and Testing Phase:** To test the performance of the models in terms of their adaptability to unseen data, separate datasets are used in validation and testing.

*D. Mathematical Formulation*

The performance measures in the model are measured as follows:.

$$Accuracy\ (Acc) = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

$$Precision\ (Prec) = \frac{TP}{TP + FP} \quad (2)$$

$$Recall\ (Rec) = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - Score\ \ (F1) = 2 \times \frac{Prec \times Rec}{Prec + Rec} \quad (4)$$

where: .

TP: True Positives
TN: True Negatives
FP: False Positives
FN: False Negative

*E. Computational Considerations*

- **Scalability:** The model demonstrates that it is capable of handling big data. Interpretability: Layer wise Relevance Propagation (LRP) and other techniques can be applied to explain the decision-making process of the model.

- **Interpretability:** The techniques are Layer-wise Relevance Propagation (LRP), which can be applied to explain how the model makes decisions

# Experimental Analysis

*A. Training and Validation Metrics:*

The training and validation metrics will be applied to the samples of the various departments.Training and Validation Metrics: The model passes through several epochs during the training stage and each epoch calculates certain training and validation measures.

The following table shows the training and validation statistics of every epoch:

TABLE I

| Epoch | Loss | Accuracy | Precision | Recall |
|---|---|---|---|---|
| 1 | 1.822 | 54.00% | 62.97% | 32.46% |
| 2 | 0.3774 | 85.48% | 88.83% | 83.03% |
| : | : | : | : | : |
| 10 | 0.0119 | 99.84% | 100.0% | 99.67% |

Model training metrics over epochs

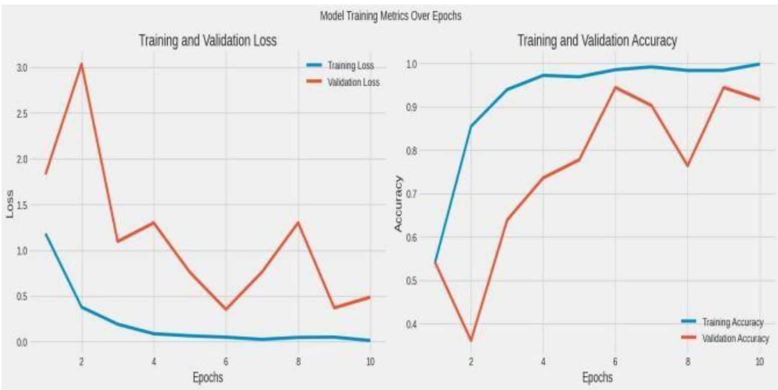



Figure. 4. Training Results

*B. Model Evaluation Metrics*

TThe model is measured against the test data in terms of the following:

Train Loss: 0.0033, Train Accuracy: 99.84%
Validation Loss: 0.4864, Valid Accuracy: 91.67%
Test Loss: 0.3084, Test Accuracy: 92.38%

*C. Confusion Matrix and Classification Report*

The confusion matrix and the classification report are the two major elements that are used in the evaluation of the model within categories.

- **Confusion Matrix:**This is a visualization of actual and predicted classes in the form of a Heatmap.
- **Classification Metrics:** The Precision, Recall and F1 Score of each category are computed.

TABLE II

Classification Report

| Class | Prediction | Recall | F1-score | Support |
|---|---|---|---|---|
| 0 | 0.88 | 0.95 | 0.92 | 120 |
| 1 | 0.86 | 0.82 | 0.84 | 51 |
| 2 | 1.00 | 0.94 | 0.97 | 54 |
| 3 | 0.98 | 0.93 | 0.95 | 90 |

Accuracy: 92%, Macro Avg: 93%, Weighted Avg: 92% These findings explain why the model has been able to categorize various classes with a high accuracy rate. capability to deal with intricate data trends.

## Conclusion

This study pushes the sphere of learning into the world of the use with the purpose of categorizing medical images with the help of the advanced Xcep- tion model. The findings of the discoveries do not contribute to our intelligence and medical imaging but also opens the door to better approaches to diagnostics in health-care. Our paper has presented a methodology-driven and objective data-based research that revealed that the Xception model is superior to the old techniques and methods in detecting patterns in images with higher accuracy and faster performance. This enhancement highlights the capability of deep learning algorithms in improving imaging in the detection of early diseases and improving patient care.

