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Original Paper

Using Convoluted Neural Networks in Diagnosing Lung Cancer on Computed Tomography Scans

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ABSTRACT: Introduction: Lung cancer represents a major health issue of the modern world, accounting for both most new cases and highest mortality rates worldwide. Early diagnosis and treatment remain essential in managing the disease; therefore, developing novel computer-assisted tools for processing large quantities of imaging data can prove indispensable. Our aim was to develop a novel convoluted neural network (CNN) to classify lung computed tomography (CT) images of suspect nodules. Materials and Methods: After obtaining ethical clearance, we included consenting patients with a lung mass found on a chest radiography, visible lung tumor on computer tomography and positive pathology or follow-up. After data augmentation, we trained a deep learning model to classify input images into two classes, malignant or benign. We evaluated the model by calculating accuracy, recall and precision. Results: We successfully enrolled 176 patients from a total of 192 cases. Most were male (135 cases, accounting for 76.7%) and came from urban areas (111 cases, 63%). Most tumors were found on the right lung (103 cases). The model performed well on an imbalanced dataset, with recall values at 79.31%, while precision reached 62.16%, a training accuracy of 76.34% and a validation accuracy of 77.01%. Conclusions: We proved that a CNN model can easily be implemented on regular hardware to successfully classify malignant and benign lung lesions on CT images. Future CNN implementations can greatly improve the imaging diagnosis of lung lesions; however, the physicians should always decide the medical management.

KEYWORDS: *Lung cancers, computed tomography, convolutional neural network, diagnosis.*

Introduction

Lung cancer is among the top causes of death worldwide and a significant public health issue.

According to the International Agency for Research on Cancer's (IARC) GLOBOCAN 2020 cancer incidence and mortality predictions, pulmonary cancer is the leading cause of death from cancer, accounting for 1.8 million deaths (18%) in 2020 [1].

Lung cancer, besides its high incidence and mortality rate, has a feature that predisposes to late diagnosis: it develops in lung tissue without producing many symptoms, such as pain or dyspnea, until advanced stages, when the cancerous cells spread to adjacent structures [2].

Thus, the finding of a neoplasic lesion may be unintentional, especially in circumstances where surgical procedures remain a curative option. As a result, radiographic investigations are an essential tool for both raising the suspicion of lung cancer and staging it, which is a deciding element in evaluating the prognosis of such patients [3].

The integration of artificial intelligence (AI) into medical imaging has ushered in transformative advancements, particularly in the interpretation of computed tomography (CT) scans for the detection and characterization of lung tumors [4,5].

AI systems, often leveraging deep learning algorithms such as convolutional neural networks (CNNs), have demonstrated remarkable proficiency in identifying subtle patterns and anomalies within imaging data that may elude the human eye [5-7].

These algorithms are trained on vast datasets of annotated CT scans, enabling them to recognize features associated with malignant and benign lesions with high sensitivity and specificity. For instance, studies have reported that AI-driven models can achieve diagnostic accuracy comparable to, and in some cases surpassing, that of experienced radiologists in detecting early-stage lung cancers, thereby facilitating timely intervention and improving patient outcomes [4-8].

Beyond detection, AI contributes significantly to the quantitative analysis of lung

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tumors, providing detailed insights into tumor size, growth rate, and morphological characteristics [4,5].

Radiomics, a field that extracts large amounts of quantitative data from medical images, has been greatly enhanced by AI techniques, allowing for the identification of imaging biomarkers that correlate with tumor behavior and prognosis. Machine learning models can integrate these radiomic features with clinical data, such as patient history and genetic profiles, to generate predictive models for tumor aggressiveness and treatment response. This holistic approach not only aids in personalized treatment planning but also reduces inter-observer variability inherent in traditional radiological assessments, fostering greater consistency in diagnostic interpretations across medical institutions [4-8].

Despite its potential, the adoption of AI in interpreting CT scans of lung tumors is not without challenges. Issues such as algorithmic bias, the need for robust validation across diverse populations, and the interpretability of AI decisions remain critical points to address [4-8].

Moreover, the ethical implications of over-reliance on automated systems and the potential for reduced human oversight in diagnostics necessitate careful consideration. Nonetheless, ongoing research and collaborative efforts between clinicians, data scientists, and regulatory bodies aim to address these concerns, paving the way for the seamless integration of AI into clinical workflows [8,9].

As these technologies continue to evolve, AI is poised to become an indispensable tool in the fight against lung cancer, enhancing both the precision and efficiency of diagnostic processes [8-10].

