Deep learning algorithms for lung cancer detection in CT images: A narrative review

Michał Gałuszewski*,[1,A-B,D-F], Michał Henryk Wizner*,[1,B,D-G,K], Natalia Wizner*,[1,B,D-F], Ewelina Porzycka[1,D-E], Tomasz Biedulski[1,D-E], Michał Azierski[1,A-B,D-E,G,K]

[1] *Students' Scientific Association of MedTech at the Center for Remote Learning and Educational Effects Analysis, Faculty of Medical Sciences in Katowice, Medical University of Silesia, Katowice, Poland*

** – These authors contributed equally to this work and share first authorship; A – Development of the concept and methodology of the study; B – Query – a review and analysis of the literature; C – Submission of the application to the appropriate Bioethics Committee; D – Collection of research material; E – Analysis of the research material; F – Preparation of draft version of manuscript; G – Critical analysis of manuscript draft version; H – Statistical analysis of the research material; I – Interpretation of the performed statistical analysis; K – Technical preparation of manuscript in accordance with the journal regulations; L – Supervision of the research and preparation of the manuscript*

Abstract

Lung cancer remains a leading cause of cancer-related mortality, primarily due to late-stage diagnosis. Deep learning (DL) algorithms, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for the early detection of pulmonary nodules in computed tomography (CT) images, demonstrating high sensitivity and specificity. This review explores the effectiveness and accuracy of these algorithms, highlighting their ability to surpass traditional diagnostic methods. However, the widespread clinical implementation of DL faces significant challenges, including the need for large, annotated datasets, the "black box" nature of models which limits their interpretability, and high implementation costs. This paper discusses potential solutions to these obstacles, such as explainable AI (XAI) methodologies like SHAP and LIME, the development of unified datasets, and the integration of hybrid intelligence systems. Furthermore, we explore future directions, including the application of edge computing to enable real-time analysis and enhance data privacy. Despite the existing hurdles, the continued advancement of DL technologies holds the promise of revolutionizing lung cancer diagnostics, leading to earlier detection and improved patient outcomes.

Keywords: lung cancer, artificial intelligence, computed tomography (CT), deep learning.

