

Advanced CNN Based Lung Cancer Stage Prediction with Visualization Using Heat Maps and Report Generation

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ABSTRACT

Lung cancer is one of the major causes of cancer-related deaths worldwide, and early detection of the tumor stage is very important for providing effective treatment by this, rate of survival will be increased. This work presents a deep learning-based approach for automatic lung cancer stage prediction and severity analysis using medical images such as CT and X-ray images. The model combines two advanced convolutional neural networks architectures, ResNet50 and DenseNet121, in an ensemble framework so that both structural patterns and fine texture details from lung images can be effectively captured. By combining these two algorithms then the ensemble model has the capacity to perform each stage of analysis with greater accuracy than an individual deep learning framework. The system classifies the given image into different stages of lung cancer and also produces heat-map visualization to highlight the areas that are effected which helps the doctors to identify easily. In addition, a simple web based interface allows doctors to upload medical images and obtain stage prediction and severity report generation. In general, this work shows the potential of deep learning methods to help clinicians

analyse medical images and make faster decisions in lung cancer detection.

Keywords: Lung Cancer Stage Prediction, Deep Learning, Ensemble CNN, ResNet50, DenseNet121, Medical Image Analysis, CT Scan Classification, Severity Analysis, Heat Map Visualization, Automated Report Generation.

INTRODUCTION

In the world-wide community of cancer related deaths lung cancer still takes the largest toll [1] [4]. Early recognition of the disease and identification of its stage are very important for improving treatment effectiveness [3] [2] and increasing patient survival. Recent progress in artificial intelligence has made deep learning techniques useful for analysing medical images automatically [5] [6]. These methods can learn important patterns from imaging data and assist doctors during diagnosis [11] [8]. In this work, a deep learning-based framework is presented to assist in lung cancer stage prediction and severity evaluation. In addition, visualization methods together with automatic report generation are incorporated to make the system more helpful for clinical evaluation. In routine clinical practice, lung cancer diagnosis is usually performed by

radiologists who examine medical images to detect tumour characteristics and identify the stage of the condition [10]. The examination is generally performed manually and therefore may require a significant amount of time [7] [12]. In many cases, the early detection of the stage is very important to cure it quickly. In some situation the early stage cancer may not be detected by the doctors due the small size and too rush in the hospitals [7] [13]. So by using deep learning algorithms we can detect the cancer at the early stages [10] [14] and survival of the patients will increase. Deep learning belongs to the area of artificial intelligence and it uses neural networks to learn patterns from data [5]. In medical image analysis, Convolutional Neural Networks (CNNs) are widely used since they are able to automatically recognize useful visual features from images. Over the years, researchers have introduced several CNN architectures to improve results in tasks such as disease detection [6].

Many present day lung cancer diagnosis systems report mainly on the issue of identifying cancer or they do basic classification. While these systems are useful for diagnosis of lung cancer they also have deficiencies which include stage prediction and severity assessment and automatic report preparation. Also what little manual study of CT or X Ray images we do take time and at times the results are interpreted differently by medical professionals. This work present a deep learning based solution for lung cancer stage prediction. We use ResNet50 and DenseNet121 in an ensemble which we put forward to improve performance of feature extraction from radiology images. Also we developed heat map visualizations and automated reports to improve doctors' experience with the results. Correct classification of lung cancer stages via CT and X Ray image analysis. Better accuracy and prediction stability with use of ensemble learning which combines models in CNN. We generate visual results using

heat maps and in depth reports for medical professionals. The generated report can be downloaded.

LITERATURE REVIEW

Medical research into the field of lung cancer diagnosis via imaging is a growing area which we are seeing as a result of progress in artificial intelligence and deep learning. We have studied a number of machine learning and deep learning techniques which include. Improve the performance of detection, reduce in-which diagnostic time, and support radiologists in clinical analysis. In this present report we present our work which builds upon lung cancer detection and stage classification we review also the use of deep learning in medical image analysis. CNN approaches have been widely used by researchers to analyse lung cancer in discovery [9] and classification tasks. In past work largely we saw binary classification [18] which was to determine if medical images indicated cancer or not. Those approaches did present improved results over traditional machine learning methods but many of them did not address multi-stage classification or severity. In the past annotated datasets have been sparse which is why transfer learning has seen wide adoption in medical imaging research. Researchers have applied pre-trained architectures such as VGGNet, ResNet, and Inception to obtain deep features from CT scan images [19]. Among these, ResNet50 has proven effective because its residual learning technique enables deeper networks to be trained without suffering from degradation problems. Similarly, DenseNet121 also has Its design connects layers closely so that information learned in earlier layers can still be useful in later stages of the network. Recent research has looked into hybrid and ensemble methods as a way to achieve better classification performance. In ensemble learning, several models are used together and their results are combined to improve prediction reliability [20].

