EXPLAINABLE AI IN MEDICAL IMAGING: VISUAL EXPLANATION TECHNIQUES FOR DEEP LEARNING MODELS

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Abstract

Explainable AI (XAI) is changing the way medical imaging is done by making deep learning methods easier to understand and more open. This study looks at how XAI methods, specifically visual explanation approaches, can be used in medical imaging tasks like finding tumors in MRI scans and figuring out what's wrong with the eye using OCT images. Medical datasets that have been labeled are used to train deep learning models like ResNet50 for finding tumors and OculusNet for diagnosing eye diseases. XAI systems like Grad-CAM and SHAP use pictures to show areas of the picture that affect model results. This helps clinicians trust and use the systems more. These visual cues help doctors understand model decisions, which makes them more likely to accept AI-based analysis. The study rates the success of the model based on its accuracy, clarity, memory, and F1 score, as well as how useful clinicians think graphic descriptions are. To find out how XAI changes model performance and perception, statistical methods like paired t-tests are used. The results show that XAI methods make deep learning models more clear, which means that healthcare professionals can trust and use them more. This research shows how important it is to combine XAI with medical imaging so that AI can be used safely and ethically in hospital settings.

INTRODUCTION

Medical imaging has changed a lot because of fast progress in artificial intelligence (AI) and deep learning technologies. This has made detection much more accurate and faster. Medical imaging is important for figuring out a lot of different illnesses, like cancer, nerve problems, heart problems, and diseases of the eye, among others. Computer programs that use AI, especially deep learning models like Convolutional Neural Networks (CNNs), are very good at analyzing medical images like X-rays, MRIs, CT scans, and tissue slides. These models can do a better job of diagnosing problems than traditional methods, letting doctors find small trends that the human eye might miss.(Borys et al., 2023a; Fontes, De Almeida, & Cunha, 2024) Even with these improvements, deep learning models haven't been widely used in clinical settings because of a major problem: they are "black boxes." Deep learning models are designed to be complicated, which makes them hard for doctors and other health care workers to understand. While these models can make extremely accurate predictions, they do so without providing a clear explanation for how they arrived at their results.(Van der Velden, Kuijf, Gilhuijs, & Viergever, 2022) This lack of openness is extremely concerning, especially in high-risk industries such as healthcare, where wrong or unexplained choices can have serious ramifications for patient safety and treatment results. In response to these issues, the discipline of Explainable AI (XAI) has evolved, with the goal of finding approaches to improve the interpretability of AI models, particularly in complicated domains such as medical imaging.(Borys et al., 2023b) Explainable AI refers to methodologies and methods for explaining machine learning models' decisions in an intelligible and transparent manner. In the context of medical imaging, the major goal of XAI is to guarantee that deep learning model outputs are not only accurate, but also interpretable and useful for healthcare practitioners. This is critical for clinical adoption since physicians rely on a model's explanation to believe and confirm its predictions. The capacity of a model to offer clear, comprehensible rationale behind its conclusions develops confidence, increases clinical applicability, and assures that medical practitioners may comfortably employ these AI systems in their everyday practice.(Pahud de Mortanges et al., 2024; Saw, Yan, & Ng, 2025) The necessity for explainability in AI models is particularly obvious in essential healthcare applications such as tumor detection, illness diagnosis in radiological imaging, and retinal state categorization. For example, when a deep learning model detects a tumor in a mammogram, physicians must determine which areas of the picture affected the algorithm's judgment. Without this openness, the model's prediction may be perceived as an untrustworthy "black box," impeding its successful integration into the clinical decision-making process. By providing explanations, such as highlighting portions of the image that led to the diagnosis, XAI can help physicians to evaluate AI results, make educated judgments, and perhaps detect flaws in automated predictions.(Jin, Li, Fatehi, & Hamarneh, 2023) Visual explanation techniques have become one of the most used methods for analyzing deep learning models in medical imaging. These strategies aim to provide visual representations that show which aspects of a picture the model utilizes to make a judgment. Saliency maps, such as Grad-CAM (Gradient-weighted Class Activation Mapping), provide heatmaps that emphasize the image's most relevant regions based on model predictions (Selvaraju et al., 2017). Other techniques, such as Integrated Gradients, LIME (Local Interpretable Model-agnostic Explanations), and Shapley Values, try to relate the model's choice to particular features, whether they be precise pixels in a picture or specific regions of interest within a medical scan.