DOI: 10.12923/2083-4829/2026-0004

INTRODUCTION

Malignant neoplasms are a significant public health concern in Poland, accounting for 25% of all deaths and ranking second only to cardiovascular diseases [1]. Among all malignancies, lung cancer is the most dominant in terms of both morbidity and mortality. National Cancer Registry data indicates that 23,107 individuals succumbed to the disease in 2019. The primary contributor to this high mortality rate is late diagnosis, with the majority of patients presenting at stage III or IV. Consequently, the development of effective methods for the early detection of pulmonary lesions is a critical priority in oncological research [2-3]. High-risk populations include individuals with a smoking history exceeding 30 pack-years, current smokers, and former smokers who have quit within the last 15 years [3]. Young people are also exposed to negative effects of smoking in the future due to the increasingly common use of e-cigarettes in this age group [4]. It is estimated that in Poland among 15-year-olds, both boys and girls, 12% are smokers [5]. Standard diagnostic modalities for lung lesions encompass chest X-rays, sputum cytology, bronchoscopy, biopsy, and computed tomography (CT) [3,6]. CT is particularly valuable as it enables the measurement of nodule size, monitoring of its growth in subsequent scans, and provides a three-dimensional visualization of the diaphragm and potential mediastinal infiltration [3]. Low-dose Computed Tomography (LDCT) is the standard protocol, utilizing the minimum possible radiation dose while preserving diagnostic quality and sensitivity. Although increasing the number of CT slices can enhance detail, it generates vast amounts of data, prolonging radiologist workload and increasing the risk of overlooking pathologies [6]. The sensitivity of physician detection of nodules detection in CT images varies widely, from 30% to 97%, depending on data availability, evaluation criteria, and patient demographics [7]. In order to streamline this process, computer-aided diagnosis (CAD) systems have been developed to analyze CT data using computational algorithms [6-7]. A key advantage of CAD is its ability to identify small nodules often missed by specialists. However, its higher sensitivity is often associated with a greater number of false-positive results that require subsequent radiologist review. Artificial intelligence (AI) enhances the diagnostic process in medical imaging through two main pillars. The first, machine learning (ML), involves statistical analysis of provided data to develop an algorithm capable of processing larger information sets. The second, deep learning (DL), distinguishes itself by independently identifying patterns and features without direct human supervision in data processing. DL employs neural networks (NN), where interconnected "neurons" process and transmit data [8]. Among NNs, convolutional neural networks (CNNs) are the most widely used architecture for image analysis. CNNs apply multiple filters to images to create layered feature maps, with the initial layer being the "convolutional" layer [9]. These networks are trained on images with pre-identified nodules to learn how to detect them autonomously in new CT scans. The maturation of DL has led to its increasing integration into CAD systems, resulting in higher accuracy and fewer false-positive findings [10]. DL also facilitates patient stratification, for instance, into low-risk and high-risk groups [11]. Architectures such as U-Net, region proposal networks (RPNs), and residual networks (ResNets) are considered state-of-the-art for nodule detection [8]. The detectability of neoplastic lesions in CT images is strictly limited by spatial resolution and reconstruction parameters. In clinical trials such as the National Lung Screening Trial (NLST), the presence of at least one solid nodule with a diameter >4 mm is considered a positive screening result[12]. Under optimal conditions (thin-slice CT ≤1-1.5 mm), nodules with a diameter of approximately 3 mm represent the lower limit of reliable radiological detection, while smaller lesions may be masked by image noise and partial volume effects. This has a direct impact on machine learning. AI algorithms are trained on data containing visible and measurable nodules, which means that sub-voxel or extremely small lesions (below 2-3 mm) are underrepresented in the dataset. This constitutes a significant technical limitation, as the detection efficacy of AI-based systems decreases with reduced lesion size. For instance, phantom studies have shown that the sensitivity of AI-CAD for 5 mm nodules was as low as 0.091, whereas radiologists achieved 0.140, illustrating the severe diagnostic challenge posed by small lesions even with advanced support systems [13].

While DL techniques demonstrate superior sensitivity in detecting pulmonary nodules compared to a dual-radiologist review, this often comes at the expense of a higher false-positive rate [14]. Nevertheless, the application of DL, and CNNs in particular, significantly enhances the efficiency of radiologists' efficiency by drawing attention to subtle nodules, while research continues to refine these foundational algorithms.

METHODOLOGY

This review is based on a comprehensive search of the scientific literature conducted to identify relevant studies on the application of deep learning (DL) algorithms for lung cancer detection in computed tomography (CT) images. The literature search was performed using three major academic databases: PubMed, Scopus, and Google Scholar. The search strategy combined key terms and their synonyms, including "lung cancer", "deep learning", "convolutional neural networks", "artificial intelligence", "CT imaging", "nodule detection", and "computer-aided diagnosis". Boolean operators (AND, OR) were used to refine the search and capture all relevant studies. Records were screened by titles and abstracts, and duplicates were removed. The inclusion criteria were as follows:

Studies focusing on the use of deep learning for lung cancer detection, classification, or segmentation in CT images. Articles published in English. Publications from 2015 to 2024, to ensure the inclusion of the most recent and methodologically relevant research. Exclusion criteria included non-peer-reviewed papers, case reports, editorials, pediatric studies, non-English publications, and studies of low methodological quality or unrelated to diagnostic applications of artificial intelligence in thoracic oncology. After applying these criteria, a total of 235 records were initially identified (230 from databases and 5 from registers). Following screening and eligibility assessment, 16 studies met the inclusion criteria and were incorporated into the final qualitative synthesis. This narrative review employed a structured approach to literature selection. To enhance the clarity and transparency of the literature selection process, a PRISMA 2020 flow diagram was utilized to illustrate the study identification, screening, and inclusion proces, presented in Figure 1.