Materials and Methods

Patient lot

We conducted a prospective, non-interventional study on patients that underwent imaging investigation at the Clinical "Victor Babeș" Infectious Disease and Pulmonology Hospital with a suspicious chest tumor mass. We have included patients between October 1st 2020 and August 31st 2024. We explained the purpose of the study to all patients, before they agreed, in writing, to the inclusion, as required by the Ethical Boards of the University of Medicine and Pharmacy of Craiova (approval 73/07.09.2020). The study was conducted in accordance with the Helsinki convention, national and international law, as well as all GDPR legislation in effect at the time of inclusion. Inclusion criteria were age over 18 years, single or multiple tumor masses identified at a chest X-Ray, irrespective of accompanying symptoms. We collected basic demographic data, along with anonymized computed tomography recordings of the lungs. From each CT recording we selected four axial images-one at the apex, one at the inferior border (containing both thoracal and abdominal organs), one of the middle section (not containing the lesion) and one with the lesion. If the lesion interfered with the lower/upper images, we selected an additional lesion-free image from the remaining sections that did not contain abdominal organs. Patients without CT recordings or who did not have confirmation (either pathology or positive follow-up for malignancy) were excluded.

Dataset Preprocessing

The dataset used in the proposed method was comprised of lung CT images, categorized into two classes: malignant and benign cases. To enhance the robustness of the model, preprocessing techniques were applied to the dataset. Each image was normalized to pixel values between 0 and 1. Additionally, a set of geometric transformations were introduced to perform data augmentation. These transformations included random 15 degrees rotations, horizontal reflections and small adjustments in image scale and position. A common research problem in developing deep learning models, especially in healthcare, is the class imbalance of the dataset, which can bias the learning process. To address this, the distribution of samples was analyzed, and a weighting scheme was introduced to counteract the imbalance. This class weight is given by equation 1. The dataset was randomly divided into 80% samples for training and 20% for validation.

$$w_c = \frac{N}{C * n_c} \quad (1)$$

Where:

w_c is the computed weight for class c.

N is the total number of samples in the dataset

C is the total number of classes

n_c is the number of samples belonging to class c.

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By replacing N with 354, $n_{malignant}$ with 148 and n_{benign} with 295 we obtain the following class weights: $w_{malignant}$=1.196 and w_{benign}=0.600.

Finally, all the samples were resized at 224 by 224 pixels to fit the proposed model's input.

Proposed model

As mentioned, the goal of the deep learning model was to classify input images into two classes: malignant or benign. The proposed deep learning model consists of two main parts: the feature extraction module and the classification module (Figure 1).

To leverage the advantages of transfer learning, the DenseNet121 [11] architecture, pre-trained on ImageNet, was used as the feature extractor. DenseNet121 (Densely Connected Convolutional Network) is a deep learning architecture that introduces dense connections between layers to improve feature propagation and reduce redundancy [11].

DenseNet121 architecture minimizes the vanishing gradient problem. The base model was initialized with pre-trained weights, and all convolutional layers were frozen during training to retain the learned feature representations.

After the feature extraction stage, a custom classification head was added. This consisted of a global average pooling layer, which reduced the feature maps to a lower-dimensional representation while preserving essential information. The output was then passed through a fully connected layer with 512 neurons with Rectified Linear Unit (ReLU) as activation function. To prevent overfitting, a dropout layer with a 50% dropout rate was included. Finally, the last layer consists of a single neuron with a Sigmoid activation function, enabling binary classification.

The optimizer used for training was Adam with a learning rate of 0.0005 while the loss function used was weighted binary crossentropy with the weights computed by Equation 1. The model was trained for 20 epochs, in Google Colab by using Tensorflow [12] as the deep learning framework and Nvidia© T4 as a hardware platform.

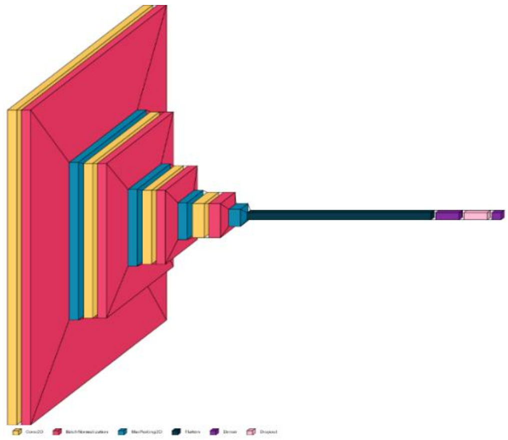

Figure 1. Diagram of the proposed model.

Results

Patient demographics and tumor site distribution

We have initially included 192 patients, of which we excluded 16 cases due to incomplete or absent CT scans (14 patients) or lack of pathology/follow-up confirmation (two cases). Of the remaining 176 patients, 135 (76.7%) were male; median age for the entire lot was 65 years, while for men was 65 years (minimum 40 years, maximum 87 years) and 64 years (minimum 22 years, maximum 87 years) for females. Most patients (111 cases, 63%) came from urban areas. A diagram of the inclusion process and site distribution is presented in Figure 2.

