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Lung Cancer Detection

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ABSTRACT—

The lung cancer detection project aims to develop an accurate and efficient system for the early detection of lung cancer using medical imaging data. The proposed system leverages machine learning algorithms and computer vision techniques to analyze medical images such as CT scans to detect lung cancer in its early stages. The system is designed to assist medical professionals in accurately diagnosing lung cancer, enabling timely and appropriate treatment interventions. The project highlights the potential of artificial intelligence in improving the accuracy and efficiency of lung cancer detection and emphasizes the importance of early detection in improving patient outcomes.

Keywords—Lung Cancer, Convolutional Neural Network, CT Scan

I. Introduction (*Heading 1*)

Lung cancer is one of the leading causes of cancer-related deaths worldwide, with a high mortality rate due to its late diagnosis and lack of effective treatment options in advanced stages. Early detection of lung cancer is critical for improving patient outcomes and survival rates. Medical imaging, such as CT scans, are widely used for the detection and diagnosis of lung cancer. However, manual interpretation of these images by radiologists can be time-consuming and subjective, leading to variations in diagnosis and potentially missed cases [18]. Medical imaging plays a vital role in the early detection of lung cancer, and with the advancement in imaging technology, it has become possible to detect cancer at an early stage. However, the interpretation of medical images is a complex and time-consuming task, requiring specialized training and expertise. Due in large part to the amazing performance of DL-based clinical decision support systems and the rapid advancement of artificial intelligence in this field of medical image analysis [2] Therefore, the development of automated tools for lung cancer detection is of great importance. Convolutional Neural Networks (CNNs) have shown remarkable success in various image recognition tasks and have been widely used in medical image analysis. CNNs are a type of deep learning algorithm that can learn to identify complex patterns in images by training on a large dataset. The use of CNNs in lung cancer detection has shown great promise, as they can effectively learn and identify subtle features that are difficult to detect by human experts.

II. Related works

a) Lung cancer classification using ensemble of convolutional neural networks with transfer learning

The study "Lung cancer classification using ensemble of convolutional neural networks with transfer learning" by Raghu et al. (2021) proposed an ensemble of convolutional neural networks (CNNs) with transfer learning for the classification of lung cancer in computed tomography (CT) images. The proposed ensemble consists of three CNNs: ResNet50, DenseNet121, and EfficientNetB7. Transfer learning was used to initialize the weights of the CNNs with pre-trained models on the ImageNet dataset. The CNNs were fine-tuned on a dataset of 1,600 CT images of lung nodules, with 800 images each for malignant and benign nodules.

The CNNs were trained using a binary cross-entropy loss function and the Adam optimizer. During training, data augmentation techniques such as random rotation, translation, and scaling were applied to increase the size of the training set and prevent overfitting. The ensemble was trained using a voting mechanism, where the final prediction was based on the majority vote of the three CNNs. The proposed ensemble achieved an accuracy of 93.12% on the test set, outperforming the individual CNN models. The results of this study demonstrate the effectiveness of ensemble and transfer learning for lung cancer classification in CT images. Overall, this study provides insights into the design and optimization of deep learning models for lung cancer prediction, and shows that ensembling and transfer learning can be powerful techniques for improving accuracy.

b) Lung cancer prediction using deep learning-based model

"Lung cancer prediction using deep learning-based model" by Balasubramanian et al. (2020). This study aimed to develop a deep learning-based model to predict lung cancer diagnosis using features extracted from CT scans. The researchers used a dataset of 1,218 CT scans of lung cancer patients and healthy controls. They extracted radiomic features from the CT scans using a software tool called PyRadiomics. Radiomic features are quantitative measurements of the tumour or lung tissue, such as texture, shape, or intensity, that can be used to describe the tumour characteristics.

The researchers used a deep learning model called a convolutional neural network (CNN) to classify the CT scans as either lung cancer or healthy. CNNs are particularly well-suited for image analysis tasks like this, as they can learn to identify relevant features automatically from the images. The CNN was trained on a subset of the dataset and evaluated on a hold-out test set. The results showed that the CNN achieved an accuracy of 92.3% in predicting lung cancer diagnosis, outperforming other machine learning models like random forests and support vector machines.

Overall, this study demonstrated the potential of deep learning models to accurately predict lung cancer diagnosis using radiomic features extracted from CT scans. This could have significant implications for early detection and treatment of lung cancer, as well as improving the accuracy of lung cancer screening programs.