Even though our findings are encouraging it presents opportunities to investigate. One of the priorities of the further research is the improvement of the models precision with datasets. The use of data sources might develop the capacities of the models and give a more detailed picture of medical conditions. Overall, this paper highlights the way deep learning is transforming imaging. The Xception model can be tested and validated as being effective in diagnostics. Brings the path of new studies that open the doors to the innovative AI based healthcare solutions.

## References

[1] Al-Shouka, T. T. & K. M. A. Alheeti. 2023. A transfer learning for intelligent prediction of lung cancer detection. En Proceedings of the Al-Sadiq International Conference on Communication and Information Technology (AICCIT),

[2] [2]Azizi, S., N. Ghassemi, A. Mirbagheri, A.Mohammadi & K. Boozar- jomehri. 2021. Big self-supervised models advance medical image clas- sification. En Proceedings of the IEEE/CVF International Conference on Computer Vision, 8826–8835

[3] Gamara, R. P. C., P. J. M. Loresco & A. A. Bandala. 2022. Medical chest x-ray image enhancement based on clahe and wiener filter for deep learning data preprocessing. En Proceedings of the IEEE 14th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Manage- ment (HNICEM).

[4] Mahmud, B. U. & G. Y. Hong. 2022. Semantic image segmentation us- ing cnn (convolutional neural network) based technique. En Proceedings of the IEEE World Conference on Applied Intelligence and Computing (AIC).

[5] Matsoukas, C., J. F. Haslum, M. Sorkhei, M. S¨oderberg & K. Smith. 2022. What makes transfer learning work for medical images: Feature reuse & other factors. En Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).

[6] Nemade, S. B. & S. P. Sonavane. 2019. Image segmentation using convolutional neural network for image annotation. En Proceedings of the International Conference on Communication and Electronics Systems (ICCES).

[7] Prasanna, D. P., J. K. Radhakrishnan, K. S. Aravind, P. R. Nambiar & N. Sampath. 2022. Detection of non-small

cell lung cancer using histopathological images by the approach of deep learning. En Pro- ceedings of the 2nd International Conference on Intelligent Technologies (CONIT).

[8] Sahoo, D. P., M. Rout, P. K. Mallick & S. R. Samanta. 2022. Com- parative analysis of medical images using transfer learning based deep learning models. En Proceedings of the International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC), 1–6. IEEE.

[9] Salehi, W., S. Khan, G. Gupta & B. I. Alabduallah. 2023. A study of cnn and transfer learning in medical imaging: Advantages, challenges, future scope. Sustainability 15(7). 5930

[10] Wang, C., Y. Chen, F. Liu, M. Elliott, C. F. Kwok, C. Pe˜na-Solorzano, H. Frazer, D. J. McCarthy & G. Carneiro. 2024. An interpretable and accurate deep-learning diagnosis framework modeled with fully and semisupervised reciprocal learning. IEEE Transactions on Medical Imaging 43(1). 392–404

[11] Wang, H. & L. Xing. 2021. Deep learning's application on radiology and pathological image of lung cancer: A review. En Proceedings of the International Conference on Information Technology and Biomedical Engineering (ICITBE),

[12] Yuvarani, P., S. Hemalatha, S. Kaviya Sri & P. Madhubala. 2023. Analysis of lungs ct image using deep learning techniques. En Proceedings of the 9th International Conference on Advanced Computing and Communication Systems (ICACCS), 1–6. IEEE

[13] Zafeiriou, A., A. Kallipolitis & I. Maglogiannis. 2023. Ensembling to leverage the interpretability of medical image analysis systems. IEEE Access 11. 76437–76447

[14] Yallavula, R., & Putchakayala, R. (2023). Governance-of-Things (GoT): A Next-Generation Framework for Ethical, Intelligent, and Autonomous Web Data Acquisition. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 4(4), 111-120.

[15] Cherukuri, R., & Putchakayala, R. (2022). Cognitive Governance for Web-Scale Systems: Hybrid AI Models for Privacy, Integrity, and Transparency in Full-Stack Applications. International Journal of AI, BigData, Computational and Management Studies, 3(4), 93-105.

[16] Parimi, S. K., & Yallavula, R. (2021). Data-Governed Autonomous Decisioning: AI Models for Real-Time Optimization of Enterprise Financial Journeys. International Journal of Emerging Trends in Computer Science and Information Technology, 2(1), 89-102

[17] Yarram, V. K., & Yallavula, R. . (2022). Adaptive Machine Learning Driven Compliance Scoring Models for Automated Risk Detection, Quality Validation of AI-Generated Content in Regulated Industries. International Journal of Emerging Research in Engineering and Technology, 3(1), 116-126.