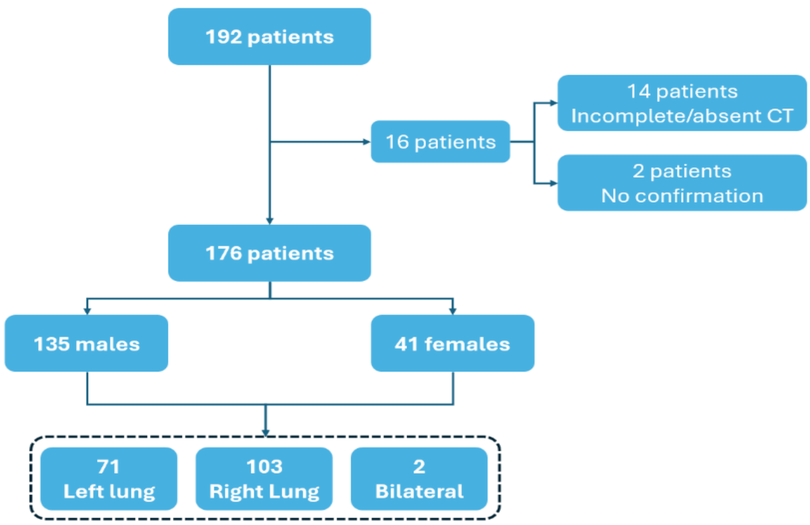

Figure 2. Patient inclusion diagram.

Regarding tumor location, we found a wide distribution of sites: 44 higher left lobe, 52 higher right lobe, 16 median lobe, 27 right lower lobe and 17 left lower lobe masses; the remaining 20 cases had tumors comprising multiple lobes (10 right lung masses, eight left lung masses and two bilateral). A representative series of CT images can be seen in Figure 3.

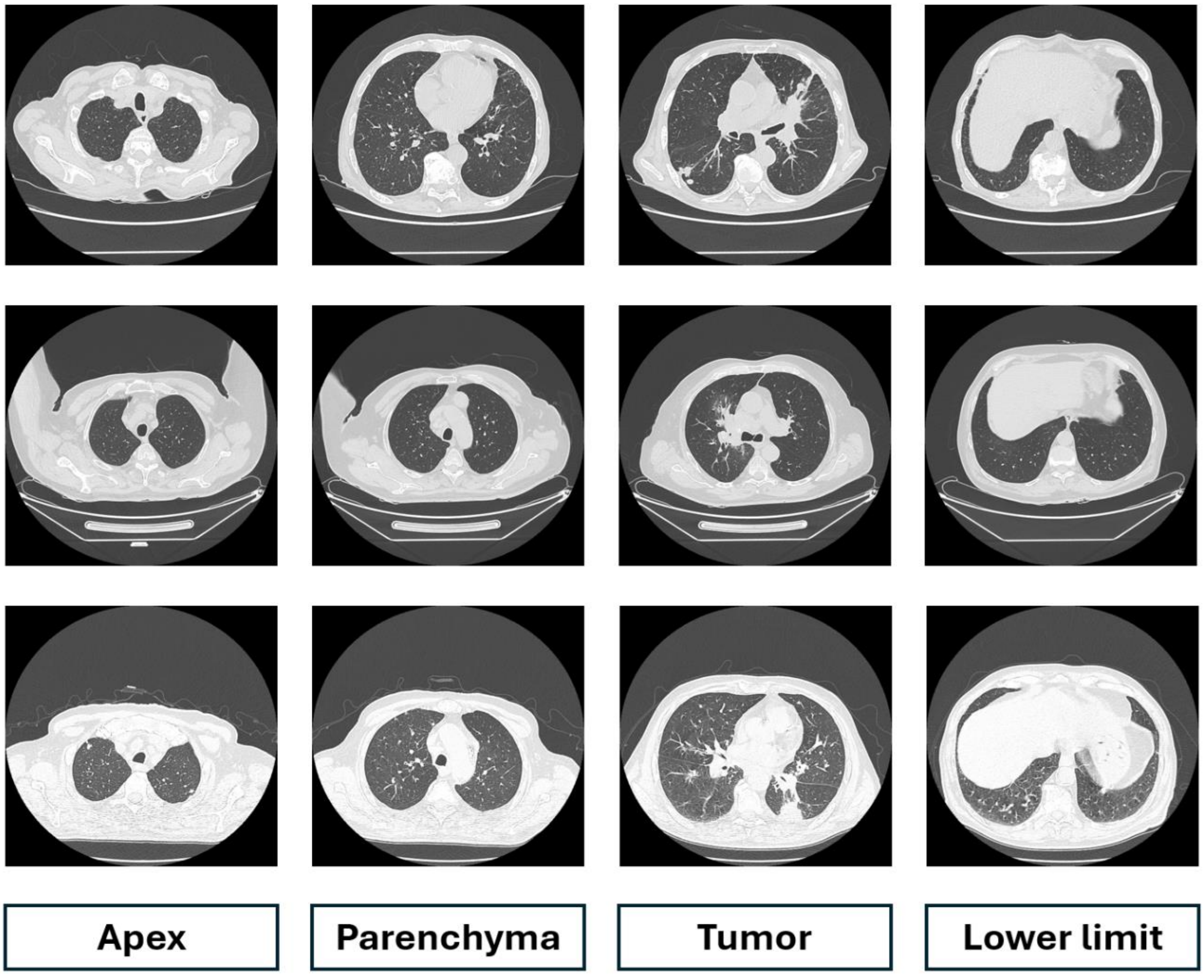

Figure 3. Series of representative CT images.