III. Methodology

A. Convolutional Neural Network

A Convolutional Neural Network (CNN) is a type of artificial neural network that is primarily used for image recognition and processing. The key feature of CNNs is the use of convolutional layers that perform a mathematical operation known as convolution. Convolutional layers consist of small filters, typically 3x3 or 5x5, that slide over the input image pixel by pixel, performing a dot product between the filter and the corresponding pixels in the input image. This operation creates a feature map that highlights certain patterns in the image, such as edges, corners, and blobs.

The output of a convolutional layer is passed through a non-linear activation function, such as ReLU, to introduce non-linearity into the network. This is important for enabling the network to learn complex representations of the input image. as shown in figure 1.1.

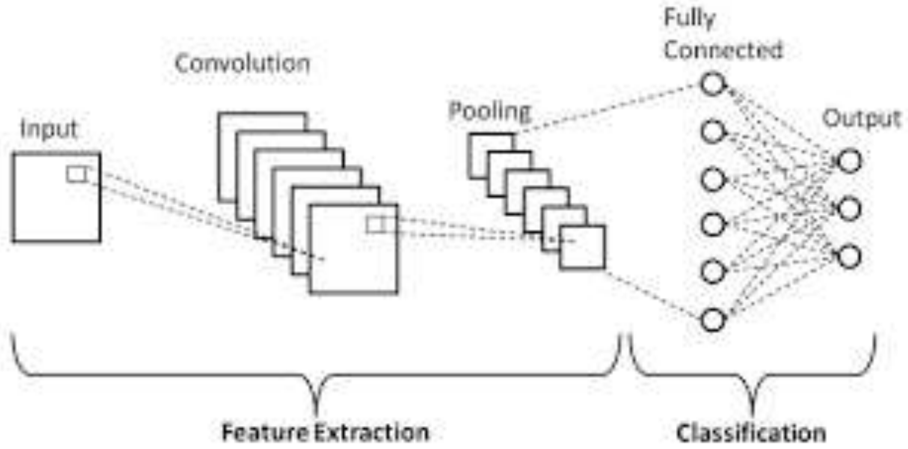

Fig. 1 Convolutional Neural Network.

a) Input Layer

The input layer uses the input lung image (CT scan). Images of a specific size and kind may be accepted by the input layer. It might, for instance, specify that images must be in RGB or grayscale format and contain a certain amount of pixels in the x and y dimensions.

b) Convolutional layer

At various spatial scales, the convolutional layer applies filters to extract local characteristics. Every filter picks up a particular feature, such edges, corners, or textures. A series of feature maps, which are matrices that reflect the presence of various features at various points in the image, is the output of the convolutional layer. Further 3D filters may be used to detect lung cancer by taking the depth of the lungs into consideration.

c) Activation function

To introduce non-linearity, the activation function applies an activation function. The output of the convolutional layer is element-wise subjected to the activation function. It is utilised to add non-linearities to the network, which can enhance its capacity to simulate intricate aspects.

d) Pooling

In deep learning, pooling is a technique used in convolutional neural networks (CNNs) to reduce the dimensionality of feature maps by down sampling. Pooling is typically applied after convolutional layers and helps to extract and preserve the most important information from the input data while reducing the computational complexity of the network.

e) Output layer

The network's final prediction is derived in this layer, including the likelihood that the input image belongs to the benign, malignant, or normal classes. Depending on the particular issue being addressed, the output layer may be constructed with one or multiple neurons. Two neurons that output the likelihood that the input image belongs to the Benign, Malignant, or Normal class class label may be present in the lung cancer detection system.

Table I Class labels

Class Label	***Image Count***
Benign Cases	120
Malignant Cases	561
Normal Cases	416

IV. Results and Discussion

The epoch value being used to train the model is 25. The model can modify its weights and biases to recognise more subtle signs of lung cancer by training for a higher epoch value. As a result, the model is more sensitive and is able to identify cancers that older models could have missed. By enabling early therapies and earlier identification of lung cancer, it can enhance patient outcomes. This can result in patients having better prognoses and survival rates, as demonstrated in Figs. 1 and 2.