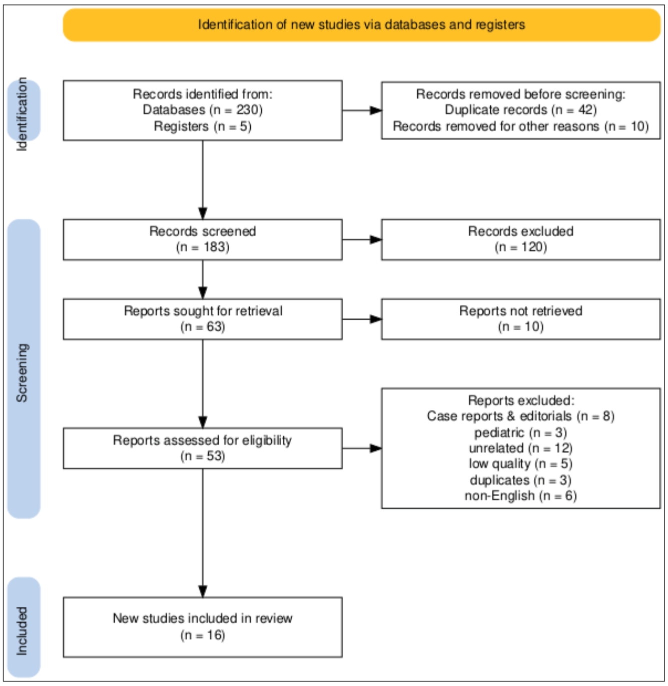

FIGURE 1. PRISMA 2020 flow diagram illustrating the study selection process for this narrative review.

RESULTS AND DISCUSSION

Effectiveness and Accuracy of Deep Learning Algorithms

The field of lung cancer imaging has witnessed a rapid evolution of AI-based diagnostic methods. Metrics such as precision, sensitivity, and specificity serve as fundamental benchmarks for the objective comparison of these technologies. Studies consistently show that DL algorithms achieve high efficacy in lung cancer detection. A systematic review and meta-analysis from 2022 reported that DL algorithms achieved a pooled sensitivity of 87% and a specificity of 89% in lung cancer diagnosis [15]. DL algorithms, especially CNNs, outperform traditional image analysis techniques. A key advantage of CNNs is their hierarchical architecture, which automatically learns to identify increasingly abstract and complex patterns from raw pixel data. A comparative study on DL techniques in lung cancer screening confirmed that CNN-based models attain superior accuracy and sensitivity over classical image segmentation and classification methods [16]. The initial layers of a CNN identify basic features like edges and textures. Intermediate layers recognize more complex structures such as shapes, while deeper layers are capable of identifying entire objects and classifying them. The application of AI and CT for lung cancer detection has been extensively documented. According to study from 2019 by Zhang et al., who introduced a 3D CNN with three specialized modules that achieved a sensitivity of 84.4% in nodule classification, exceeding the performance of manual assessment [17]. In 2022 Cifci proposed a model termed Deep Learning with Instantaneously Trained Neural Networks (DITNN), which, when combined with an enhanced clustering technique, reached a diagnostic accuracy of 98.42% [18]. Similarly, Nasser and Abu-Naser in 2019 utilized an artificial neural network (ANN) and reported a high accuracy of 96.67% [19]. A comprehensive review by Javed et al., from 2024, further substantiates that CNNs are more effective at identifying and classifying neoplastic changes than traditional computational approaches[20]. Key metrics for evaluating diagnostic algorithms are presented in Table 1.

TABLE 1. Overview of diagnostic performance metrics [11].

Notion	Definition	Explanation / Purpose
Accuracy	The proportion of all correctly classified cases (both true positives and true negatives) among all evaluated cases.	Reflects the model's overall correctness across all predictions. High accuracy means the model performs well overall, but it may be misleading in with imbalanced datasets.
Sensitivity (Recall/True Positive Rate)	The proportion of actual positive cases that are correctly identified by the model.	Measures how effectively the model detects true positives (e.g., patients with cancer). High sensitivity means few false negatives.
Specificity (True Negative Rate)	The proportion of actual negative cases that are correctly identified as negative.	Indicates the model's ability to correctly rule out non-cases. High specificity means few false positives.
AUC (Area Under the Curve)	A statistical measure representing the area under the Receiver Operating Characteristic (ROC) curve.	An AUC value approaching 1.0 signifies an excellent ability to distinguish between positive and negative cases. Studies on deep learning for lung cancer diagnosis have reported AUC values exceeding 0.9, indicating high classification performance.