CNN performance

The performance of the proposed method was assessed using the following performance metrics: **accuracy**, to measure the proportion of correctly identified cases out of the total number of samples. **recall, to** evaluate the model's ability to correctly detect malignant cases and **precision,** to address the reliability of positive predictions by determining how many of the identified malignant cases were correctly classified. The values obtained for the performance metrics observed can be found in Table 1.

Table 1. Model results.

Performance Metric	Value (training)	Value (validation)
Accuracy	0.7634	0.7701
Recall	0.8812	0.7931
Precision	0.5884	0.6216

DenseNet121 as a feature extractor for lung cancer classification showed significant improvements in model performance over the course of 20 training epochs. At first, the model obtained a relatively low accuracy of 49.89% on the training set and 60.92% on the validation set, with a loss of 0.8902 and 0.6429, respectively.

The precision and recall values during these early epochs were unstable, reflecting the model's struggle to distinguish between classes effectively.

In addition, recall values were higher than precision, suggesting a bias toward identifying positive cases. After the initial epoch, a steady improvement in classification performance was observed. After epoch 10, the validation accuracy had increased to 73.56%, with a loss reduction to 0.5623. More importantly, the recall values for the validation set remained high (≥86.21% from epoch 5onward), demonstrating

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the model's ability to correctly identify positive cases. This scenario is very important for medical applications, where sensitivity is a key factor in minimizing false negatives. The final results, at epoch 20, achieved a training accuracy of 76.34% and a validation accuracy of 77.01%.

The validation loss had further reduced to 0.4542, indicating a well-generalized model with minimal overfitting. Additionally, recall values remained strong at 79.31%, while precision reached 62.16%, signifying an improved balance between the two metrics. The performance metric values are presented in Figures 4-6, while the loss values are presented in Figure 7.

The Receiver Operating Characteristic Curve (ROC) can be observed in Figure 8.

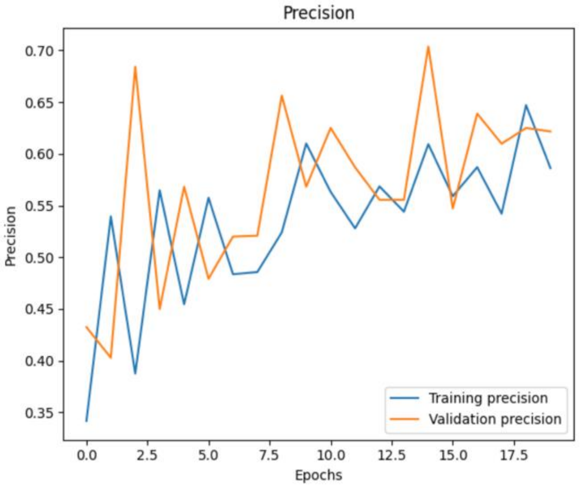

Figure 4. Precision of the CNN model during the training and validation phases.

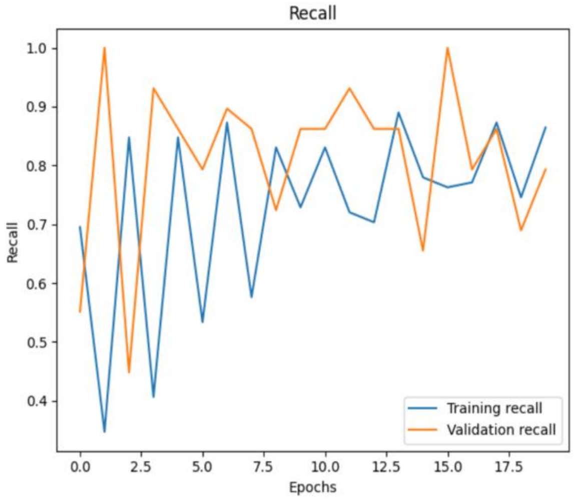

Figure 5. Recall of the proposed AI model during the training and validation phases.

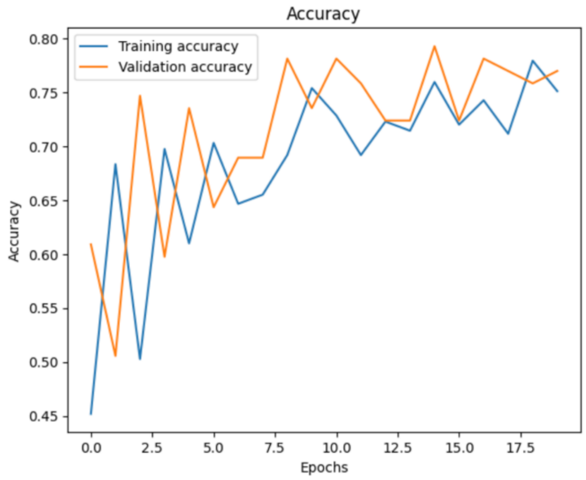

Figure 6. Accuracy during training and validation.

