From Black-Box to Explainability: Advancing AI in Lung Cancer Detection with Robust XAI Methods

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Abstract. Explainable Artificial Intelligence or XAI aims to improve the interpretability and transparency of AI systems and in particular deep learning models which can be explained in terms of their reasoning. The proposed study is aimed at exploring the ways XAI can be used to identify lung cancer and establish the trust of doctors due to increased transparency. It discusses various XAI techniques deployed in medical imaging and compares them with the traditional black-box AI models. The paper focuses on the issues with the existing XAI methods and highlights the necessity to enhance deep learning models with the interpretability tools. In addition, the paper highlights the importance of designing dynamic, user-friendly interfaces and standardizing frameworks which could be used to evaluate the quality and usability of AI explanations in clinical practice. In general, XAI progress is highly promising in developing explainable lung cancer diagnostic systems that can improve early detection.

Keywords: Lung cancer, Artificial intelligence, Machine learning, Explainable AI, Medical imaging

1 Introduction

Lung cancer remains one of the most lethal types of cancer and it kills a considerable number of cancer patients annually [1]. Lung cancer is a type of cancer that occurs in the lung tissues, mostly in those that cover the airways [2]. It occurs when uncontrolled abnormal proliferation of cells in the lung tissue develops usually in the form of tumors that have the potential to disturb ordinary functioning of the lungs [3]. It most often occurs as a result of a prolonged exposure to dangerous substances, especially tobacco smoke, which is the main risk factor [4]. These cancerous cells develop tumours that have the potential to travel close tissues and to other body parts, and hence, early diagnosis and treatment is essential [5]. Medical imaging advances Lung cancer detection Lung cancer can be spotted with medical imaging, which is using artificial intelligence to analyse CT scans and other medical imaging data to enhance accuracy, speed, and consistency to allow patients to be given an opportunity to intervene earlier and achieve better outcomes [6].

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Machine learning has evolved as an innovative strategy in medical diagnostic within the last several years. Diagnosis of lung cancer has become easy with the use of machine learning [7]. It has transformed the method of cancer diagnosis as it was being done previously. Traditional methods often rely on the visual inspection of the imaging data such as CT scans but machine learning algorithms can analyze a vast amount of data such as images, clinical data, and genetic data to identify hidden patterns that are sometimes not easily noticed by humans [8].

Expanding on the strength of machine learning, Explainable AI (XAI) has become an essential innovation, helping to overcome one of the largest issues of AI in the operationalization of the manner in which such systems arrive at their decisions [9]. Clinicians need transparency to trust AI-driven information in healthcare, as trust and accountability are crucial in this field [10]. XAI techniques also allow such complicated models to be more understandable by pointing out what features or image segments affected a prediction [11]. The given black box opening assists clinicians in verifying the outcomes and making correct decisions, balancing technology and human skill [12]. In the instance of lung cancer, it can mean the better way of how the characterization of the tumors is known and the more personalized treatments.

The most recent breakthrough in the field of lung cancer diagnosis is the machine learning and Explainable AI (XAI) [13]. They are able to enhance detection speed, more accurate diagnosis, and better patient outcomes and maintain doctors in charge of critical decisions [14]. With the aid of deep learning of CT and pathology data, AI can discover lung cancer faster and more accurately, and with XAI, it also outlines its results in a manner that might guide doctors to make more effective treatment decisions [15].

Clarity and trust mean everything in the sphere of healthcare. Physicians adopt AI to assist in diagnosis of conditions, prescribing of medicine, and patient monitoring [16]. However, most advanced AI models, in particular, the ones with deep learning, act as black boxes and it is difficult to explain how they arrive at their decisions [17]This may render doctors uncertain in their dependence on them. Explainable AI (XAI) can assist in resolving this issue by providing how the AI has arrived at the conclusions [18]. It indicates what information or characteristics influenced the outcome, and doctors know, check and believe the information suggested by the AI.