A comparison of deep learning algorithms with the clinical experience of radiologists shows a complex relationship between sensitivity and specificity. DL models often achieve higher sensitivity, resulting in fewer false negatives compared to humans, but this comes at the cost of an increased number of false positives. Studies using chest phantoms have shown that 5 out of 7 radiologists achieved significantly higher accuracy (pooled accuracy 0.59) than the AI system (accuracy 0.47), which had a tendency to misclassify structures such as pleural adhesions or rib fractures as neoplastic lesions [13]. This phenomenon leads to overdiagnosis and exposes patients to unnecessary invasive diagnostic procedures. On the other hand, combining forces – the AI system as a "second reader" – increases detection sensitivity from 0.67–0.68 (double medical description) to 0.77-0.81 (doctor + AI) [12]. Therefore, despite high AUC values in laboratory tests, in clinical practice AI systems should be treated as supporting tools rather than independent diagnostic entities[12,13].

Technical and Practical Challenges of Implementing Algorithms

While AI holds the potential to revolutionize radiology in oncology by automating image analysis, a number of significant challenges must be addressed before its widespread clinical adoption. These challenges include the heterogeneity of training data, ethical and legal issues surrounding data acquisition, financial costs, and the limited interpretability of AI-generated results [21]. In a 2020 review, Sakamoto et al. highlighted the scarcity of high-quality training and validation data as a primary obstacle [22]. Furthermore, inter-observer variability among physicians in image interpretation complicates the creation of a standardized "gold standard" for training AI algorithms [2]. In 2022 this concern was echoed by Zhang and Chen, who identified limited access to expertly annotated datasets as one of the most pressing challenges in the field [23]. Other barriers noted by Sakamoto include the substantial cost of integrating AI into hospital workflows and the sensitivity of models to variations in imaging equipment and protocols. A major conceptual hurdle is the "black box" problem, which refers to the difficulty in explaining the decision-making process of complex DL models, potentially leading to unforeseen errors [22]. A 2024 study conducted by Quanyang et al. emphasized the importance of model transparency, arguing that DL systems should be able to articulate the correlations they identify between input data and diagnostic outputs. The study authors also pointed to the challenge of model generalization, noting that current high-performing models are often highly specialized and may not perform well on data from different sources or patient populations [8]. Zhang and Zhu in their review from 2018 further elaborated on these issues, noting that models can inherit biases from their training data and may possess "blind spots" that lead to misclassifications. The high computational demands and lack of universal metrics for interpretability also impede model optimization and evaluation. From a practical standpoint, seamless integration with existing clinical systems and adherence to regulatory standards are crucial for successful implementation [24]. Addressing these issues-primarily by enhancing the quality and accessibility of annotated data and improving the interpretability of model outputs-is essential for the clinical translation of AI in radiology.

Potential Solutions and Future Directions

To address the "black box" problem, methods in eXplainable AI (XAI) such as SHapley Additive exPlanations(SHAP) and Local Interpretable Model-agnostic Explanations (LIME) have been developed. These techniques provide insights into how a model arrives at a particular decision, thereby increasing transparency and user trust. The XAI methodology can also identify which patient features are most influential in a model's prediction [25]. XAI can make complex algorithms more understandable to clinicians by generating visualizations of a model's internal logic, [26]. For instance, SHAP and LIME have been applied to CT images to highlight features critical for lung cancer prediction, potentially improving early detection and patient outcomes [27]. Studies show that while different models may achieve similar predictive accuracy, XAI methods can reveal subtle differences in their underlying decision-making processes [25]. SHAP quantifies the contribution of each feature to a prediction, while LIME approximates the behavior of a complex model with a simpler, more interpretable one for individual predictions [28].