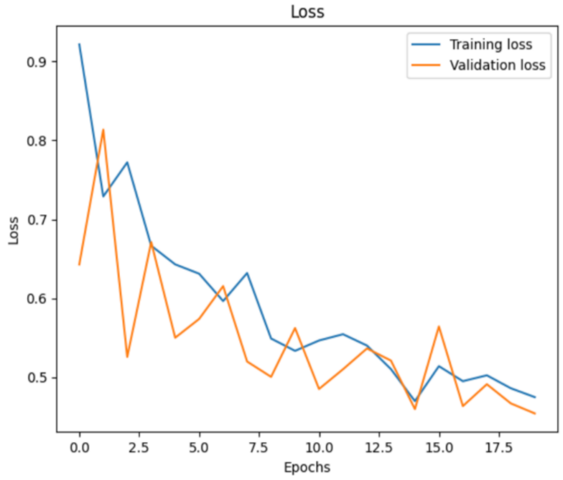

Figure 7. Validation and training Loss pattern.

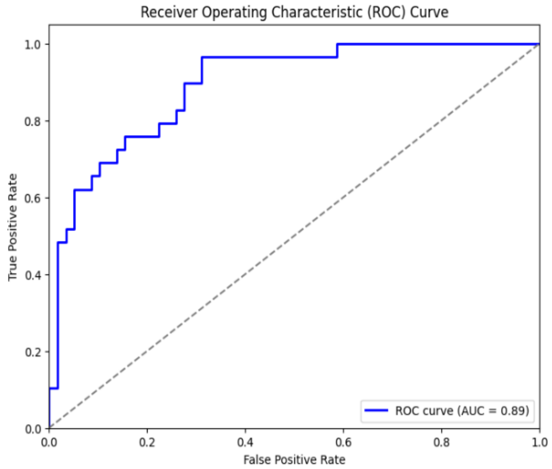

Figure 8. Return Operator Curve.

Discussions

This study presents a deep learning-based approach for the classification of lung CT images, leveraging DenseNet121 as a feature extractor to enhance classification performance.

The model incorporated preprocessing techniques and a transfer learning strategy to improve feature representation while addressing class imbalance through a weighted loss function. This ensured that minority class instances contribute proportionally to the learning process, reducing potential bias in model predictions.

The evaluation of the model was done using multiple performance metrics, including accuracy, recall, and precision. The training results indicate feature learning, as evidenced by a steady improvement in accuracy and loss reduction over successive epochs. The recall values remained high, especially in later epochs, demonstrating the model's ability to correctly identify malignant cases. Precision improved progressively, suggesting that the model effectively learned to distinguish between benign and malignant samples. The validation results further support the model's effectiveness, with an overall accuracy of 77.01% and balanced precision-recall performance. The results presented in this study underscore the potential of advanced deep learning models, such as DenseNet121, in supporting medical professionals with lung cancer detection. Future work may explore fine-tuning the deeper layers of DenseNet121 or integrating attention mechanisms. Finally, expanding the dataset to include more diverse imaging conditions would help improve model reliability in real-world clinical applications.

There are multiple diagnostic methods, as lung cancer is one of the most extensively studied malignancies over time [3].

Classical diagnostic techniques, which are more accessible and straightforward but lack high specificity, include imaging examinations [13,14] and sputum analysis [15].

Other techniques include lung tissue biopsy [16], considered the gold standard, and bronchoscopy [3].

Pulmonary biopsy requires exceptional precision, as the need for repeat sampling may lead to complications associated with the disease [3].

A chest X-ray is a very common imaging test, it uses small doses of radiation to create a picture of the chest, heart, lungs and with other structures inside the chest, like mediastinum [17].

Chest X-rays are often used to detect lung abnormalities and are often the first radiological tool in detection of lung cancer, but, compared to other, more advanced radiological techniques, like CT scans, the sensitivity is relatively low. Chest X-rays may sometimes miss small tumors, especially in early-stage lung cancer, but they are still useful as an basic screening instrument, or when a patient presents with hemoptysis, chest pain or persistent cough, especially in a smoker or ex-smoker patient [18].

The sensitivity and specificity of chest radiography in the diagnosis of lung cancer is still a topic of interest. Although there is relatively few clear evidence, high-quality studies suggest that the sensitivity of chest radiography for symptomatic lung cancer is only 77% to 80% [19].