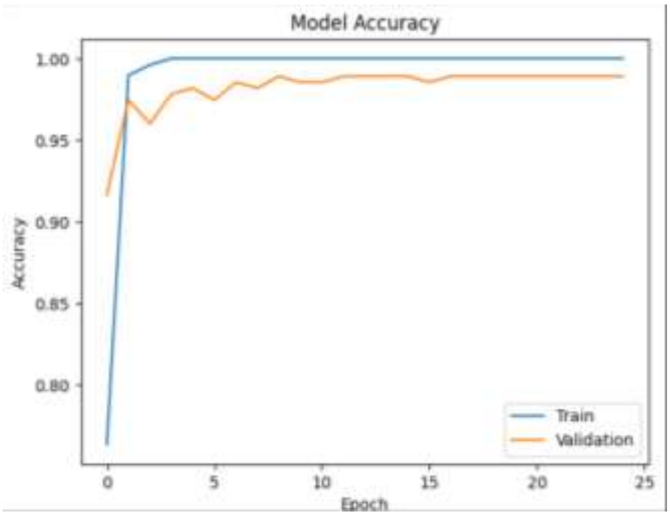

Fig.1 Accuracy graph (Epoch value 25)

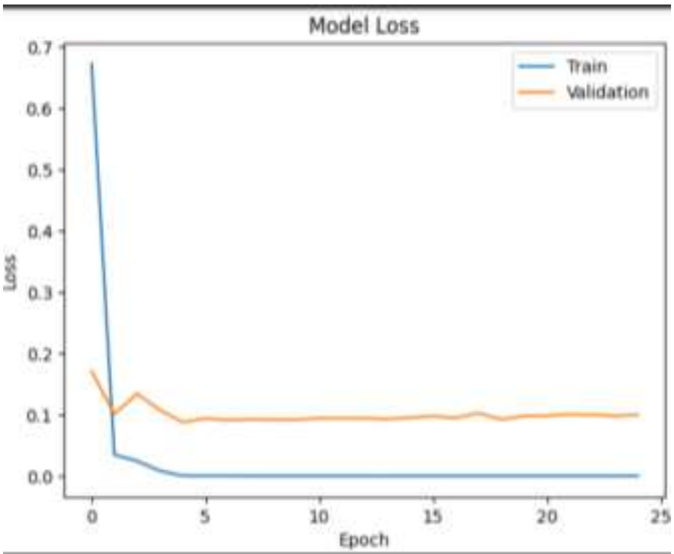

Fig.2 Model loss graph (Epoch value 25)

The epoch value being used to train the model is 50. A longer training period enables the model to learn from and evaluate a bigger collection of photos, improving its sensitivity and accuracy in identifying cancer. To improve patient outcomes, a model trained with an epoch value of 50 offers a more dependable and accurate tool for identifying and treating lung cancer.

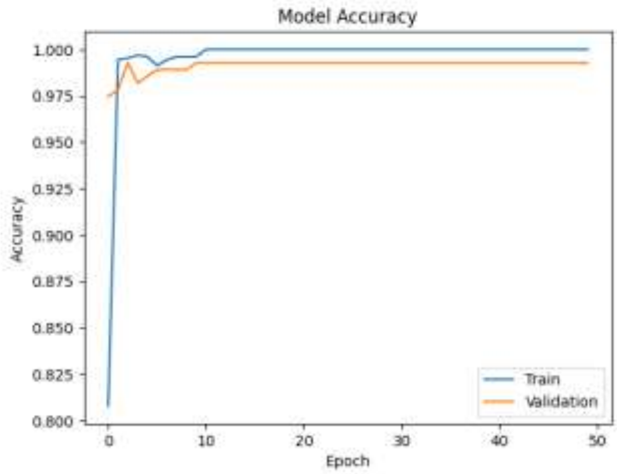

Fig.3 Accuracy graph (Epoch value 50)

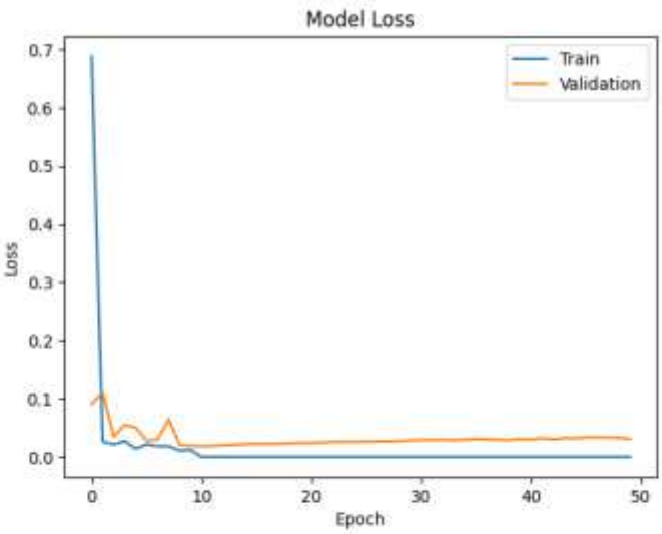

Fig.4 Model loss graph (Epoch value 50)

V. Conclusion

This research describes how to identify lung cancer using a convolutional neural network algorithm. To determine which epoch value the model performs best, the models are trained with several values.

