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Artificial Intelligence For Lung Cancer: A Review Of Diagnostic And Therapeutic Applications

[1]Samruddhi Bagal, [2]Deepa Padwal, [3]Dr. Manjusha Tatiya
[1]Student, [2]Assistant Professor, [3]Head of Department
[1]Department of Artificial Intelligence and Data Science
[1] Indira College of Engineering and Management, Pune, India

***Abstract**:* This review investigates how artificial intelligence (AI) is enhancing the diagnosis and treatment of lung cancer, a leading cause of fatalities linked to cancer. The study explores various AI methods, including machine learning (ML) and deep learning (DL), aimed at boosting the accuracy of lung cancer detection and treatment options. It focuses on the use of these techniques for identifying nodules, evaluating genomic data, and creating personalized medical plans. Key factors such as the performance of algorithms, data quality, and integration into clinical settings are analyzed to understand their influence on patient outcomes. A detailed review of recent advancements in AI applications and the challenges faced during their clinical adoption is included. By identifying existing research gaps and potential areas for growth, this review aims to support the ongoing evolution of lung cancer care through AI innovations.

IndexTerms **-** Artificial Intelligence (AI), Lung Cancer, Machine Learning (ML), Deep Learning (DL), Nodule Detection Personalized Medicine, Radiomics, Reinforcement Learning, Generative Adversarial Networks (GANs), Clinical Workflow, Early Detection, Diagnostic Imaging, Predictive Analytics, Data Quality, Patient Outcomes

INTRODUCTION

Globally, lung cancer ranks as the second most common cancer, accounting for 21% of all cancer-related deaths [1]. Early discovery remains problematic, with only about 20% of cases identified at stage I, a figure that has not improved over time [7]. In addition to diagnostic difficulties, lung cancer management faces significant challenges in prognosis and treatment evaluation [11]. While recent developments in immunotherapy and targeted therapies have shown potential, their effectiveness varies considerably among patients, with inconsistent response rates [12]. Consequently, there is an urgent demand for more efficient diagnostic tools that offer high sensitivity and specificity [2]. The concept of artificial intelligence (AI), first brought to light by John McCarthy in 1956, has attracted interest for its potential in diagnosing and predicting lung cancer. AI includes several domains, such as machine learning (ML) and deep learning (DL), both of which have proven effective in analyzing cancer-related medical data [5,6]. ML allows systems to acquire knowledge from data without explicit programming, while DL employs multi-layer neural networks for concurrent feature selection and model fitting [14,9]. In the field of oncology, AI tools have been created to aid in lung segmentation, nodule identification, and classification, proving especially useful given the extensive data produced by chest CT scans and radiographs [3,10]. These tools enhance radiologists' capacity to detect small nodules (under 5 mm) that are frequently missed during visual inspection [13].

CT scans are vital for lung cancer screening, yet the heavy workload they create for radiologists has led to the need for AI-driven computer-aided detection systems [3]. These AI technologies have demonstrated enhancements in detection accuracy, minimized radiologist fatigue, and improved efficiency in clinical environments [15].

While the incorporation of AI into clinical workflows shows significant promise, challenges remain. Although some AI models have received FDA approval for clinical use in lung cancer [8], many studies still rely on internal validation, which may not effectively translate to real-world datasets, thus limiting their clinical application [4,16]. This review examines current AI applications in lung cancer, focusing on their role in diagnosis, treatment, and management of high-dimensional medical data, highlighting the need for additional research and validation to support their routine use in oncology [24].

AI TECHNIQUES

Machine Learning and Deep Learning Approaches Artificial Intelligence (AI) techniques, specifically, Machine Learning (ML) and Deep Learning (DL), have ended up vital in progressing lung cancer investigations by improving determination and treatment procedures. These techniques analyze endless sums of quiet data, counting restorative records, imaging considers, and hereditary information, to form perceptive models custom-fitted to personal patients. This personalized approach encourages early discovery and the advancement of customized treatment procedures, eventually moving forward the administration and forecast of lung cancer patients.

Supervised Learning

A fundamental component of ML in lung cancer diagnostics is supervised learning. This method involves training algorithms using labeled datasets, where input-output pairs with known outcomes are provided. The algorithm identifies patterns in the training data and applies this knowledge to new, unfamiliar information.