In a study of 9,367 chest X-rays in 8,996 patients with various symptoms, 114 patients (1.3%) were confirmed with lung cancer within the first year after an X-ray; of these, 86 (75.4%) had radiologic modifications, and the remaining 28 (24.6%) had no lesions on a negative SR-CXR X-ray. The negative predictive value for lung cancer diagnosis within a year was at 99.7%. Two years after the initial chest radiography, 154 patients (1.7%) were diagnosed with lung cancer; 97 (63.0%) had initial radiologic abnormalities, whereas the remaining 57 (37.0%) had no changes. The incidence of cancer discovery in patients with a negative x-ray in the first year and first two years was 0.35% and 0.71%, respectively [19].

Chest x-rays have limited sensitivity when compared to more advanced imaging studies, but in a population with low lung cancer prevalence, their high specificity and negative predictive value indicate a very low possibility of this diagnosis being present after a negative x-ray [19].

A current diagnostic method with high precision is positron emission tomography (PET), although its disadvantages include high costs and the necessity of specialized medical personnel [20].

Modern approaches also focus on establishing individualized treatment plans, which require an accurate determination of both the patient's genetic and epigenetic profiles [20].

PET/CT investigation is recommended for lung cancers from stage I to stage IV [19,20].

However, it is advised that PET/CT findings be correlated with other diagnostic techniques,

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as there is a risk of false-positive or false-negative results [19].

A false-positive PET/CT result may occur in inflammatory reactions, while a false-negative result may be due to the presence of small-sized nodular formations [20].

Compared to conventional CT, PET/CT is considered superior as it provides valuable information regarding the stage of the cancerous lesion as well as data on the metastasis process [21].

The use of CT in clinical practice was implemented in the 1970s, representing at that time an innovative method. Since then, its use has not disappointed, representing to this day one of the most effective imaging methods known [22].

Computed tomography can provide excellent clinicopathological correlation [23,24].

Thus, through the multitude of imaging information provided by the CT examination, cancer can even be staged, determining the treatment and prognosis for the patient.

Regarding pulmonary nodules or masses, the additional information provided by the chest CT includes: the exact size, the precise location within the respective lobe or segment, consistency, margins, or involvement of the adjacent parenchyma [25].

Although it is not a method of maximum reliability, the CT examination can guide the clinician towards the suspicion of a benign or malignant tumor formation through the details of the image obtained, however, further investigations are mandatory [26].

Additionally, the presence of small lesions, undetected on the chest X-ray, are relatively easy to quantify in a CT examination [24,27].

In addition to the main tumor, local complications such as lymphohematogenous dissemination, represented by carcinomatous lymphangitis or metastases, accompanying pleural effusion, or local, mediastinal, or distant adenopathies can be identified, the affected lymph node stations are easily detectable on radiological films [28-30].

Artificial intelligence (AI) is an attractive and popular resource in various fields of activity. In the case of medicine, radiology seems to be the field with the greatest chance of success. Chest imaging already uses various artificial intelligence programs to read chest X-rays or computed tomography [31].

Although using different algorithms, the invention of radiomics appeared before the use of deep learning in medical imaging by just a few years. The term "radiomics" falls within a medical area that aims to obtain information apparently undetected by the human eye, thus leading to an increase in the sensitivity of imaging analysis [32].

Computer-aided detection (CAD) tools have been developed even since 2000 and were particularly useful in detecting lung nodules.

The increasing use of deep learning, along with an exponential development of more potent hardware to support it, as well as the availability of annotated image datasets containing lung nodules (making excellent training data), have led to the development of new CAD models with fewer false positive results. Recently, several deep learning CAD tools have been released, trained on public databases, and expanding coding competitions encouraged many researchers to work on this topic [33].

In a challenge conducted in on the Lung Nodule Analysis 2016 (LUNA16) dataset, comprising 1018 chest CT scans of which 888 had pulmonary nodules, 1186 participants were asked to develop a program (CAD) through which AI detects lung nodules. The chosen algorithms managed to achieve sensitivities ranging from 79.3% to 98.3%, with the amendment of some false-positive nodules from a minimum of 1 blade to a maximum of 8 per CT [34,35].

Conclusions

In the future, AI algorithms will most likely be able to provide a big helping hand in the management of lung cancer, both economically and in terms of diagnostic success rates.

Even though these tools are already used in many hospitals around the world, the basic criteria remain at the appreciation of the radiologist, AI-based tools, although they continue to achieve impressive sensitivities of imaging changes, the high rate of false-positive results continues to be an important impediment.

Conflict of interest

None to declare.

