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Explainable AI in Medical Imaging: A Review of Black-Box Deep Learning Models

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Abstract: ***The increasing volume of medical image data has generated a significant requirement for automated and interpretable medical image diagnosis tools. In this research, a medical image detection system based on deep learning has been proposed for the detection of brain tumors, lung diseases, and cardiac diseases. Various types of medical images, including Brain Tumor MRI images, Cardiac MRI images (CAD), and COVID-19 Radiography images, are integrated to form a unified framework. Before training the model, image preprocessing and harmonization techniques are applied to the dataset. Advanced deep learning architectures, especially Convolutional Neural Networks (CNNs), have been employed to accurately classify medical images. In order to increase the transparency of the proposed model, Explainable Artificial Intelligence (XAI) techniques, including Grad-CAM, LIME, and SHAP, have been integrated. Both visual and interpretable explanations are provided by the proposed model. Furthermore, a user-friendly interface has been created using Streamlit to allow clinicians to upload medical images and visualize the results. The performance of the proposed system has been evaluated using clinical performance metrics, and the results show that the proposed system can be considered an effective and reliable solution.***

Keywords: Brain MRI, X-ray Radiography, Cardiac MRI, Medical Imaging, Deep Learning, Explainable AI, Clinical Decision Support

1. Introduction

Artificial Intelligence (AI) is one of the prominent forces in the field of medicine, especially in image analysis in medicine. There is a tremendous increase in medical image data from various modalities, such as X-rays, Computed Tomography (CT) scans, and Magnetic Resonance Imaging (MRI), and this has created a huge need for efficient image processing using automated systems. Deep learning, especially Convolutional Neural Networks (CNNs), and advanced architectures such as ResNet, DenseNet, and Vision Transformers have shown better performance in disease detection and abnormality identification in medical images.

Unlike other traditional machine learning models, deep learning models are able to learn complex feature representations from images.

However, despite their high predictive accuracy, such models tend to work as a "black box," offering little insight into the process. In healthcare, such a lack of transparency creates a major problem. In healthcare settings, not only are predictions required to be accurate, but accountability, interpretability, and transparency in diagnostic results are also necessary. For example, if a model predicts pneumonia from a chest X-ray image or a brain tumor from an MRI image scan but does not provide any explanation, healthcare professionals are likely to be concerned. This lack of transparency may lead to a lack of trust in such AI-based systems. There are more chances of such AI-based systems being rejected unless a clear explanation of results is provided. Thus, a need arises to make such AI-based systems explainable.

Explainable Artificial Intelligence (XAI) helps to overcome these problems because it offers insights into the internal workings of AI models. XAI techniques allow for the visualization of significant regions in medical images, measure the importance of various features, and offer human-understandable explanations for the predictions made by the model. Gradient-weighted Class Activation Mapping (Grad-CAM), Local Interpretable Model-agnostic Explanations (LIME), and SHapley Additive Explanations (SHAP) are some techniques that have been extensively explored to explain deep learning models in the medical domain. These techniques convert black-box models to more transparent models by relating the predictions to meaningful evidence. For example, Grad-CAM can be used to highlight regions in the lungs where pneumonia is present, and SHAP can be used to measure the importance of patterns surrounding tumors.

Despite The significance of XAI in medical images goes beyond the technical aspect. For instance, transparent systems are crucial for accountability, as they enable clinicians to verify and trace the reasoning behind the predictions, as well as identify biases and align them with medical knowledge. Additionally, XAI is crucial for regulatory compliance, as there is a need to ensure interpretability in AI-based clinical systems, as mandated by healthcare authorities and ethics. Furthermore, XAI is crucial for effective collaboration

between humans and AI, as radiologists can utilize the insights from the algorithm and their expertise to obtain accurate and reliable results.

2. Theoretical Framework

The proposed system is based on the fusion of artificial intelligence, medical image processing, and explainable artificial intelligence (XAI). Medical image processing offers tools for extracting useful information from raw medical images, artificial intelligence, especially deep learning, offers tools for disease prediction, and XAI offers tools for ensuring transparency in black-box models. The fusion of these areas offers a robust theoretical basis for developing reliable, transparent, and practical disease diagnosis systems [5], [12]. The framework ensures that the proposed system does not only offer high accuracy in disease prediction but also offers interpretability, transparency, and practicality in disease diagnosis.