Data Sources:

Algorithms are trained using various data types, such as:

Imaging Results: CT scans, MRI, and PET scans offer crucial details about the presence and characteristics of lung nodules.

Genomic Data: Understanding the genetic composition of tumors aids in determining malignancy and guiding targeted therapies.

Support Vector Machines (SVM):

SVMs remain robust classifiers that function by determining the optimal hyperplane to separate different data classes in high-dimensional space. For lung cancer, SVMs can effectively categorize nodules as benign or malignant based on features extracted from imaging data and patient demographics. Their strength lies in handling complex datasets with non-linear relationships.

Decision Trees:

Decision trees provide a clear and interpretable method for clinical decision-making. They model decisions using a series of hierarchical rules derived from input features. In lung cancer diagnosis, decision trees can evaluate patient characteristics—such as age, smoking history, and imaging results—against known outcomes (e.g., presence of cancer). Their visual structure allows healthcare professionals to understand the reasoning behind a diagnosis, making them accessible in clinical settings.

Applications:

Nodule Classification: SVMs and decision trees effectively distinguish between benign and malignant nodules, reducing false positives and improving patient care.

Risk Stratification: By analyzing different factors, such as imaging characteristics and clinical histories, these algorithms can assist in grouping patients according to their lung cancer risk, facilitating targeted screenings and preventive strategies.

Treatment Outcome Prediction: Machine learning models can evaluate treatment responses to predict results for particular therapies, thereby aiding in personalized treatment planning.

Unsupervised Learning

When labeled data is scarce, unsupervised learning becomes essential for revealing hidden patterns and structures within datasets. This is especially important in exploratory studies of lung cancer, enabling researchers to detect new patient subtypes, responses to treatment, and possible risk factors that might not be readily apparent through conventional approaches.

K-means Clustering:

K-means is a widely used algorithm for dividing patients into distinct groups based on shared characteristics, such as demographic data, clinical features, and imaging properties.

Feature Selection: Choosing relevant attributes from patient information, including tumor dimensions, stage, and histological properties.

Cluster Formation: Organizing patients into K separate clusters, where K is predetermined. The algorithm repeatedly adjusts these clusters to reduce variance within each group.

Subtype Discovery: By employing K-means clustering, scientists can identify previously unknown categories of lung cancer patients. This can result in customized treatment plans and enhanced prognostic evaluations, as different clusters may exhibit varying responses to therapies.

Hierarchical Clustering:

Hierarchical clustering constructs a tree-like structure (dendrogram) that showcases the connections between various patient groups based on their attributes.

This method can be divided into two approaches:

Agglomerative Clustering: Begins with individual patients as distinct clusters and progressively combines them based on similarity until a single cluster remains.

Divisive Clustering: Starts with all patients in one cluster and systematically divides them into smaller groups.

Reinforcement Learning

Reinforcement learning represents a cutting-edge and flexible method in the realm of adaptive radiation therapy for treating lung cancer. This approach differs from conventional machine learning techniques by emphasizing the acquisition of optimal actions through experimentation, guided by environmental feedback—specifically, the patient's treatment response.

In the context of adaptive radiation therapy, reinforcement learning algorithms consistently assess patient reactions to radiation doses.

This process encompasses:

Instantaneous Input: Observing patient responses, including side effects or tumor size alterations, offers immediate data to the model.

Dose Modification: Utilizing this input, the algorithm acquires the ability to adjust subsequent radiation doses, enhancing therapeutic effectiveness while reducing negative impacts.

Tailored Medicine:

By customizing treatment strategies through reinforcement learning, cancer specialists can deliver more targeted interventions suited to each patient. This method seeks to maximize the therapeutic range, ensuring patients receive the most beneficial dose without excessive toxicity.

Convolutional Neural Networks (CNNs)

CNNs are specialized neural networks designed for processing structured data, especially images. Their structure, which includes convolutional layers, pooling layers, and fully connected layers, enables the automatic extraction of layered features from visual data.