Beyond model interpretability, data unification is critical. Healthcare systems generate vast and diverse biomedical data, making it challenging to derive consistent insights. The development of large, unified datasets that integrate information from multiple sources is essential for training robust and generalizable models [29]. Another promising avenue is the development of hybrid intelligence systems, which combine the computational power of AI with the critical thinking and ethical judgment of human clinicians. This synergy can enhance clinical efficiency while mitigating AI limitations such as bias and data misinterpretation. Concepts from AI development can be adapted to enhance clinical decision-making. For instance, the backpropagation, which is a technique for refining models based on prediction errors,can be conceptually applied to clinical practice, encouraging physicians to continually refine their diagnoses as new information emerges. Similarly, quantization, which simplifies complex data for efficient processing, mirrors how clinicians prioritize information to focus on the most critical aspects of a patient's case. Strategies to prevent model overfitting, which can lead to more generalizable AI, can also inform clinical practice by discouraging premature conclusions based on limited evidence. Such frameworks that merge AI strengths with human expertise have the potential to foster more effective and confident clinical decision-making [30].

CONCLUSIONS

Deep learning algorithms offer substantial advantages for lung cancer diagnosis, including high precision for early detection, the capacity to analyze high-dimensional imaging data, and the automation of laborious tasks, thereby reducing the burden on radiologists. In the case of early-stage non-small cell lung cancer (NSCLC) (stages I, II, and selected IIIa cases), surgical resection is the primary approach. However, only approximately 20% of patients are eligible for this procedure. In instances where surgery is microscopically non-radical or the assessment of mediastinal lymph nodes is unfeasible, adjuvant radiotherapy is implemented. Radiotherapy is also applied in locally advanced lung cancer and combined with chemotherapy, constitutes the cornerstone of small cell lung cancer (SCLC) treatment [31, 32]. The use of algorithms improves diagnostic accuracy, shortens interpretation times and allows for more precise tumor delineation, enabling the maximization of the radiation dose delivered to the tumor while simultaneously sparing healthy tissues [33, 34]. However, significant limitations persist, including the challenge of model interpretability, the need for large and diverse training datasets, the risk of errors stemming from biased training data, and the high computational costs. In order to address these challenges, research is exploring innovative solutions such as the integration of DL with edge computing. This paradigm involves processing data near its source,for instance, directly on medical devices, rather than transmitting it to a central cloud server. This approach enables real-time image analysis, which can lead to significantly earlier disease detection. Lung cancer in the early stages usually presents no symptoms or only non-specific symptoms, which means it is often detected at more advanced stages, thereby limiting treatment options and worsening the prognosis [35]. Combining edge computing with AI also enhances the extraction of salient features from CT scans, improving the differentiation between malignancy and benign tissue [36]. This technology can also be applied to real-time patient monitoring, such as analyzing data from pulse oximeters to detect abnormalities in respiratory function [37]. Furthermore, local data processing inherent to edge computing enhances patient privacy and data security, and it also enables diagnostic capabilities in regions with limited internet connectivity [38]. While the application of deep learning in CT-based lung cancer diagnosis faces challenges, its future is promising. Continued progress will depend on the development of more robust and interpretable algorithms, the availability of high-quality, large-scale datasets, and effective integration into clinical workflows. Despite these hurdles, AI is poised to elevate the field of cancer diagnostics, ushering in a new era of personalized and precision medicine.