MATERIALS & METHODS

A. Introduction

In this section, the design and development of the proposed lung cancer stage prediction system are described. The purpose of the proposed system is to develop an automated deep learning framework which is capable of analysing CT scan images, predicting cancer stages, and generating report which helps the doctors in assisting. The system uses a single workflow that includes image preprocessing, feature extraction with an ensemble model, classification, visualization, and report generation.

Prediction stability is improved in the proposed system by using more than one deep learning architecture.

B. experimental design

The process of the system begins with acquiring CT scan images from medical data. Due to differences in image resolution and intensity values, pre-processing steps including resizing, normalization, and format standardization are used. All images are standardized to the same dimensions to make them suitable for deep learning model training and evaluation.

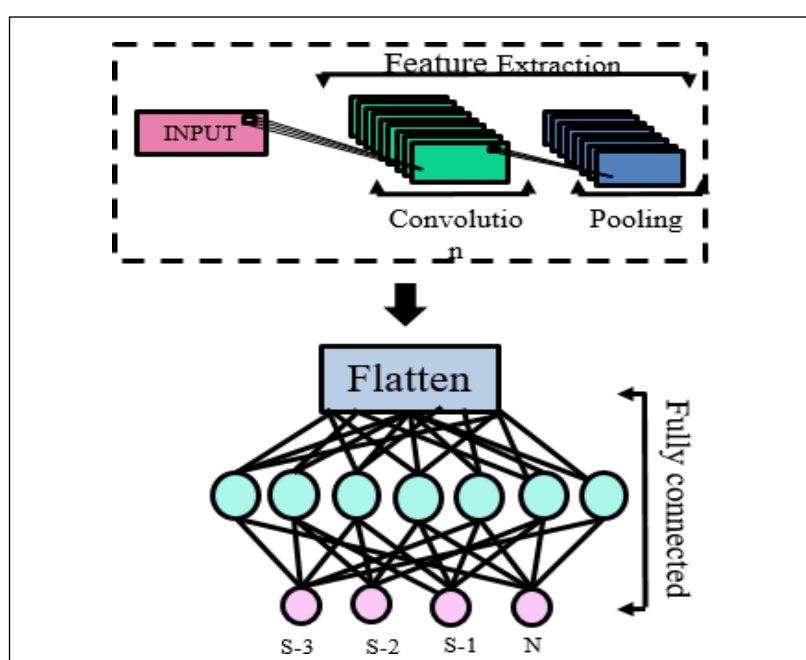


Fig. 1 CNN Algorithm Architecture

The above figure is the architecture of CNN algorithm which is used in the model. The core of the system is based on an ensemble Convolutional Neural Network (CNN) architecture combining ResNet50 and DenseNet121. Pre-trained weights are used in transfer learning so the model can take advantage of previously learned visual patterns for lung cancer detection. ResNet50 learns deep image features through residual connections that help overcome training issues in deep neural networks. These residual connections allow the model to learn complex spatial patterns present in lung CT images. Here

DenseNet121 uses closely connected layers so that learned features can be reused while learning detailed texture patterns. Such capability helps in recognizing slight tumour differences that are important for stage identification.

The proposed system uses feature-level fusion instead of performing classification independently with each model. Features out of ResNet50 and DenseNet121 which we use to construct a single joint representation. This put together feature vector includes global structural features as well as in depth textural ones that in turn which increase the models' discriminative

performance. We pass this joint feature representation through fully connected layers with ReLU activation to improve its learning capacity. The network applies dropout to reduce over fitting and make the model more reliable. Finally, the model uses SoftMax to generate probability scores for the possible lung cancer stages.

C. Component Diagram/Architecture Diagram

The proposed method uses preprocessing, ensemble deep learning, feature fusion, and automated reporting together in one pipeline to predict lung cancer stages. By combining ResNet50 and DenseNet121 in an ensemble framework, the system obtains more reliable feature extraction and stable predictions. Visual outputs and generated reports help doctors use the system in practical situations.