Nodule Detection: CNNs are highly effective at detecting lung nodules in CT scans with great precision, often outperforming human radiologists. Recent research shows that CNNs can achieve area under the curve (AUC) scores exceeding 0.9, which aids in earlier diagnosis and treatment.

Segmentation: CNNs are capable of segmenting lung images to outline tumor edges, delivering vital information for treatment planning. This is particularly important in radiation therapy, where accurate targeting is critical.

Radiomics Analysis: By combining CNNs with radiomic features, researchers can derive quantitative metrics from imaging data—such as texture and shape that can anticipate tumor behavior and malignancy, which further enhances treatment approaches.

Generative Adversarial Networks (GANs)

GANs comprise two competing neural networks: the generator and the discriminator. They learn from one another to create realistic synthetic data. This framework is especially advantageous in situations where labeled data is scarce.

Data Augmentation: GANs can generate synthetic CT images to augment existing datasets, addressing the problem of data scarcity in training deep learning models. This ensures that models are trained on diverse data, improving generalizability.

Diversity in Training: By producing various patient scenarios and imaging characteristics, GANs help create more robust models that can better generalize across different populations, reducing biases and enhancing diagnostic equity.

RELATED WORKS

Cancer cells' high mortality rates highlight their substantial danger. To enhance cancer treatment accuracy, predictive models have been developed [29]. Lung cancer, particularly hazardous and often challenging to diagnose, necessitates quick and precise evaluation of pulmonary nodules [25]. Chest CT scan images are vital in lung cancer screening and diagnosis[20]. Early detection is crucial, as it significantly enhances patients' chances of recovery. Technology plays a pivotal role in effective cancer detection, with numerous approaches suggested for diagnosing lung cancer at its early stages.[17].

Research conducted by Kadir and Gleeson[27] has brought to light diagnostic models based on machine learning for lung cancer, assisting doctors in handling uncertain pulmonary nodules, whether identified through random screening or other methods. These systems are designed to reduce inconsistency in nodule classification, improve decision-making, and lower the number of unnecessary procedures on benign nodules. Obulesu et al.[19] point out that cancer presents a significant global health challenge, highlighting the rise in mortality rates in recent years. Advanced machine learning techniques now allow for a clearer distinction between patients with lung cancer and those who are healthy, indicating substantial advancements in diagnostic abilities.

Chaturvedi et al.[28] observe that lung cancer has once again become the most widespread illness affecting people, emphasizing the vital nature of early detection for patient recovery. While predictive models are important for cancer identification, the accuracy of machine learning models still needs enhancement to ensure total reliability. Radhika et al.[21] describe the spread of cancer cells within the lungs as a pressing health issue, reinforcing the need for effective diagnostic methods.

The increasing rate of lung cancer cases is linked to higher mortality rates among both men and women. Researchers maintain that lung cancer is the most prevalent disease across the globe. Machine learning algorithms have aided in the diagnosis of lung cancer, with several convolutional neural network (CNN) architectures enhancing image segmentation. The Kaggle Data Science Bowl competition aimed to refine algorithmic precision in the classification and detection of malignant lung nodules on CT images. It utilized a two-stage process: the first stage offered a substantial training dataset that included 1,397 patients, 362 of whom were lung cancer patients, along with an initial validation set of 198 patients. The second stage featured a previously unseen dataset containing 506 patients, ensuring that competitors could not guess the labels of the test set.[32]

Göltepe's research[18] highlights the grave repercussions of delays in lung cancer diagnosis, often leading to fatalities. Prompt diagnosis greatly enhances treatment success rates. As machine learning techniques evolve rapidly, healthcare professionals are increasingly utilizing them to classify and diagnose early-stage diseases.

Sajad et al.[26] note that lung cancer remains the leading cause of cancer-related fatalities, pointing out that X-ray images can identify irregular masses or nodules. Nonetheless, precise laboratory diagnoses can take time. This study employs deep learning techniques to facilitate earlier cancer detection based on the medical histories of previous patients.