References

1. Filho AM, Laversanne M, Ferlay J, Colombet M, Piñeros M, Znaor A, Parkin DM, Soerjomataram I, Bray F. The GLOBOCAN 2022 cancer estimates: Data sources, methods, and a snapshot of the cancer burden worldwide. Int J Cancer, 2025, 156(7):1336-1346.
2. Ruano-Ravina A, Provencio M, Calvo de Juan V, Carcereny E, Moran T, Rodriguez-Abreu D, Lopez-Castro R, Cuadrado Albite E, Guirado M, Gomez Gonzalez L, Massuti B, Ortega Granados AL, Blasco A, Cobo M, Garcia-Campelo R, Bosch J, Trigo J, Juan O, Aguado de la Rosa C, Domine M, Sala M, Oramas J, Casal-Rubio J, Cerezo S. Lung cancer symptoms at diagnosis: results of a nationwide registry study. ESMO Open, 2020, 5(6):e001021.
3. Liam CK, Liam YS, Poh ME, Wong CK. Accuracy of lung cancer staging in the multidisciplinary team setting. Transl Lung Cancer Res, 2020, 9(4):1654-1666.
4. Papageorgiou VE, Petmezas G, Dogoulis P, Cordy M, Maglaveras N. Uncertainty CNNs: A path to enhanced medical image classification performance. Math Biosci Eng, 2025, 22(3):528-553.
5. Ali F, Almuhaimeed A, Alghamdi W, Aldossary H, Asiry O, Masmoudi A. Leveraging deep learning for epigenetic protein prediction: a novel approach for early lung cancer diagnosis and drug discovery. Health Inf Sci Syst, 2025, 13(1):28.
6. Aftab J, Khan MA, Arshad S, Rehman SU, AlHammadi DA, Nam Y. Artificial intelligence based classification and prediction of medical imaging using a novel framework of inverted and self-attention deep neural network architecture. Sci Rep, 2025, 15(1):8724.
7. Zamanidoost Y, Ould-Bachir T, Martel S. OMS-CNN: Optimized Multi-Scale CNN for Lung Nodule Detection Based on Faster R-CNN. IEEE J Biomed Health Inform, 2025, 29(3):2148-2160.
8. Çay T. Lung cancer diagnosis with GAN supported deep learning models. Biomed Mater Eng, 2025:9592989241308775.
9. van den Berk IAH, Jacobs C, Kanglie MMNP, Mets OM, Snoeren M, Montauban van Swijndregt AD, Taal EM, van Engelen TSR, Prins JM, Bipat S, Bossuyt PMM, Stoker J; OPTIMACT study group. An AI deep learning algorithm for detecting pulmonary nodules on ultra-low-dose CT in an emergency setting: a reader study. Eur Radiol Exp, 2024, 8(1):132.
10. Huang F, Lin X, Hong Y, Li Y, Li Y, Chen WT, Chen W. The feasibility and cost-effectiveness of implementing mobile low-dose computed tomography with an AI-based diagnostic system in underserved populations. BMC Cancer, 2025, 25(1):345.
11. Huang G, Liu Z, Van Der Maaten L, Weinberger KQ. Densely Connected Convolutional Networks. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017: 2261-2269.
12. TensorFlow, 2025, An end-to-end platform for machine learning [online]. Available at: https://www.tensorflow.org [Accessed 25.02.2025].
13. Nooreldeen R, Bach H. Current and Future Development in Lung Cancer Diagnosis. Int J Mol Sci, 2021, 22(16):8661.
14. Sobue T, Moriyama N, Kaneko M, Kusumoto M, Kobayashi T, Tsuchiya R, Kakinuma R, Ohmatsu H, Nagai K, Nishiyama H, Matsui E, Eguchi K. Screening for lung cancer with low-dose helical computed tomography: anti-lung cancer association project. J Clin Oncol, 2002, 20(4):911-920.
15. Risse EK, van't Hof MA, Vooijs GP. Relationship between patient characteristics and the sputum cytologic diagnosis of lung cancer. Acta Cytol, 1987, 31(2):159-165.
16. Ettinger DS, Wood DE, Aisner DL, Akerley W, Bauman J, Chirieac LR, D'Amico TA, DeCamp MM, Dilling TJ, Dobelbower M, Doebele RC, Govindan R, Gubens MA, Hennon M, Horn L, Komaki R, Lackner RP, Lanuti M, Leal TA, Leisch LJ, Lilenbaum R, Lin J, Loo BW, Jr., Martins R, Otterson GA, Reckamp K, Riely GJ, Schild SE, Shapiro TA, Stevenson J, Swanson SJ, Tauer K, Yang SC, Gregory K, Hughes M. Non-Small Cell Lung Cancer, Version 5.2017, NCCN Clinical Practice Guidelines in Oncology. J Natl Compr Canc Netw, 2017, 15(4):504-535.
17. Gefter WB, Post BA, Hatabu H. Commonly Missed Findings on Chest Radiographs: Causes and Consequences. Chest, 2023, 163(3):650-661.
18. Kim J, Kim KH. Role of chest radiographs in early lung cancer detection. Transl Lung Cancer Res, 2020, 9(3):522-531.
19. Bradley SH, Hatton NLF, Aslam R, Bhartia B, Callister ME, Kennedy MP, Mounce LT, Shinkins B, Hamilton WT, Neal RD. Estimating lung cancer risk from chest X-ray and symptoms: a prospective cohort study. Br J Gen Pract, 2021, 71(705):e280-e286.
20. Hu Q, Li K, Yang C, Wang Y, Huang R, Gu M, Xiao Y, Huang Y, Chen L. The role of artificial intelligence based on PET/CT radiomics in NSCLC: Disease management, opportunities, and challenges. Front Oncol, 2023, 13:1133164.
21. Salehjahromi M, Karpinets TV, Sujit SJ, Qayati M, Chen P, Aminu M, Saad MB, Bandyopadhyay R, Hong L, Sheshadri A, Lin J, Antonoff MB, Sepesi B, Ostrin EJ, Toumazis I, Huang P, Cheng C, Cascone T, Vokes NI, Behrens C, Siewerdsen JH, Hazle JD, Chang JY, Zhang J, Lu Y, Godoy MCB, Chung C, Jaffray D, Wistuba I, Lee JJ, Vaporciyan AA, Gibbons DL, Gladish G, Heymach JV, Wu CC, Zhang J, Wu J. Synthetic PET from CT improves diagnosis and prognosis for lung cancer: Proof of concept. Cell Rep Med, 2024, 5(3):101463.
22. Liguori C, Frauenfelder G, Massaroni C, Saccomandi P, Giurazza F, Pitocco F, Marano R, Schena E. Emerging clinical applications of computed tomography. Med Devices (Auckl), 2015, 8:265-278.
23. Bradley SH, Abraham S, Callister ME, Grice A, Hamilton WT, Lopez RR, Shinkins B, Neal RD. Sensitivity of chest X-ray for detecting lung cancer in people presenting with symptoms: a systematic review. Br J Gen Pract, 2019, 69(689):e827-e835.
24. Gadkowski LB, Stout JE. Cavitary pulmonary disease. Clin Microbiol Rev, 2008, 21(2):305-333.