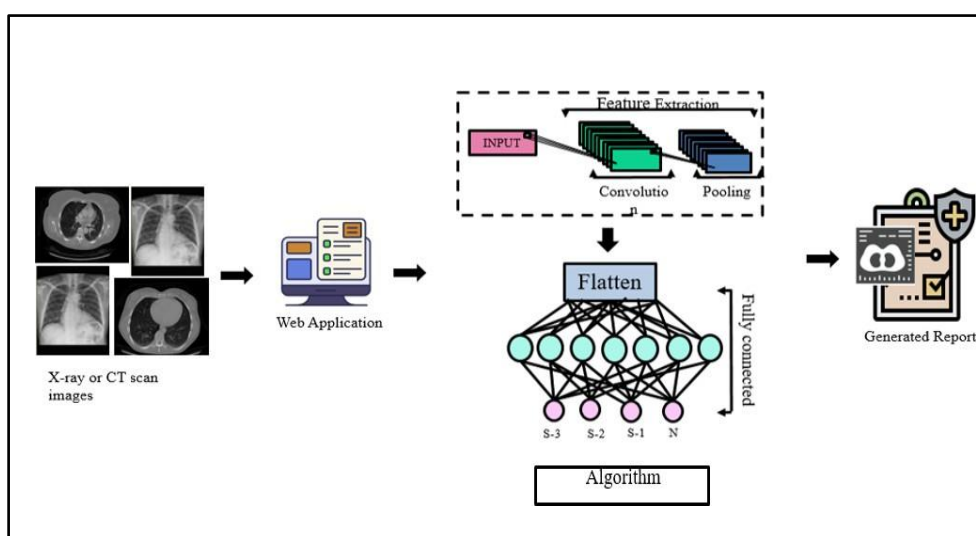


Fig. 2 Architecture Diagram

D. Summary

The system uses ensemble deep learning and feature fusion along with automated reports to form a single diagnostic framework. The system combines ResNet50 and DenseNet121 so that it can learn different image features and improve classification accuracy. Classifying accurately and analyzing the severity and report generation. These features allow the system to be more easily used in hospitals and clinical environments

RESULTS AND ANALYSIS

Here, we discuss the experimental results produced by the proposed ensemble deep learning approach. The goal of the evaluation is to study the performance of the combined ResNet50 and DenseNet121 architecture in classifying CT scan images by cancer stage. The performance of the

system is assessed in terms of classification accuracy, prediction stability, and interpretability through visualization.

A. Stepwise Understanding of Results

The first stage of the workflow was the collection and pre-processing of lung CT scan images. Due to differences in image resolution and intensity values, pre-processing steps including resizing, normalization, and format standardization are requirements of the deep learning models. The dataset was divided into training and testing portions after pre-processing to check the model's effectiveness. The ensemble CNN model was then trained using transfer learning. Pre-trained versions of ResNet50 and DenseNet121 were used and modified to learn features from single-channel medical images. In the training phase, the model

learned patterns that indicate Normal lungs as well as various cancer stages. As shown in the figure bellow.

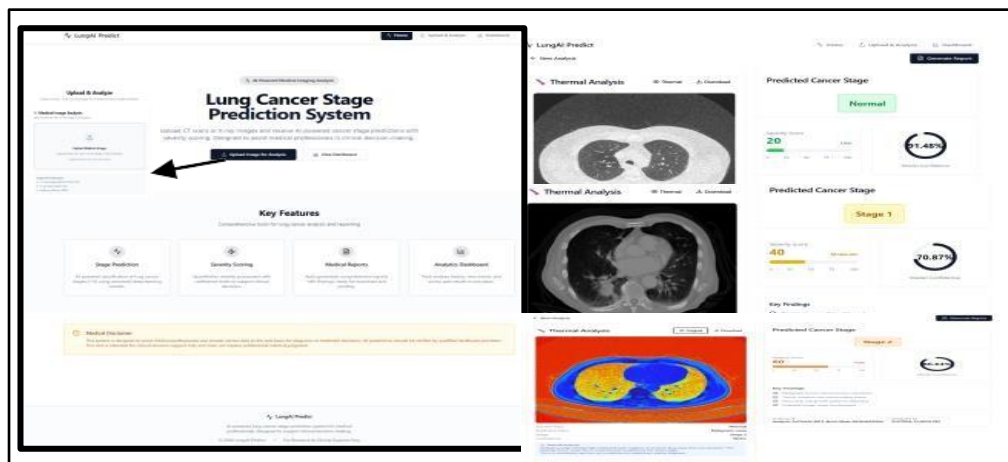


Fig. 3 web application images

The model was tested on new CT scan images after the training stage. The ensemble feature fusion method performed more consistently than individual models. With the fused features, the model could more easily tell apart early-stage and advanced cancer cases.