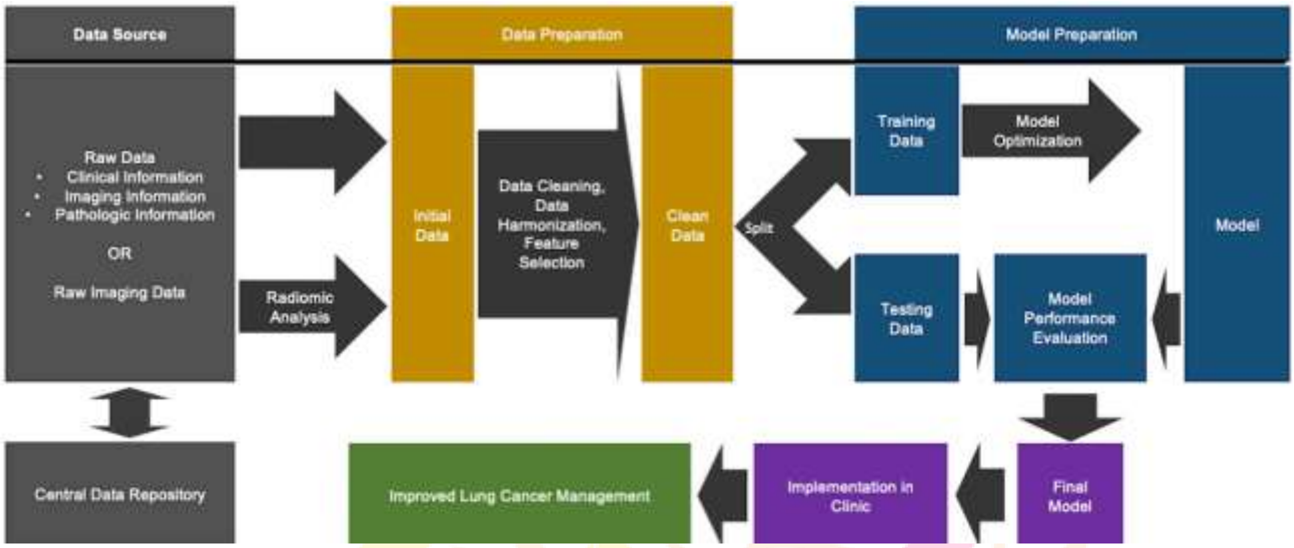

Figure 1. Clinical AI workflow schema [33]
A simplified overview of the workflow for implementing AI in lung cancer clinics based on best practices in artificial intelligence

CURRENT CHALLENGES

1. **Data Acquisition and Organization**: Data Collection and Organization: Effective AI models rely on extensive and varied datasets. However, current research frequently depends on small sample sizes, which can introduce biases and limit the general applicability of findings. This underscores the necessity for larger, more diverse patient groups to improve the reliability of models.[22]
2. **Reproducibility**: Differences in AI research results among various institutions stress the need for standardized approaches. A deficiency in external validation may exaggerate performance metrics and compromise the trustworthiness of AI applications in clinical environments.[34]
3. **Limited Application to Patient Care**: There exists a notable divide between AI research and its actual implementation in patient care. The majority of studies conduct retrospective data analysis, and very few have assessed AI interventions within real clinical contexts. This restricts the understanding of AI's potential effects on patient outcomes.[30]
4. **Data Integration and Centralization**: Institutional barriers impede the effective use of data for AI models. Centralized data repositories are vital for incorporating a variety of factors, such as patient demographics and tumor details, thereby enhancing the overall performance of AI systems.[30]
5. **Study Design**: Robust study designs are essential to minimize biases and avoid overfitting in AI models. Careful consideration of model testing and validation is critical to ensuring credible results.
6. **Ethical Considerations**: Ethical concerns arise regarding patient confidentiality and the implications of incorrect AI predictions. Addressing issues related to patient consent and liability is crucial as AI becomes more integrated into lung cancer management.[35]
7. **Complexity and Understandability**: The complexity of AI models can impede their adoption in clinical settings. Developing explainable AI frameworks is necessary to ensure that clinicians can interpret AI outputs effectively, fostering trust and facilitating integration into patient care

FUTURE DIRECTIONS

To successfully integrate AI into lung cancer clinics, it's crucial to tackle the shortcomings noted in existing practices. The focus should be on creating strong, accessible, and validated AI models that are tailored to enhance patient care. Reaching this objective will lay the groundwork for personalized medicine in lung cancer treatment.