References

[1]. *Ahmed Medjahed S., AitSaadi T., Benyettou A., Ouali M. Kernel-based learning and feature selection analysis for cancer diagnosis. Applied Soft Computing . 2017;51:39–48. doi: 10.1016/j.asoc.2016.12.010. [CrossRef] [Google Scholar]*

[2]. *Deepa N., Prabadevi B., Maddikunta P. K., et al. An AI-based intelligent system for healthcare analysis using Ridge-Adaline Stochastic Gradient Descent Classifier. The Journal of Supercomputing . 2021;77(2):1998–2017. doi: 10.1007/s11227-020-03347-2. [CrossRef] [Google Scholar]*

[3]. *Liu C., Hu S. C., Wang C., Lafata K., Yin F. F. Automatic detection of pulmonary nodules on CT images with YOLOv3: development and evaluation using simulated and patient data. Quantitative Imaging in Medicine and Surgery . 2020;10(10):1917–1929. doi: 10.21037/qims-19-883. [PMC free article] [PubMed] [CrossRef] [Google Scholar]*

[4]. Jasti V., Zamani A. S., Arumugam K., et al. Computational technique based on machine learning and image processing for medical image analysis of breast cancer diagnosis. Security and communication networks . 2022;2022:7. doi: 10.1155/2022/1918379.1918379 [CrossRef] [Google Scholar]

[5]. De Potter B., Huyskens J., Hiddinga B., et al. Imaging of Urgencies and Emergencies in the Lung Cancer Patient. Insights into imaging . 2018;9(4):463–476. doi: 10.1007/s13244-018-0605-6. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[6]. Chaudhury S., Krishna A. N., Gupta S., et al. Effective image processing and segmentation-based machine learning techniques for diagnosis of breast cancer. Computational and Mathematical Methods in Medicine . 2022;2022:6. doi: 10.1155/2022/6841334.6841334 [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[7]. Li J., Wang Y., Song X., Xiao H. Adaptive multinomial regression with overlapping groups for multi-class classification of lung cancer. Computers in Biology and Medicine . 2018;100:1–9. doi: 10.1016/j.compbiomed.2018.06.014. [PubMed] [CrossRef] [Google Scholar]

[8]. Halder A., Kumar A. Active learning using Fuzzy-Rough Nearest Neighbor classifier for cancer prediction from microarray gene expression data. Journal of Biomedical Informatics . 2020;34(1):p. 2057001. doi: 10.1142/S0218001420570013. [PubMed] [CrossRef] [Google Scholar]

[9]. Zamani A. S., Anand L., Rane K. P., et al. Performance of machine learning and image processing in plant leaf disease detection. Journal of Food Quality . 2022;2022:7. doi: 10.1155/2022/1598796.1598796 [CrossRef] [Google Scholar]

[10]. Sandhiya S., Kalpana Y. An artificial neural networks (ANN) based lung nodule identification and verification module. Medico-Legal Update . 2019;19(1):p. 193. doi: 10.5958/0974-1283.2019.00039.2. [CrossRef] [Google Scholar]

[11]. Palani D., Venkatalakshmi K. An IoT based predictive modelling for predicting lung cancer using fuzzy cluster based segmentation and classification. Journal of Medical Systems . 2019;43(2):p. 21. doi: 10.1007/s10916-018-1139-7. [PubMed] [CrossRef] [Google Scholar]

[12]. Bhatia S., Sinha Y., Goel L. Soft Computing for Problem Solving . Singapore: Springer; 2019. Lung cancer detection: a deep learning approach; pp. 699–705. [Google Scholar]

[13]. Joon P., Bajaj S. B., Jatain A. Progress in Advanced Computing and Intelligent Engineering . Singapore: Springer; 2019. Segmentation and detection of lung cancer using image processing and clustering techniques; pp. 13–23. [CrossRef] [Google Scholar]

[14]. Nithila E. E., Kumar S. S. Segmentation of lung from CT using various active contour models. Biomedical Signal Processing and Control . 2019;47:57–62. doi: 10.1016/j.bspc.2018.08.008. [CrossRef] [Google Scholar]

[15]. Lakshmanaprabu S. K., Mohanty S. N., Shankar K., Arunkumar N., Ramirez G. Optimal deep learning model for classification of lung cancer on CT images. Future Generation Computer Systems . 2019;92:374–382. doi: 10.1016/j.future.2018.10.009. [CrossRef] [Google Scholar]