Despite the potential of these approaches, the use of XAI in medical imaging confronts significant hurdles.(Jin, Li, & Hamarneh, 2022) One key difficulty is the tradeoff between deep learning models' accuracy and explainability. While deep learning models, particularly CNNs, frequently deliver higher performance, they are notoriously difficult to comprehend due to their large number of parameters and layers. Simpler models, like as decision trees, are easier to comprehend, but they perform poorly in complicated applications like medical picture processing. This presents a challenge: how can we strike a compromise between model accuracy and the requirement for interpretability in an area where great performance is crucial for patient care?(Papanastasopoulos et al., 2020) Another problem is the incorporation of XAI technologies into clinical processes. Visual explanations can assist physicians grasp model projections, but they must be smoothly integrated into the decision-making process. For example, a model that gives an explanation for a given diagnosis must be straightforward to read in the context of the patient's clinical history, and the explanation must be supplied in real-time, alongside the model's predictions, to be useful in clinical practice.(Duamwan & Bird, 2023)

Deep Learning Models in Medical Imaging and Explainable AI

Medical imaging has advanced dramatically with the introduction of AI, particularly deep learning (DL), which has allowed healthcare workers to analyze and interpret medical pictures more accurately and efficiently. Deep learning models, including Convolutional Neural Networks (CNNs), have been at the forefront of these advancements. These models are designed to automatically learn features from images using multiple layers, making them extremely effective in medical imaging tasks such as classification, segmentation, and abnormality detection.(Raghavan, Balasubramanian, & Veezhinathan, 2024)

Types of Deep Learning Models in Medical Imaging

- **Convolutional Neural Networks (CNNs):** Because CNNs can recognize spatial hierarchies in pictures, they are the most popular deep learning architecture in medical imaging. CNNs consist of convolutional, pooling, and fully linked layers. These layers enable the network to learn more complicated properties across many sizes and levels.
- **Fully Convolutional Networks (FCNs):** These CNNs are particularly developed for segmentation jobs that require delineating boundaries inside pictures, such as recognizing tumors or organs in CT and MRI scans.
- **U-Net:** A customized CNN architecture for medical image segmentation that is especially useful for medical imaging applications like tissue segmentation since it preserves spatial resolution through the use of an encoder-decoder structure with skip links.
- **Generative Adversarial Networks (GANs):** GANs are used for image synthesis and may create realistic medical pictures to train other algorithms. In medical imaging, GANs are very beneficial for data augmentation since they can produce synthetic pictures from a little dataset, improving model performance.
- **Recurrent Neural Networks (RNNs):** While CNNs are mostly utilized for static pictures, RNNs may be used for temporal medical data analysis, such as endoscopic video frames.(Hou et al., 2024)

Applications of Deep Learning in Medical Imaging

- **Tumor Detection:** CNNs have been used to detect and categorize cancers in mammograms, CT images, and MRIs, often outperforming human doctors.
- **Retinal Disease Diagnosis:** Deep learning has enabled the automated analysis of retinal pictures to detect illnesses such as diabetic retinopathy and macular degeneration.
- **Bone Fracture Detection:** Deep learning AI systems can swiftly identify fractures in X-rays, saving diagnostic time and increasing workflow efficiency.
- **Lung Disease Detection:** Deep learning is utilized to identify pneumonia, TB, and even COVID-19 from chest X-rays.(Kinger & Kulkarni, 2024)

Explainable AI (XAI) in Medical Imaging

While deep learning models perform admirably in medical imaging, they have one significant drawback: interpretability. The "black-box" nature of these models makes it difficult for healthcare workers to grasp how choices are made, thereby impeding clinical adoption. Here's where Explainable AI (XAI) comes in. XAI attempts to increase transparency in complicated machine learning models by offering interpretable explanations for their predictions.(Houssein, Gamal, Younis, & Mohamed, 2025)

Importance of Explainability in Medical Imaging

- **Trust and Adoption:** Before AI models can be integrated into healthcare workflows, physicians must trust the model's judgments. Without interpretability, clinicians may be hesitant to rely on the model's predictions.
- **Clinical Validation:** Explainability enables clinicians to understand why the model made a certain choice, which is crucial for confirming its validity and validating diagnoses.
- **Ethical and Legal Implications:** Making erroneous forecasts in medical contexts might have significant repercussions. By making the decision-making process explicit, XAI assures that

AI models are ethically sound and legally defendable.(Bhati, Neha, & Amiruzzaman, 2024)