1. **Developing Strong Models**: Creating validated AI models is vital for improving patient care. By concentrating on building models that use extensive, centralized datasets, researchers can boost the effectiveness and applicability of AI in lung cancer therapies.[23,31]
2. **Enhancing Algorithms**: The growth in computational power offers opportunities to boost the performance and efficiency of AI systems. Such advancements will support the practical implementation of AI in clinical environments, enabling faster and more precise analyses.[36]
3. **Promoting Collaborative Data Sharing**: Fostering cooperation among researchers to combine varied datasets helps overcome key hurdles in utilizing AI for lung cancer treatment. Shared data resources can contribute to more thorough models and enhance the overall influence of AI on patient outcomes.
4. **Algorithmic Improvements**: Advances in computational power present opportunities to enhance the performance and efficiency of AI systems. These improvements will facilitate the practical application of AI in clinical settings, allowing for quicker and more accurate analyses.[36]
5. **Collaborative Data Sharing**: Encouraging collaboration among researchers to pool diverse datasets addresses significant barriers to the effective use of AI in lung cancer care. Shared resources can lead to more comprehensive models and improve the overall impact of AI on patient outcomes.
6. **Inclusive Development**: Involving input from all stakeholders—including patients, physicians, and healthcare administrators—ensures that AI systems are designed to be user-friendly and meet the practical needs of those in the clinical environment. This collaborative approach fosters acceptance and smooth integration into routine practice.
7. **Integrating Clinical Context**: Incorporating clinical data alongside imaging findings is essential for improving decision-making processes in patient care. This integration supports a more holistic approach to treatment, enabling shared decision-making between healthcare providers and patients, ultimately enhancing care outcomes

CONCLUSION

The domain of lung cancer treatment has experienced significant advancements through precision medicine, fueled by innovative technologies such as artificial intelligence (AI). The use of methods—including machine learning (ML), deep learning (DL), natural language processing (NLP), and explainable AI (XAI)—holds great promise for enhancing multiple facets of lung cancer management. By adeptly analyzing vast datasets, AI facilitates earlier diagnoses, improved treatment choices, and more precise predictions regarding treatment results, all of which contribute to better patient outcomes. The importance of early detection in boosting recovery rates for patients cannot be overstated. Nevertheless, challenges remain, particularly in differentiating between tumors due to the complexities of CT imaging and the need for comprehensive datasets to inform clinical decisions. For instance, a study demonstrated an automated lung cancer detection system that employed convolutional neural networks (CNN) and achieved an impressive accuracy rate of 94%. This method not only accelerates diagnostic processes but also minimizes human error.

While the potential of AI in managing lung cancer is encouraging, it is essential to acknowledge the limitations and challenges that come with its application. Issues surrounding data quality, model transparency, and ethical implications need to be addressed to secure effective implementation in clinical environments. By tackling these concerns, we can fully leverage AI's capabilities, fostering a more efficient and personalized approach to lung cancer treatment that emphasizes patient safety and efficacy.