It is imperative to instill strong Explainable AI (XAI) in the case of AI systems in the detection of lung cancer so that they can be wholly relied upon and implemented in the actual clinical practice [12]. Models should not merely be able to provide an explanation and the explanation should be reliable, understandable and clinically significant and also should be translated across various hospitals, scanners and patient groups. This is important in the imaging of lung cancer whereby subtle variations in CT scan may alter diagnostic outcomes.

The methods of post-hoc visual explanation can be incredibly important to assist physicians in getting acquainted with how AI models rational decisions [19]. These techniques indicate precisely what regions of a CT scan informed the prediction that the model made, and the entire process will become more open. Grad-CAM, Grad-CAM++, and Score-CAM are tools that generate heatmaps indicating where the decision-maker is focused, whereas LRP can be used to step through the decision-making process step-by-step. This is to assist radiologists to verify that the AI is indeed targeting the suspicious parts of the body rather than other irrelevant parts

such as ribs or airways which are critical in establishing trust. SHAP and LIME are feature-attribution techniques that provide an extra degree of visibility [20]. They demonstrate the contribution of each of the features to prediction, and this is particularly valuable when the model uses a mixture of images with clinical data of CT. The outcome is a more holistic image which translates to more assertive clinical decisions.
Increasingly, there is also interest in explainable AI models such as attention-based networks and prototype-based systems since they are more naturally aligned with the nature of how clinicians perceive medical images.

The healthcare need behind this piece of work is a very tangible one: There is a gap between highly accurate AI models and explanations that clinicians may rely on. Stronger, more transparent XAI tools in lung cancer detection have the potential to support better diagnoses, improve patient outcomes, and make AI systems safer to use in everyday clinical practice. By designing human-centered and clinically meaningful explanation methods, this research hopes to help move AI from promising research prototypes to practical tools that can truly support medical professionals and ultimately help save lives.

This paper gives a brief look at recent progress in Explainable AI (XAI) for lung cancer detection, focusing on the need for transparency as well as accuracy. After the introduction, it discusses how XAI helps in detecting lung cancer, reviews different XAI methods used in medical imaging, compares them with traditional black-box models, highlights current challenges, looks at future research directions, and ends with key takeaways.

2 Explainable AI in Lung Cancer Detection

The term "explainable AI" (XAI) describes methods that make AI models particularly deep learning systems—transparent and intelligible by disclosing the reasons behind their judgements [21] . This increases adoption, accountability, and trust by providing clear and intelligible explanations of forecasts. It helps clinicians understand exactly what the model focusses on by providing clear visualisations, such heatmaps, that emphasise important areas in medical pictures. Additionally, XAI ranks feature relevance, indicating which imaging features or patient data had the biggest impact on the [22] AI's prognosis.

Clinicians may validate and confidently act upon these insights thanks to this insight, which helps them comprehend the reasoning behind AI suggestions. By incorporating interpretability into clinical procedures, XAI promotes cooperation between AI and human knowledge, enhancing patient outcomes and diagnostic precision while guaranteeing responsibility.

Figure 1 shows the difference between black-box AI and explainable AI (XAI) in medical imaging. In the black-box model, the system predicts outcomes such as “COVID-19 infected” without revealing how the decision was actually made, leading to user confusion and lack of trust. On the other hand, explainable AI provides visual and interpretable reasoning, highlighting the image regions that influenced the forecast. This transparency allows health professionals to understand the decision process of the model, verify its correctness, and build greater trust in AI-assisted diagnosis.

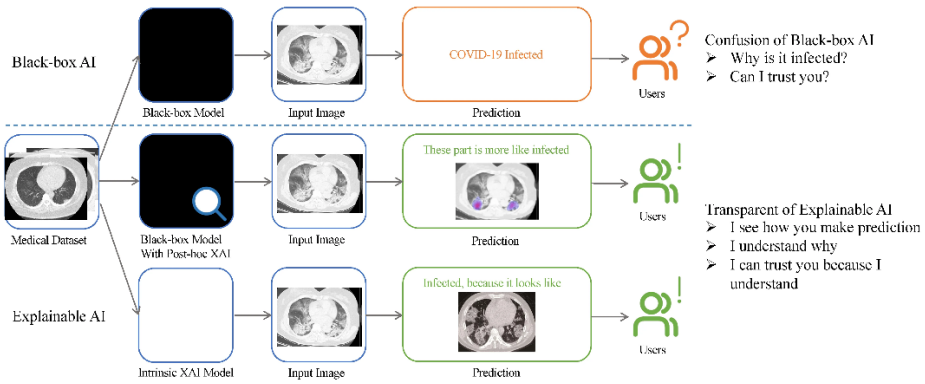


Fig. 1. Comparison of Traditional AI and XAI [23]