- **Medical Image Acquisition and Preprocessing:** For the AI-based diagnostic system to be effective, accurate acquisition and preprocessing of medical images are critical. Acquisition of medical images mainly involves datasets such as Brain MRI, Chest X-ray, and Cardiac MRI datasets [12] and [13]. The images may be prone to noises, resolutions, and inconsistencies. Normalization, resizing, reduction of noises, and data augmentation are some of the processes carried out to improve the quality and consistency of the medical images. This process is critical in enhancing the performance and accuracy of the system by improving the classification process.
- **Feature Learning through Deep Learning Models:** The system uses advanced deep learning architectures, which include CNN, ResNet, DenseNet, and Vision Transformers, for the automatic learning of hierarchical features from medical images [10], [15]. These models are capable of learning features from medical images, which can be either high-level features, such as shapes, patterns, and abnormalities related to diseases, or low-level features, which can include edges and textures. Models such as ResNet and DenseNet enhance the performance of the networks by allowing for deeper networks, which are achieved through skip connections in the networks, thereby improving the performance of the networks. Despite the high performance of deep learning models in medical image analysis, these models are considered black boxes, which makes it difficult to interpret the decision-making process [5].
- **Black-Box Model Behavior and Limitations:** The deep learning models that are used in medical imaging are not transparent; that is, there is no way to reason about the predictions made by these models. This is a problem in clinical settings, as validation and accountability are critical factors [5], [6]. There is a chance that there might be hesitation in using AI systems in healthcare due to the inability to reason about a specific decision made by the model. Therefore, the black-box problem is a major challenge in AI-based diagnosis systems.
- **Explainable AI (XAI) Techniques:** To address the limitations of black box models, the system utilizes techniques from Explainable AI, which include Grad-CAM, LIME, and SHAP, providing insights regarding the decision-making process of the model [1], [2], [3]. Grad-CAM provides heat maps for each class, which highlight the regions of the image that are most influential for the model's prediction. LIME provides explanations for individual predictions by approximating the model locally, providing interpretable representations, whereas SHAP provides importance values for the features based on cooperative game theory, providing a local and global explanation for the model.
- **Interpretability and Decision Support Framework:** The addition of XAI converts the system into a clinical decision support system (CDSS), whereby prediction is accompanied by explanations that can aid in understanding the decision-making process [12]. This helps healthcare professionals verify whether the attention of the model is on features of interest from a clinical perspective. The system, therefore, helps in making more informed decisions through the collaboration of AI-generated information and human expertise, ensuring more accurate decision-making and efficiency in healthcare delivery.
- **Multi-Domain Medical Diagnosis:** The The proposed framework is intended for multiple medical domains, i.e., brain tumor detection, lung diseases, and cardiac conditions, etc. [13], [14]. This feature of handling multiple domains will increase the flexibility of the proposed framework, which is beneficial for a variety of medical applications. This is because the proposed framework is intended for multiple medical domains, which reduces the complexity of the system and eliminates the need for developing separate models for different medical applications.
- **Ethical and Transparency Considerations:** However, the use of AI in healthcare also brings forth ethical concerns, which are transparency, accountability, fairness, and safety, as highlighted in [5, 6]. In addition, the use of black-box models without interpretability can result in mistrust, especially in situations where predictions are made incorrectly or are biased. Explainable AI can help solve these problems, as the results can be made transparent and explainable, thus ensuring that auditing and validation can be conducted by medical professionals, thereby ensuring compliance with standards and the ethical, safe, and responsible use of AI in healthcare.

3. Survey of Existing Work

1) Classical Machine Learning and Early Approaches

- Traditionally, research works on medical image analysis have utilized classical machine learning approaches along with feature engineering. Classical machine learning approaches such as SVM, Random Forest, and k-NN are often utilized to perform medical image classification tasks using features such as texture, intensity, and shape [11], [14], [22].
- These approaches were effective and required expertise to perform feature engineering. These approaches were not able to generalize well on large-scale and complex medical images. These approaches were not able to capture complex spatial relationships within medical

images. These approaches were also shown to perform poorly compared to deep learning approaches, as shown by earlier surveys [21], [22].

2) *Deep Learning-Based Medical Image Classification*

With the fast development of deep learning methods, Convolutional Neural Networks (CNNs) have become the best option for medical image classification tasks. Models such as ResNet, DenseNet, and Vision Transformers have shown high performance in detecting various diseases such as tumors, pneumonia, and COVID-19 using medical images [10], [15], [16], [18].

These models learn feature representations hierarchically, both at the low level (edges, textures) and high level (disease patterns), making feature extraction unnecessary. Advanced models have also shown better performance using complex architectures that employ residual connections, dense connections, and attention mechanisms. Even though these models show high accuracy and robustness in medical image classification tasks, they are still black box models that have led to a lack of trust in their clinical applications [5], [21].