REFERENCES

[1] 1. Jacobs, C.; van Ginneken, B. Google's lung cancer AI: A promising tool that needs further validation. Nat. Rev. Clin. Oncol. 2019, 16, 532–533. [CrossRef] [PubMed]
[2] Xu, K.; Zhang, C.; Du, T.; Gabriel, A.N.A.; Wang, X.; Li, X.; Sun, L.; Wang, N.; Jiang, X.; Zhang, Y. Progress of exosomes in the diagnosis and treatment of lung cancer. Biomed. Pharmacother. 2021, 134, 111111. [CrossRef]
[3] Coughlin, J.M., Zang, Y., Terranella, S., Alex, G., Karush, J., Geissen, N., Chmielewski, G.W., Arndt, A.T., Liptay, M.J., Zimmermann, L.J., et al. (2020). Understanding barriers to lung cancer screening in primary care. J. Thorac. Dis. 12, 2536–2544.
[4] Chiu, H.Y.; Chao, H.S.; Chen, Y.M. Application of artificial intelligence in lung cancer. Cancers 2022, 14, 1370. [CrossRef]
[5] Amisha; Malik, P.; Pathania, M.; Rathaur, V.K. Overview of artificial intelligence in medicine. J. Fam. Med. Prim. Care 2019, 8, 2328–2331. [CrossRef] [PubMed]
[6]. Hamet, P.; Tremblay, J. Artificial intelligence in medicine. Metabolism 2017, 69, S36–S40. [CrossRef]
[7] Bidzi ´nska, J.; Szurowska, E. See lung cancer with an AI. Cancers 2023, 15, 1321. [CrossRef] [PubMed] of clinical outcome in immunotherapy and targeted therapy of lung cancer. Semin. Cancer Biol. 2022, 86 Pt 2, 146–159. [CrossRef]
[8] Ladbury, C.; Amini, A.; Govindarajan, A.; Mambetsariev, I.; Raz, D.J.; Massarelli, E.; Williams, T.; Rodin, A.; Salgia, R. Integration of artificial intelligence in lung cancer: Rise of the machine. Cell Rep. Med. 2023, 4, 100933. [CrossRef]
[9] Lawson, C.E.; Marti, J.M.; Radivojevic, T.; Jonnalagadda, S.V.R.; Gentz, R.; Hillson, N.J.; Peisert, S.; Kim, J.; Simmons, B.A.; Petzold, C.J.; et al. Machine learning for metabolic engineering: A review. Metab. Eng. 2021, 63, 34–60. [CrossRef]
[10] K. Awai et al., "Pulmonary nodules at chest CT: effect of computer-aided diagnosis on radiologists' detection performance," Radiology, vol. 230, no. 2, pp. 347–352, 2004, doi: 10.1148/radiol.2302030049.
[11] Cellina, M.; Cè, M.; Irmici, G.; Ascenti, V.; Khenkina, N.; Toto-Brocchi, M.; Martinenghi, C.; Papa, S.; Carrafiello, G. Artificial intelligence in lung cancer imaging: Unfolding the future. Diagnostics 2022, 12, 2644. [CrossRef]
[12] Yin, X.; Liao, H.; Yun, H.; Lin, N.; Li, S.; Xiang, Y.; Ma, X. Artificial intelligence-based prediction
[13] Yamashita, R., Nishio, M., Do, R.K.G., and Togashi, K. (2018). Convolutional neural networks: an overview and application in radiology. Insights Imaging 9, 611–629
[14] Goyal, H.; Mann, R.; Gandhi, Z.; Perisetti, A.; Zhang, Z.; Sharma, N.; Saligram, S.; Inamdar, S.; Tharian, B. Application of artificial intelligence in pancreaticobiliary diseases. Clin. Med. Insights Gastroenterol. 2021, 14, 263177452199305. [CrossRef]
[15] K. Doi, "Computer-aided diagnosis in medical imaging: historical review, current status and future potential," Computerized Medical Imaging and Graphics, vol. 31, no. 4–5, pp. 198–211, 2007, doi: 10.1016/j.compmedimag.2007.02.002.
[16] Jones, G.S.; Baldwin, D.R. Recent advances in the management of lung cancer. Clin. Med. 2018, 18 (Suppl. 2), s41–s46. [CrossRef] [PubMed]
[17] V. K. Lam, M. Miller, L. Dowling, S. Singhal, R. P. Young, and E. C. Cabebe, "Community low-dose CT lung cancer screening: a prospective cohort study," Lung, vol. 193, no. 1, pp. 135–139, 2015, doi: 10.1007/s00408-014-9671-9.
[18] Y. Göltepe, "Performance of lung cancer prediction methods using different classification algorithms," Computers, Materials and Continua, vol. 67, no. 2, pp. 2015–2028, 2021, doi: 10.32604/cmc.2021.014631.
[19] O. Obulesu et al., "Adaptive diagnosis of lung cancer by deep learning classification using wilcoxon gain and generator," Journal of Healthcare Engineering, vol. 2021, pp. 1–13, 2021, doi: 10.1155/2021/5912051.
[20] K. Doi, "Computer-aided diagnosis in medical imaging: historical review, current status and future potential," Computerized Medical Imaging and Graphics, vol. 31, no. 4–5, pp. 198–211, 2007, doi: 10.1016/j.compmedimag.2007.02.002.
[21] P. R. Radhika, R. A. S. Nair, and V. G., "A comparative study of lung cancer detection using machine learning algorithms," in 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), 2019, pp. 1–4, doi: 10.1109/ICECCT.2019.8869001.
[22] Vabalas, A., Gowen, E., Poliakoff, E., and Casson, A.J. (2019). Machine learning algorithm validation with a limited sample size. PLoS One 14, e0224365.
[23] Clark, K., Vendt, B., Smith, K., Freymann, J., Kirby, J., Koppel, P., Moore, S., Phillips, S., Maffitt, D., Pringle, M., et al. (2013). The Cancer Imaging Archive (TCIA): maintaining and operating a public information repository. J. Digit. Imaging 26, 1045–1057.