2.1 XAI Methods in Medical Imaging

The transparency and interpretability of AI-driven medical image analysis are improved by Explainable Artificial Intelligence (XAI) techniques. These approaches make physicians more trusting, reliable, and more willing to accept AI systems in lung cancer diagnosis as it helps them understand how algorithms make their decisions [24] . The two major types of XAI approaches in medical imaging are visual explanation and feature-based [25] approaches. Visual explanation methods are used to highlight the areas of medical images that have the greatest influence on the prediction of a model. As one example, Local Interpretable Model-Agnostic Explanations (LIME) determine the effect of modifying individual regions of pictures on predictions, or Gradient-weighted Class Activation Mapping (Grad-CAM) uses heatmaps to visualize regions of significance in cancer-diagnostic predictions [26] .

Similarly, SHapley Additive explanations (SHAP) allow local and global explanations based on the quantification of the contribution of each feature [20].

The primary aim of feature-based XAI methods is to find the meaning of quantifiable image features including tumour size, texture, and form which are often employed with traditional image classification models including Decision Trees or Random Forests. These methods enabled medical experts to validate predictions and make clear, informed judgments in diagnostic imaging by improving the connection between advanced AI systems and clinical reasoning.

2.2 Comparative analysis of XAI methods in medical imaging

Explainable AI (XAI) techniques are essential for improving the transparency and reliability of deep learning models in lung cancer detection. Grad-CAM is one of the most popular techniques, it helps radiologists readily see tumour spots in CT scans by producing heatmaps that highlight picture areas impacting a model's prediction [27] .However, Grad-CAM occasionally lacks global context and mostly provides local explanations. By measuring the significance of each pixel or region to the classification, SHAP and LIME offer feature-level explanations. These techniques improve comprehension, although they can be computationally

intensive. Expert-driven models such as ClinicXAI, which link explanations with clinical ideas for more meaningful interpretation and show resilience against adversarial attacks, are also being investigated in recent work.

By placing forecasts in context, prototype-based explanations that highlight comparable known cases increase physician trust. A more thorough understanding of AI decisions can be obtained by combining several XAI techniques, such as feature attribution techniques, local explanations, and case-based reasoning, even though heatmap visualisations are still frequently utilised. Balancing interpretability, computational efficiency, and clinical significance continues to be a challenge.

With the help of subject matter specialists, XAI techniques specifically designed for lung cancer imaging have started to provide explanations that closely resemble radiologists' evaluations, which has increased adoption. Overall, by making AI decision-making more understandable, facilitating safer clinical adoption, and directing individualised treatment planning, explainable AI has great promise for enhancing early lung cancer diagnosis.

The popular Explainable AI (XAI) techniques used in medical imaging are compared in the Table 1. Each technique is listed together with the imaging modality it supports and whether it is more general or bound to certain models. It emphasises the advantages and disadvantages of each method, as well as the kinds of visual explanations they provide and their practicality in clinical settings. Readers are better able to comprehend the trade-offs between various XAI strategies and their usefulness in assisting medical decisions thanks to this side-by-side view.