3) *Explainable AI Techniques in Medical Imaging*

To overcome the limitations of black-box models, various Explainable AI (XAI) methods have been proposed for better interpretability in medical imaging tasks. Grad-CAM, LIME, and SHAP are some of the most popular methods for explaining the predictions made by deep learning models [1], [2], [3], [24]. Grad-CAM provides class-specific heatmaps that help in identifying the important areas in medical images. This allows doctors to visually verify whether the model is focusing on the important areas of the image or not. Similarly, LIME provides local explanations for the predictions made by the model using the local linear approximation of the model around a particular prediction. SHAP provides both local and global feature importance using a game-theoretic approach [7], [24], [25].

4) *Hybrid and Comparative XAI Approaches*

- Some recent studies have also tried to explore the hybridization of different XAI techniques for better explanation results. For instance, integrating Grad-CAM with LIME or SHAP provides a comprehensive understanding of the model's behavior, as shown in [8], [11], [25].
- Some comparative studies have shown that Grad-CAM is very effective for intuitive visualization, SHAP is reliable for feature attribution, and LIME is very useful for local interpretability. However, a combination of different techniques is found to be more appropriate for handling the limitations of each technique, which is useful for medical imaging applications, as shown in [10], [25].

5) *Clinical Decision Support Systems (CDSS)*

- Some research works have also explored the idea of integrating deep learning with XAI methods for the development of clinical decision support systems (CDSS). These systems are capable of providing diagnostic predictions as well as explanations, thereby assisting healthcare professionals in verifying the results provided by the AI system and making appropriate decisions [12], [20].
- CDSS can help in improving diagnostic accuracy by leveraging the power of high computational efficiency along with clinical expertise, thereby improving the quality of patient care. These systems can also help in real-time decision-making, reducing diagnostic errors, and managing large amounts of medical information. With the integration of interpretability, CDSS can also help in improving the trust of clinicians for the practical application of AI in healthcare environments [21].

6) *Multimodal and Advanced Explainability Models*

- Some of the recent advancements in the field of explainable AI are multimodal frameworks that have been developed for using medical images along with other data sources such as textual information or the history of the patients. Such frameworks have been developed for providing better explanations using multimodal information, thereby making the AI system more interpretable and usable [13], [14].
- Moreover, transformer-based architectures with attention mechanisms have also become popular for their ability to handle long-range dependencies in data while providing better explanations for the data using the attention mechanisms. Such architectures have been considered a significant step toward developing more advanced and intelligent AI systems for healthcare [15], [18].

7) *Limitations and Research Gaps*

- Despite such developments, several issues need to be addressed. First and foremost, it has been noted that the current XAI models may not provide a stable explanation of the results when slight changes are incorporated into the input. This has led to a question of the robustness of the models [6], [24].
- In addition, a standard evaluation metric is yet to be developed to assess the quality, faithfulness, and utility of the explanations. Several models face computational efficiency and scalability issues. These issues need to be addressed to ensure the reliability and efficiency of the explainable medical AI models [21], [25].

Table I: Comparison of Deep Learning Architectures for Medical Image Diagnosis

Feature/ Model	CNNs	ResNet	DenseNet
Best Used For	Basic feature extraction (edges, texture) from medical images.	Deep feature learning for complex diseases.	Efficient feature reuse for detailed image analysis.
Strengths	Fast, simple, and efficient for local pattern detection.	Support for deep networks through skip connections, High accuracy.	Improves gradient flow and reuses features efficiently.
Limitations	Lacks global context understanding.	Higher computational complexity.	Memory-intensive due to dense connections.
Medical Application	Detection of tumors and pneumonia.	Brain tumor and multi-class detection.	Complex multi-d disease classification tasks.

8) Human-Centered Explainable AI

- Another new area of research being explored within this domain is the creation of human-centered explainable AI systems, which focus on the usability and interpretability of the explanations from a clinician's point of view. The focus here is on the creation of explanations that are not only technically correct but also meaningful and understandable by the healthcare professionals [5], [14].
- Human-centered XAI focuses on the creation of explanations and visualizations that are intuitive and simple, aligning well with the reasoning of the clinicians. This makes it more convenient and reliable to work with AI systems.

9) Robustness and Reliability of XAI Methods

- Recently, the research community has been more focused on assessing the robustness and reliability of the explanation methods for AI systems. It has been noticed that certain explanation methods, specifically the saliency-based explanation methods, may not be reliable under certain conditions where small changes are introduced to the input image [6], [24].
- This has raised a concern for the reliability and consistency of the explanation methods for AI systems, specifically for medical imaging applications. Hence, the reliability and consistency of the explanation methods for AI systems have been an active research topic, and the research community is working on more reliable explanation methods for AI systems.