REFERENCES

1. Krajowy Rejestr Nowotworów. Nowotwory złośliwe w Polsce [Internet]. Warszawa: KRN; 2021 Sep 28 [cited 2025 Oct 5]. Available from: https://onkologia.org.pl/pl/epidemiologia/nowotwory-zlosliwe-w-polsce
2. Blandin Knight S, Crosbie PA, Balata H, et al. Progress and prospects of early detection in lung cancer. Open Biol. 2017;7(9):170070. https://doi.org/10.1098/rsob.170070
3. Nooreldeen R, Bach H. Current and future development in lung cancer diagnosis. Int J Mol Sci. 2021;22(16):8661. https://doi.org/10.3390/ijms22168661
4. Grzywacz E, Grzymkowska M, Chmielowiec J, et al. Nicotine addiction – a health problem in adolescents in a neurobiological context nicotine addiction. Pol J Public Health. 2022;132:21-24.
5. Lewandowska KSL, Calleja N. Influence of smoking on changes in indicators of bronchitis, asthma and lung cancer – comparison on the example of Poland, Malta and other European Union countries. Pol J Public Health. 2024;134:17-21.
6. Al Mohammad B, Brennan PC, Mello-Thoms C. A review of lung cancer screening and the role of computer-aided detection. Clin Radiol. 2017;72(6):433-442. https://doi.org/10.1016/j.crad.2017.01.002
7. Rubin GD. Lung nodule and cancer detection in computed tomography screening. J Thorac Imaging. 2015;30(2):130-138. https://doi.org/10.1097/RTI.0000000000000140
8. Quanyang W, Yao H, Sicong W, et al. Artificial intelligence in lung cancer screening: detection, classification, prediction, and prognosis. Cancer Med. 2024;13(7):e7140. https://doi.org/10.1002/cam4.7140
9. Murphy A, Skalski M, Gaillard F. The utilisation of convolutional neural networks in detecting pulmonary nodules: a review. Br J Radiol. 2018;91(1090):20180028. https://doi.org/10.1259/bjr.20180028
10. de Margerie-Mellon C, Chassagnon G. Artificial intelligence: a critical review of applications for lung nodule and lung cancer. Diagn Interv Imaging. 2023;104(1):11-17. https://doi.org/10.1016/j.diii.2022.11.007
11. Hosny A, Parmar C, Coroller TP, et al. Deep learning for lung cancer prognostication: a retrospective multi-cohort radiomics study. PLoS Med. 2018;15(11):e1002711. https://doi.org/10.1371/journal.pmed.1002711
12. Schreuder A, Scholten ET, van Ginneken B, et al. Artificial intelligence for detection and characterization of pulmonary nodules in lung cancer CT screening: ready for practice?. Transl Lung Cancer Res. 2021;10(5):2378-2388. https://doi.org/10.21037/tlcr-20-591
13. Peters AA, Decasper A, Munz J, et al. Performance of an AI based CAD system in solid lung nodule detection on chest phantom radiographs compared to radiology residents and fellow radiologists. J Thorac Dis. 2021;13(5):2728-2737. https://doi.org/10.21037/jtd-20-3522
14. Li L, Liu Z, Huang H, et al. Evaluating the performance of a deep learning-based computer-aided diagnosis (DL-CAD) system for detecting and characterizing lung nodules: comparison with the performance of double reading by radiologists. Thorac Cancer. 2019;10(2):183-192. https://doi.org/10.1111/1759-7714.12921
15. Forte GC, Altmayer S, Silva RF, et al. Deep learning algorithms for diagnosis of lung cancer: a systematic review and meta-analysis. Cancers (Basel). 2022;14(16):3856. https://doi.org/10.3390/cancers14163856
16. Thanoon MA, Zulkifley MA, Mohd Zainuri MAA, et al. A review of deep learning techniques for lung cancer screening and diagnosis based on CT images. Diagnostics (Basel). 2023;13(16):2617. https://doi.org/10.3390/diagnostics13162617
17. Zhang C, Sun X, Dang K, et al. Toward an expert level of lung cancer detection and classification using a deep convolutional neural network. Oncologist. 2019;24(9):1159-1165. https://doi.org/10.1634/theoncologist.2019-0115
18. Cifci MA. SegChaNet: a novel model for lung cancer segmentation in CT scans. Appl Bionics Biomech. 2022;2022:1139587. https://doi.org/10.1155/2022/1139587