 10.12865/CHSJ.51.01.09

25. Gould MK, Donington J, Lynch WR, Mazzone PJ, Midthun DE, Naidich DP, Wiener RS. Evaluation of individuals with pulmonary nodules: when is it lung cancer? Diagnosis and management of lung cancer, 3rd ed: American College of Chest Physicians evidence-based clinical practice guidelines. Chest, 2013, 143(5 Suppl):e93S-e120S.
26. Power SP, Moloney F, Twomey M, James K, O'Connor OJ, Maher MM. Computed tomography and patient risk: Facts, perceptions and uncertainties. World J Radiol, 2016, 8(12):902-915.
27. Del Ciello A, Franchi P, Contegiacomo A, Cicchetti G, Bonomo L, Larici AR. Missed lung cancer: when, where, and why? Diagn Interv Radiol, 2017, 23(2):118-126.
28. Khan AN, Al-Jahdali HH, Irion KL, Arabi M, Koteyar SS. Solitary pulmonary nodule: A diagnostic algorithm in the light of current imaging technique. Avicenna J Med, 2011, 1(2):39-51.
29. Ahmed R, Qureshi NR, Rintoul RC. Investigation and management of the solitary pulmonary nodule. Clin Med (Lond), 2013, 13 Suppl 6:s36-40.
30. Parkar AP, Kandiah P. Differential Diagnosis of Cavitary Lung Lesions. J Belg Soc Radiol, 2016, 100(1):100.
31. Mello-Thoms C, Mello CAB. Clinical applications of artificial intelligence in radiology. Br J Radiol, 2023, 96(1150):20221031.
32. Forghani R, Savadjiev P, Chatterjee A, Muthukrishnan N, Reinhold C, Forghani B. Radiomics and Artificial Intelligence for Biomarker and Prediction Model Development in Oncology. Comput Struct Biotechnol J, 2019, 17:995-1008.
33. Murchison JT, Ritchie G, Senyszak D, Nijwening JH, van Veenendaal G, Wakkie J, van Beek EJR. Validation of a deep learning computer aided system for CT based lung nodule detection, classification, and growth rate estimation in a routine clinical population. PLoS One, 2022, 17(5):e0266799.
34. Setio AAA, Traverso A, de Bel T, Berens MSN, Bogaard CVD, Cerello P, Chen H, Dou Q, Fantacci ME, Geurts B, Gugten RV, Heng PA, Jansen B, de Kaste MMJ, Kotov V, Lin JY, Manders JTMC, Sóñora-Mengana A, García-Naranjo JC, Papavasileiou E, Prokop M, Saletta M, Schaefer-Prokop CM, Scholten ET, Scholten L, Snoeren MM, Torres EL, Vandemeulebroucke J, Walasek N, Zuidhof GCA, Ginneken BV, Jacobs C. Validation, comparison, and combination of algorithms for automatic detection of pulmonary nodules in computed tomography images: The LUNA16 challenge. Med Image Anal, 2017, 42:1-13.
35. Chassagnon G, De Margerie-Mellon C, Vakalopoulou M, Marini R, Hoang-Thi TN, Revel MP, Soyer P. Artificial intelligence in lung cancer: current applications and perspectives. Jpn J Radiol, 2023, 41(3):235-244.

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