4. Discussion, Challenges, and Future Directions

1) Technical and Practical Challenges

- Despite significant advancements in deep learning and explainable AI, several technical challenges are associated with developing reliable medical image diagnosis systems. One of the major challenges is data variability, as images captured using different medical devices and under different medical conditions are difficult for AI models to generalize [21, 22].
- Another significant challenge is the need for large annotated datasets for training deep learning models. The annotation of medical images is time-consuming, requiring expert-level knowledge from medical professionals like radiologists. This makes it difficult for developers to obtain reliable annotated datasets. Another significant challenge is computational complexity, as deep learning models like ResNet and DenseNet require significant computational resources for processing images [12, 21].

2) Ethical and Regulatory Challenges

- There are various ethical and legal issues related to the use of AI systems in the healthcare sector. One of the main issues is the question of accountability, as it is not clear whether the AI system or the medical practitioner is responsible for incorrect predictions by the system [5]. This is a challenge for legal and decision-making processes.
- Another ethical issue related to the use of AI systems is bias in the training data. This may cause unfair predictions for certain groups of patients. Fairness is a crucial factor for the creation of reliable AI systems. Moreover, the privacy and security of the data are major issues related to the use of AI systems. Healthcare regulations and standards should be followed for the safe use of AI systems.

3) Challenges in Explainability and Interpretability

- Although the use of techniques such as Grad-CAM, LIME, and SHAP increases the transparency of the model, several problems also arise. One of the problems is that the explanations produced by the model are not stable, as even a small variation in the input image may cause a large difference in the explanations produced by the model [6], [24]. This is a great concern for the reliability of the model.
- Another problem is that some models are not easy for clinicians to interpret, as not all the output of the model is easy to understand. Some models produce explanations that are too complex, which may cause confusion for the clinicians. In addition, different XAI models produce different explanations for the same prediction, which may not be clear which explanation is reliable [5], [25].

4) Future Directions in Explainable Medical AI

- Future research in this field is expected to focus on improving both performance and interpretability of AI systems. One promising direction is the development of **hybrid XAI frameworks** that combine multiple explanation techniques to provide more robust and comprehensive insights [8], [25].
- Another ethical issue related to the use of AI systems is bias in the training data. This may cause unfair predictions for certain groups of patients. Fairness is a crucial factor for the creation of reliable AI systems. Moreover, the privacy and security of the data are major issues related to the use of AI systems. Healthcare regulations and standards should be followed for the safe use of AI systems.

5. Conclusion

The suggested work offers a viable resolution to a significant obstacle in AI-driven medical image diagnosis—the opacity of deep learning models. Advanced architectures like CNN, ResNet, and DenseNet have shown to be very good at finding diseases in medical images, but they are not widely used in important healthcare settings because they are "black boxes." The system improves interpretability by using Explainable AI (XAI) methods like Grad-CAM, LIME, and SHAP to give both visual and quantitative explanations for model predictions. This makes clinical decision-making more trustworthy and reliable [1], [2], [3].

The developed framework successfully integrates predictive performance with interpretability, converting conventional black-box models into transparent and clinically valuable instruments. The system can handle many medical fields, such as finding brain tumours, classifying lung diseases, and

analysing heart conditions. This shows that it can be used in many different ways. Also, the addition of a user-friendly interface makes it possible for healthcare professionals to upload medical images, see predictions with confidence scores, and look at explanation outputs. This makes the system useful for real-world clinical use. Even with these contributions, there are still some problems. The effectiveness of deep learning models is significantly influenced by the quality and diversity of training data, and variability within medical datasets can impact generalisation. Also, some XAI methods may give different explanations when the input changes slightly, which makes people worry about their reliability. Computational complexity and real-time deployment continue to pose challenges, especially in healthcare environments with limited resources.

Future research may concentrate on mitigating these constraints by creating more resilient and stable explanatory methodologies, incorporating multimodal data including clinical reports and patient histories, and refining models for real-time implementation. Adding advanced architectures and lightweight models can make the system even more efficient and easy to use.

Thus, in conclusion, the proposed system is a step forward in the development of transparent, interpretable, and reliable AI systems in the healthcare domain. By bridging the gap between high-performance DL models and the importance of interpretability, this research contributes to the development of reliable AI systems that can aid medical professionals in their tasks, thereby improving the quality of care for patients.

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