19. Nasser IM, Abu-Naser SS. Lung cancer detection using artificial neural network. Int J Eng Inf Syst. 2019;3(3):17-23.
20. Javed R, Khan T, Khan A, et al. Deep learning for lung cancer detection: a review. Artif Intell Rev. 2024;57:118. https://doi.org/10.1007/s10462-024-10807-1
21. Majumder A, Sen D. Artificial intelligence in cancer diagnostics and therapy: current perspectives. Indian J Cancer. 2021;58(4):481-492. https://doi.org/10.4103/ijc.IJC_399_20
22. Sakamoto T, Furukawa T, Lami K, et al. A narrative review of digital pathology and artificial intelligence: focusing on lung cancer. Transl Lung Cancer Res. 2020;9(5):2255-2277. https://doi.org/10.21037/tlcr-20-591
23. Zhang K, Chen K. Artificial intelligence: opportunities in lung cancer. Curr Opin Oncol. 2022;34(1):44-53. https://doi.org/10.1097/CCO.0000000000000796
24. Zhang QS, Zhu SC. Visual interpretability for deep learning: a survey. Front Inf Technol Electron Eng. 2018;19(1):27-39. https://doi.org/10.1631/FITEE.1700808
25. Kobylińska K, Orłowski T, Adamek M, et al. Explainable machine learning for lung cancer screening models. Appl Sci. 2022;12(4):1926. https://doi.org/10.3390/app12041926
26. Ladbury C, Zarinshenas R, Semwal H, et al. Utilization of model-agnostic explainable artificial intelligence frameworks in oncology: a narrative review. Transl Cancer Res. 2022;11(10):3853-3868. https://doi.org/10.21037/tcr-22-1081
27. Raptis S, et al. From pixels to prognosis: unveiling radiomics models with SHAP and LIME for enhanced interpretability. Biomed Phys Eng Express. 2024;10(3):035016. https://doi.org/10.1088/2057-1976/ad3004
28. Oli YR, Regmi L, Poudel P, et al. Unlocking the potential of CT scans: an explanation-driven deep learning model for predicting lung cancer. Int J Eng Technol. 2023;1(1):223-231.
29. Ali R, Siddiqi MH, Idris M, et al. GUDM: automatic generation of unified datasets for learning and reasoning in healthcare. Sensors (Basel). 2015;15(7):15772-15798. https://doi.org/10.3390/s150715772
30. Hirosawa T, Suzuki T, Shiraishi T, et al. Adapting artificial intelligence concepts to enhance clinical decision-making: a hybrid intelligence framework. Int J Gen Med. 2024;17:5417-5422. https://doi.org/10.2147/IJGM.S481232
31. Smolarz B, Łukasiewicz H, Samulak D, et al. Lung cancer-epidemiology, pathogenesis, treatment and molecular aspect (review of literature). Int J Mol Sci. 2025;26(5):2049. https://doi.org/10.3390/ijms26052049
32. Kim SY, Park HS, Chiang AC. Small cell lung cancer: a review. JAMA. 2025;333(21):1906-1917. https://doi.org/10.1001/jama.2025.0560
33. Han Z, Wang Y, Wang W, et al. Artificial intelligence-assisted delineation for postoperative radiotherapy in patients with lung cancer: a prospective, multi-center, cohort study. Front Oncol. 2024;14:1388297. https://doi.org/10.3389/fonc.2024.1388297
34. Wang TW, Hong JS, Huang JW, et al. Systematic review and meta-analysis of deep learning applications in computed tomography lung cancer segmentation. Radiother Oncol. 2024;197:110344. https://doi.org/10.1016/j.radonc.2024.110344
35. Balata H, Quaife SL, Craig C, et al. Early diagnosis and lung cancer screening. Clin Oncol (R Coll Radiol). 2022;34(11):708-715. https://doi.org/10.1016/j.clon.2022.08.036
36. Zhang C, Aamir M, Guan Y, et al. Enhancing lung cancer diagnosis with data fusion and mobile edge computing using DenseNet and CNN. J Cloud Comput (Abingdon). 2024;13(1):91. https://doi.org/10.1186/s13677-024-00597-w
37. Joo MI, Kang DY, Kang MS, et al. A patient management system using an edge computing-based IoT pulse oximeter. Appl Sci. 2024;14(1):414. https://doi.org/10.3390/app14010414
38. Bourechak A, Zedadra O, Kouahla MN, et al. At the confluence of artificial intelligence and edge computing in IoT-based applications: a review and new perspectives. Sensors (Basel). 2023;23(3):1639. https://doi.org/10.3390/s23031639

ORCID

Michał Henryk Wizner https://orcid.org/0000-0003-2359-2486
Natalia Wizner https://orcid.org/0009-0008-1574-4762

Corresponding author
Michał Azierski
Student Scientific Association of MedTech at the Center for Remote Learning and Educational Effects Analysis, Faculty of Medical Sciences in Katowice, Silesian Medical University, Katowice, Poland
e-mail: michal.azierski@gmail.com