Table 1. Analysis of XAI methods in medical imaging

Method	**Modality**	**Model Specificity**	**Strengths**	**Limitations**	**Visualization**	**Clinical Usefulness**
Grad-CAM [28]	Imaging	Model-specific (CNNs)	Intuitive heatmaps; highlights regions	Limited to CNNs; coarse localization	High	High (image-focused)
SHAP [29]	Imaging/Tabular	Model-agnostic	Feature-level contributions; consistency	Computationally intensive; less visual for images	Medium	High (multimodal features)
LIME [30]	Imaging/Tabular	Model-agnostic	Local explanation	Sampling instability; less	Medium	Moderate to High

			s; fast prototyping	suited for complex images		
Eigen CAM [31]	Imaging	Model-specific (CNNs)	Data-driven saliency; captures variance	Can be less interpretable; sensitivity to outliers	Medium	Moderate
Example-based [32]	Imaging/Tabular	Model-agnostic	Shows similar examples; relatable	Needs large labeled dataset; rare case limitation	Variable	Moderate to High (case context)

2.3 Comparison of XAI models with traditional black-box models

Explainable AI (XAI) assists in the management of detecting lung cancer as AI predictions are easier to interpret compared to the traditional models that are black-box in nature. XAI relies on such tools as Grad-CAM that displays heatmaps and SHAP that highlights significant features that influenced the outcome. This will enable the physicians to have a glimpse of how the AI came to its findings and will find it easy to trust and apply it in practice. Black-box models can be true but it is difficult to predict their decisions hence making them less reliable by doctors.

1. **Interpretability:**
    - XAI models provide transparent explanations through visual heatmaps (e.g., Grad-CAM) or feature attributions (e.g., SHAP), helping clinicians understand why a prediction was made.
    - Traditional black-box models offer high accuracy but little or no insight into their decision-making, making them “opaque” and harder to trust.
2. **Trust and Adoption in Clinical Practice:**
    - XAI builds trust through comprehending and clinically significant AI decisions that enhance physician confidence and AI tool acceptance.
    - Black-box models have the disadvantage of being uninterpretable, in which case their use in clinical applications is inhibited despite excellent prediction accuracy.
3. **Accuracy and Robustness:**

- The accuracy of both XAI-improved and black-box models to detect lung cancer is high (usually above 95). Other papers indicate that XAI models are also more robust against adversarial inputs.
- Black-box models can be marginally more accurate on a raw-basis but lack transparency.

4. **Integration with Clinical Workflows:**
    - XAI models facilitate interactive visualization and feedback relationships, and allow clinicians to refine, question, and validate AI outputs, thereby facilitating a more successful integration.
    - Black-box models do not have this type of interaction, and clinicians are often passive receivers of predictions.
5. **Privacy and Data Security:**
    - Some XAI frameworks incorporate federated learning and blockchain to maintain data privacy while enabling collaborative model training.
    - Traditional black-box models may not explicitly address these concerns.
6. **Model Complexity and Computation:**
    - XAI techniques can add computational overhead due to explanation generation and interpretability modules.
    - Black-box models are often optimized solely for accuracy and speed.
7. **Ethical and Regulatory Compliance:**
    - Explainability enhances ethical AI deployment by revealing biases and ensuring accountability, supporting regulatory approval for clinical use.
    - Black-box models face challenges meeting these transparency demands.

3 Challenges and Gaps in Current XAI Approaches

The most recent study considered on Explainable AI (XAI) in lung cancer diagnosis showed that there are many challenges and gaps that should be addressed. Avoidance of excessive computational load [21] of complex deep learning models is one of the limiting factors because it prevents the use of these models in resource-limited clinical environments [33]. Also, data privacy concerns and the inability to share massive medical data among organizations make it hard to create strong and generalized models [34]. A related problem is the question of AI algorithm interpretability, in most models, they are black boxes and it is difficult to have medical practitioners rely on their outputs and not have explanations that are transparent and reliable. Additionally, most of the available XAI systems cannot be clinically relevant and consistent, and their explanations do not even correlate with the insights and understanding of medical professionals.

The quality of explanation is also not well standardized with few clinical tests of these techniques which casts doubt on its practical usefulness. Moreover, differences in imaging modalities, data quality, and population diversity are also other difficulties to developing generalizable XAI solutions.

3.1 Clinical challenges in using Explainable AI (XAI) for lung cancer detection

Clinical challenges in using Explainable AI (XAI) for lung cancer detection shows that while the technology is promising, it is still far from ready for routine clinical practice. One major issue is inter-radiologist variability. Radiologists often disagree when labeling medical images, because interpretation can be subjective. If experts themselves differ, it becomes difficult for AI models to learn a single reliable "ground truth," and even harder to trust the explanations XAI provides.