B. Test Execution Analysis

The study reports that we which saw improved performance in stage by stage

classification results from the ensemble model. Also, our research found that the combined feature approach did better as compared to single networks. We also noted that the model's output probabilities which in turn gave us an idea of how sure the model was of each stage classification. Here are graphs of the ensemble method accuracy and confusion matrix.

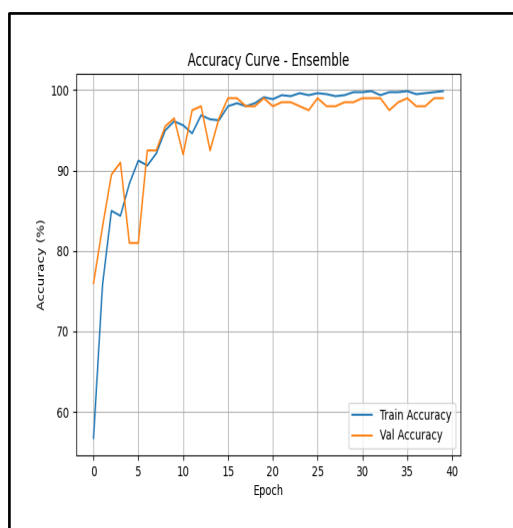


Fig. 4 Accuracy Graph

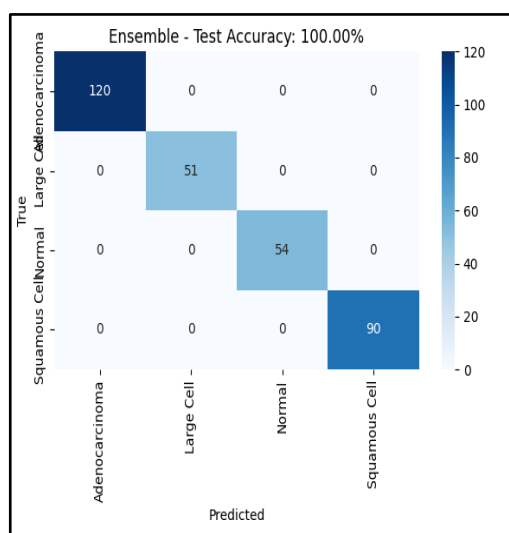


Fig. 5 Confusion Matrix

In the heat map we looked at which areas of the lung images played key role in the prediction. What we saw was that the model

had focused on abnormal lung tissue areas which in turn related to what we see in clinical practice.0020Via the web interface

we made available to the user the model's output along with the probability info and also a generated medical report. We saw that the tool analysed the input CT images very efficiently and turned around predictions in a short amount of time.

C. Recorded Observations

- The fusion of features from multiple models improves the consistency of the predictions.

- ResNet50 identified large structural changes in lung images, whereas DenseNet121 detected subtle texture differences.
- The differences between the individual methods and ensemble method can be seen in final model comparison.

Table 1- Final Model Comparison

S No.	model	Train Accuracy	Val Accuracy	Best Accuracy	ValBest F1	Test accuracy	Training time(min)
0	ResNet50	99.750	98.5	99.00	0.990042	100.0	12.045061
1	DenseNet121	100.000	97.5	98.5	0.984796	100.0	11.922682
2	Ensemble	99.875	99.0	99.0	0.990000	100.0	18.986335

- Heat map visualization improved result interpretation and helped verify the predictions clinically.
- Automatic report generation improved system performance in terms of ease and speed of use.
- Also for better model understanding and to see how each classification works which you may see in the class report.

Table 2- Classification Report

	precision	recall	F1-score	Support
Adenocarcinoma	1.0000	1.0000	1.0000	195
Large Cell	0.9913	0.9913	0.9913	115
Normal	1.0000	1.0000	1.0000	148
Squamous Cell	0.9935	0.9935	0.9935	155
Accuracy			0.9967	613
Macro avg	0.9962	0.9962	0.9962	613
Weighted avg	0.9967	0.9967	0.9967	613

CONCLUSION

A. Conclusion

We used deep learning which helped in the automatic detection of lung cancer stages via CT scan data. Our architecture which is combined did a great job in terms of structural abnormality as well as in identifying subtle texture patterns in the lungs. As compared to a single network the ensemble approach we used provided better results. We found from our tests that the model does very reliably. Stage by stage analysis which reports that ensemble deep learning models do better in lung cancer diagnosis.