[16]. Talukdar J., Sarma P. A survey on lung cancer detection in CT scans images using image processing techniques. International Journal of Current Trends in Science and Technology . 2018;8(3):20181–20186. [Google Scholar]

[17]. Yu K. H., Zhang C., Berry G. J., et al. Predicting non-small cell lung cancer prognosis by fully automated microscopic pathology image features. Nature Communications . 2016;7(1):p. 12474. doi: 10.1038/ncomms12474. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[18]. Cirujeda P., Cid Y. D., Muller H., et al. A 3-D Riesz-covariance texture model for prediction of nodule recurrence in lung CT. IEEE transactions on medical imaging . 2016;35(12):2620–2630. doi: 10.1109/TMI.2016.2591921. [PubMed] [CrossRef] [Google Scholar]

[19]. Sangamithraa P. B., Govindaraju S. Lung tumour detection and classification using EK-mean clustering. Proceedings of the 2016 IEEE International Conference on Wireless Communications, Signal Processing and Networking, WiSPNET; 2016; Chennai, India. [Google Scholar]

[20]. Kurkure M., Thakare A. Lung cancer detection using genetic approach. Proceedings -2nd International Conference on Computing, Communication, Control and Automation, ICCUBEA; 2017; Pune, India. [Google Scholar]

[21]. Kureshi N., Abidi S. S. R., Blouin C. A predictive model for personalized therapeutic interventions in non-small cell lung cancer. IEEE journal of biomedical and health informatics . 2016;20(1):424–431. doi: 10.1109/JBHI.2014.2377517. [PubMed] [CrossRef] [Google Scholar]

[22]. Kumar A., Gautam B., Dubey C., Tripathi P. K. A review: role of doxorubicin in treatment of cancer. International Journal of Pharmaceutical Sciences and Research . 2014;5(10):4117–4128. [Google Scholar]

[23]. Kulkarni A., Panditrao A. Classification of lung cancer stages on CT scan images using image processing. IEEE International Conference on Advanced Communication, Control and Computing Technologies, ICACCCT; 2014; Ramanathapuram,

[24]. Westaway D. D., Toon C. W., Farzin M., et al. The International Association for the Study of Lung Cancer/American Thoracic Society/European Respiratory Society grading system has limited prognostic significance in advanced resected pulmonary adenocarcinoma. Pathology . 2013;45(6):553–558. doi: 10.1097/PAT.0b013e32836532ae. [PubMed] [CrossRef] [Google Scholar]

[25]. Chaudhary A., Singh S. S. Lung cancer detection on CT images by using image processing. Proceedings: Turing 100 - International Conference on Computing Sciences, ICCS; 2012; Phagwara, India. [Google Scholar]

[26]. Almarzouki H. Z., Alsulami H., Rizwan A., Basingab M. S., Bukhari H., Shabaz M. An internet of medical things-based model for real-time monitoring and averting stroke sensors. Journal of Healthcare Engineering . 2021;2021:9. doi: 10.1155/2021/1233166.1233166 [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[27]. Gupta A., Awasthi L. K. GCA . Las Vegas, Nevada, USA: CSREA Press; 2008. Secure thyself: securing individual peers in collaborative peer-to-peer environments; pp. 140–146. [Google Scholar]

[28]. Chaudhury S., Shelke N., Sau K., Prasanalakshmi B., Shabaz M. A novel approach to classifying breast cancer histopathology biopsy images using bilateral knowledge distillation and label smoothing regularization. Computational and Mathematical Methods in Medicine . 2021;2021:11. doi: 10.1155/2021/4019358.4019358 [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[29]. Gupta A., Koul N. SWAN: a swarm intelligence based framework for network management of IP networks. International Conference on Computational Intelligence and Multimedia Applications (ICCIMA 2007); 2007; Sivakasi, India. [Google Scholar]

[30]. Karadağ K., Tenekeci M. E., Taşaltın R., Bilgili A. Detection of pepper fusarium disease using machine learning algorithms based on spectral reflectance. Sustainable Computing: Informatics and Systems . 2020;28, article 100299 doi: 10.1016/j.suscom.2019.01.001. [CrossRef] [Google Scholar]

[31]. Thakur T., Batra I., Luthra M., et al. Gene expression-assisted cancer prediction techniques. Journal of Healthcare Engineering . 2021;2021:9. doi: 10.1155/2021/4242646. [PMC free article] [PubMed] [CrossRef] [Google Scholar]