Another challenge is domain shift. Images vary across hospitals, scanning machines, and protocols. An AI model that works well in one setting may fail or give misleading explanations in another. The methods of the XAI should be made stronger in case they are to be employed extensively and in a safe manner.

Subtle imaging artifacts can also be mistaken by XAI tools, which highlights irrelevant areas in other cases. Clinicians may suppose that the explanation has some meaning, thereby making erroneous judgments in case they take it without checking.

To make it even more, most XAI tools have not been used on real clinicians in real workflows. We are yet to learn how these explanations have been perceived and how useful they are to doctors in practice, without usability studies.

All these indicate that modern XAI systems in the detection of lung cancer are not as stable as they should be used in clinical practice. These tools need more validation, enhanced human-focused design, an improved internal cross-hospital generalization, and increased regulatory compliance to warrant the confidence and usage of numerous people.

4 Prospects for Future Research

According to recent studies, explainable AI (XAI) in the diagnosis of lung cancer has several interesting future directions. First, it is a certain opportunity to establish more credible and clinically important XAI procedures that provide explanations in accordance with the knowledge of medical professionals, increasing acceptance and confidence. Good explainability tools such as SHAP and LIME can be enhanced by using advanced deep learning models such as EfficientNet and Vision Transformers to increase accuracy and interpretability. Further expansion of the datasets with a wide range of multi-modal data, including imaging, genomics, and patient clinical data, will support the creation of more generally applicable models. The use of federated learning and other privacy-sensitive measures is also gaining importance, enabling the establishment of collaboration between institutions without compromising confidential patient data.

Another important field of research is the development of smooth clinical workflow with interactive, user-friendly XAI technologies that can assist radiologists and oncologists with making their decisions.

To guarantee reliability and safety of XAI systems to be used in real-life clinics, there should be clear evaluation criteria and strong clinical validation criteria. The ethical considerations necessary to ensure responsible implementation of AI in health care will include minimizing bias, ensuring justice, and achieving transparency. Generally, future research must shift towards opaque black-box models and explainable, accurate, and customised AI systems capable of assisting in the early lung cancer diagnosis and eventually improving patient outcomes.

5 Discussion

This study highlights some key challenges in the current XAI methods and suggests that future work is needed to explore solutions and improvements. Some of the key challenges are excessive computational load, data privacy concerns, clinical relevance and standardisation in the quality of explanation. This study also points out some key issues faced specifically in the clinical settings. These issues include inter-radiologist variability, domain shift and subtle imaging artifacts mistaken by XAI tools etc. This paper suggests that more credible and clinically important XAI methods to be established and good explainability tools such as SHAP and LIME with deep learning models to be used to improve accuracy and interpretability. Diverse datasets with a wide range of multi-modal data are suggested to be used. To guarantee reliability and safety of XAI systems to be used in real-life clinics, there should be clear evaluation criteria and strong clinical validation criteria.

6 Conclusion

The paper emphasizes the significance of Explainable AI (XAI) in lung cancer detection, and narrows down to transparency and clear rationale as important elements of earning the trust of clinicians. Despite the fact that AI can assist in diagnosing lung cancer more effectively and quicker, the current explainable AI (XAI) systems still have a number of real-life issues. They tend to be very power hungry, may pose privacy challenges, and their explanations may be ambiguous or even unintelligible to doctors. In the future, attention should be paid to the development of XAI tools that are efficient, clinician-friendly, and developed on the basis of sophisticated deep learning models and interpretability applications such as SHAP and LIME. The model can be more reliable with the help of more diverse data and approaches that are privacy-friendly such as federated learning. Moreover, by creating easy-to-use and interactive tools to be introduced into the clinical processes and developing universal assessment indicators, the wider and safer use of AI will be also facilitated. Ethical concerns on prejudice and equality should also be mentioned. In the long term, a better XAI can make us a step closer to the personalized and comprehensible diagnostics of lung cancer, which is created by close cooperation between scientists, physicians, and regulators.

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