B. Future Directions

Although the current results are consistent and solid, progress can be made in future work:

- Future versions of the system may include classification of additional lung diseases.
- Future work can include training the model with more data collected from various hospitals.
- Advanced feature learning methods and attention modules may help in classifying more disease.
- Future work may include adding clinical data such as patient history and test reports.

With the introduction of these features the system may become a full Lung diagnostic framework.

Declaration by Authors

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REFERENCES

1. Sung, H., Ferlay, J., Siegel, R. L., Laversanne, M., Soerjomataram, I., Jemal, A., & Bray, F. (2021). Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *CA: a cancer journal for clinicians*, 71(3), 209-249.
2. Detterbeck, F. C., Boffa, D. J., Kim, A. W., & Tanoue, L. T. (2017). The eighth edition lung cancer stage classification. *Chest*, 151(1), 193-203.
3. Goldstraw, P., Chansky, K., Crowley, J., Rami-Porta, R., Asamura, H., Eberhardt, W. E., ... & Yokoi, K. (2016). The IASLC lung cancer staging project: proposals for revision of the TNM stage groupings in the forthcoming (eighth) edition of the TNM classification for lung cancer. *Journal of Thoracic oncology*, 11(1), 39-51.
4. Kratzer, T. B., Bandi, P., Freedman, N. D., Smith, R. A., Travis, W. D., Jemal, A., & Siegel, R. L. (2024). Lung cancer statistics, 2023. *Cancer*, 130(8), 1330-1348.
5. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *nature*, 521(7553), 436-444.
6. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical image analysis*, 42, 60-88.
7. Armato III, S. G., McLennan, G., Bidaut, L., McNitt-Gray, M. F., Meyer, C. R., Reeves, A. P., ... & Clarke, L. P. (2011). The lung image database consortium (LIDC) and image database resource initiative (IDRI): a completed reference database of lung nodules on CT scans. *Medical physics*, 38(2), 915-931.
8. Lundervold, A. S., & Lundervold, A. (2019). An overview of deep learning in medical imaging focusing on MRI. *Zeitschrift fuer medizinische Physik*, 29(2), 102-127.
9. Pandian, R., Vedanarayanan, V., Kumar, D. R., & Rajakumar, R. (2022). Detection and classification of lung cancer using CNN and Google net. *Measurement: Sensors*, 24, 100588.
10. Ardila, D., Kiraly, A. P., Bharadwaj, S., Choi, B., Reicher, J. J., Peng, L., ... & Shetty, S. (2019). End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography. *Nature medicine*, 25(6), 954-961.
11. Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., ... & Dean, J. (2019). A guide to deep learning in healthcare. *Nature medicine*, 25(1), 24-29.
12. Setio, A. A., Jacobs, C., Ciompi, F., van Riel, S. J., Wille, M. M. W., Dirksen, A., ... & van Ginneken, B. (2015, March). Computer-aided detection of lung cancer: combining pulmonary nodule detection systems with a tumor risk prediction model. In *Medical Imaging 2015: Computer-Aided Diagnosis* (Vol. 9414, pp. 442-447). SPIE.
13. Giger, M. L. (2002). Computer-aided diagnosis in radiology. *Academic Radiology*, 9(1), 1-3.
14. Shen, W., Zhou, M., Yang, F., Yang, C., & Tian, J. (2015, June). Multi-scale convolutional neural networks for lung nodule classification. In *International conference on information processing in medical imaging* (pp. 588-599). Cham: Springer International Publishing.
15. Raghu, M., Zhang, C., Kleinberg, J., & Bengio, S. (2019). *Transfusion: Understanding transfer learning for medical imaging*. *Advances in neural information processing systems*, 32.
16. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).
17. Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4700-4708).
18. Saleh, A. Y., Chin, C. K., Penshie, V., & Al-Absi, H. R. H. (2021). Lung cancer

medical images classification using hybrid CNN-SVM.

19. Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.
20. Dietterich, T. G. (2000, June). Ensemble methods in machine learning. In International workshop on multiple classifier systems (pp. 1-15). Berlin, Heidelberg: Springer Berlin Heidelberg.

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