[24] Roosan, M.R.; Mambetsariev, I.; Pharaon, R.; Fricke, J.; Baroz, A.R.; Chao, J.; Chen, C.; Nasser, M.W.; Chirravuri-Venkata, R.; Jain, M.; et al. Evaluation of somatic mutations in solid metastatic pan-cancer patients. Cancers 2021, 13, 2776. [CrossRef] [PubMed]

[25] D. M. Abdullah and N. S. Ahmed, "A review of most recent lung cancer detection techniques using machine learning," International Journal of Science and Business, vol. 5, no. 3, pp. 159–173, 2021, doi: 10.5281/zenodo.4536818.

[26] F. Sajad, V. V, C. C. L, J. V, and A. P. S., "Effect of principal component analysis on lung cancer detection using machine learning techniques," International Research Journal of Engineering and Technology (IRJET), vol. 6, no. 5, pp. 6783–6791, 2019.

[27] T. Kadir and F. Gleeson, "Lung cancer prediction using machine learning and advanced imaging techniques," Translational Lung Cancer Research, vol. 7, no. 3, pp. 304–312, 2018, doi: 10.21037/tlcr.2018.05.15.

[28] P. Chaturvedi, A. Jhamb, M. Vanani, and V. Nemade, "Prediction and classification of lung cancer using machine learning techniques," IOP Conference Series: Materials Science and Engineering, vol. 1099, no. 1, pp. 1–19, 2021, doi: 10.1088/1757- 899x/1099/1/012059.

[29] E. S. N. Joshua, M. Chakkravarthy, and D. Bhattacharyya, "An extensive review on lung cancer detection using machine learning techniques," Revue d'Intelligence Artificielle, vol. 34, no. 3, pp. 351–359, 2020, doi: 10.18280/ria.340314.

[30] Lambin, P., Leijenaar, R.T.H., Deist, T.M., Peerlings, J., de Jong, E.E.C., van Timmeren, J., Sanduleanu, S., Larue, R.T.H.M., Even, A.J.G., Jochems, A., et al. (2017). Radiomics: the bridge between medical imaging and personalized medicine. Nat. Rev. Clin. Oncol. 14, 749–762.

[31]Tomczak, K., Czerwinska, P., and Wiznerowicz, M. (2015). Review the cancer Genome Atlas (TCGA): an immeasurable source of knowledge. Contemp. Oncol. 19, 68–77.

[32] Booz, Allen, and Hamilton, "Data science bowl 2017," kaggle, 2017. https://www.kaggle.com/c/data-science-bowl-2017 (accessed Dec. 10, 2022).

[33] Ladbury, C., Amini, A., Govindarajan, A., Mambetsariev, I., Raz, D. J., Massarelli, E., Williams, T., Rodin, A., & Salgia, R. (2023). Integration of artificial intelligence in lung cancer: Rise of the machine. *Review*, 4(2100933).

[34] Zwanenburg, A., Abdalah, M., Ashrafinia, S., et al. (2018). Results from the image biomarker standardisation initiative. Radiother. Oncol. 127, S543–S544.

[35] Rigby, M.J. (2019). Ethical dimensions of using artificial intelligence in health care. AMA Journal of Ethics 21, 121–124

[36] Kann, B.H., Hosny, A., and Aerts, H.J.W.L. (2021). Artificial intelligence for clinical oncology. Cancer Cell 39, 916–927