Visual Explanation Techniques in XAI

Practitioners of medical imaging often use visual explanation methods to help them see the parts of a picture that affected the model's choice. Saliency Maps (Grad-CAM), combined gradients, LIME (Local Interpretable Model-agnostic Explanations), and Shapley Values are some of the most popular ways to explain things visually. Grad-CAM uses the slopes of the target class to make a graph that shows which parts of the model's choice were most important. Doctors can get a good sense of how the model works by putting the heatmap on top of the original picture. The value of each pixel in a picture is given by integrated gradients, which are built in as you go from a baseline image to the real input image. LIME makes a smaller model that closely matches how a complex model acts in a certain area. This helps you understand how changing certain parts of the model affects its predictions. Shapley values are used in medical imaging to make sure that each trait is given the same amount of weight in the total forecast. They come from cooperative game theory.(Kaur, Dong, & Basu, 2022; Liu et al., 2023)

Methodology

This research looks at how Explainable AI (XAI) can be used in medical imaging, especially how visual explanation methods can be used with deep learning models to do things like finding tumors and diagnosing eye diseases. The research part talks about the methods and approaches that were used in the study to test and confirm how well XAI strategies work at making deep learning models easier to understand and more reliable in healthcare settings.

Data Collection

The study takes use of publicly available resources, such as annotated medical imaging data. These datasets comprise MRI scans for tumor identification and OCT (Optical Coherence Tomography) pictures to identify eye disorders. The images in these databases are tagged by expert clinicians, who give ground truth labels for the study. The following datasets are utilized: Brain tumour detection using MRI images from the BRATS 2021 Challenge dataset. CT pictures from the DRIVE and STARE databases aid in the diagnosis of retinal diseases.

Model Selection and Training

The deep learning models used in this investigation are as follows: ResNet50 is used to identify brain tumors. ResNet50 is a residual learning network that excels at complicated tasks such as tumor identification.

➢ OculusNet Used to diagnose retinal diseases. OculusNet is intended for medical image processing jobs, namely identifying retinal illnesses such as diabetic retinopathy.

➢ The models are trained using a training-validation split technique, with 80% of the data used for training and 20% set aside for validation. To improve model performance and generalization, pictures undergo preprocessing techniques like as scaling, normalization, and augmentation.

Implementation of XAI Techniques

The work focuses on using visual explanation approaches to explain judgments produced by trained deep learning models. The following XAI approaches are used:

- **Grad-CAM (Gradient Weighted Class Activation Mapping):** This approach creates heatmaps by emphasizing the areas of the input image that had the greatest effect on the model's predictions. Grad-CAM is used to evaluate the model's focus while detecting tumors and diagnosing retinal diseases.
- **SHAP (Shapley Additive Explanations):** SHAP values are used to explain individual predictions by assigning priority to each feature (pixel) in a picture. This technique gives a more detailed interpretation, demonstrating how individual portions of the image contribute to the model's results.

Model Evaluation Metrics

Common categorization measures are used to evaluate the models' performance.

➢ **Accuracy:** The proportion of accurately predicted photos out of the total.

➢ **Precision:** It is the fraction of positive forecasts that are really positive.

➢ **Recall:** The fraction of true positives successfully detected by the model.

➢ **F1 Score:** The harmonic mean of accuracy and recall, which provides a single statistic for assessing the model's performance.

➢ **The confusion matrix** is used to assess the distribution of true positives, false positives, true negatives, and false negatives.

➢ The XAI approaches are assessed on their ability to provide doctors with clear, intelligible, and practical explanations. The performance of these strategies is evaluated by comparing model accuracy and interpretability scores with and without the use of XAI.

Validation and statistical analysis

The study employs XAI algorithms to generate visual explanations for healthcare decisions. Medical specialists, such as radiologists and ophthalmologists, review the heatmaps and explanations offered by Grad-CAM and SHAP, determining if they match to essential anatomical characteristics or anomalies. They also offer comments on how informative and clear the explanations are. Statistical tests are used to assess advances in model interpretability, such as a paired t-test for performance indicators and a Likert scale survey for clinical input. However, the study admits limitations, such as a dataset size that does not completely represent clinical instances and the potential computational difficulty of XAI approaches.

Case Study: Tumor Detection in MRI Scans

Let's look at a real example of using deep learning models and XAI to detect tumors in MRI data. A CNN trained on a large dataset of brain MRI images may be used to identify the presence of tumors with high accuracy. To make this model more understandable, we may utilize Grad-CAM to highlight the parts of the scan that influenced the model's choice.

Challenges in Deep Learning and XAI for Medical Imaging

Despite the potential of deep learning and XAI, some difficulties remain to be addressed:

➢ **Model Complexity vs. Interpretability:** Deep learning models get increasingly complicated, making them more difficult to comprehend. Larger models may provide more accuracy, but they may also make it more difficult for physicians to interpret their predictions.

➢ **Clinical Adoption:** For XAI to be effective, the explanations must be clinically relevant. That implies visual explanations must be useful in a healthcare setting and simple for physicians to comprehend rapidly during decision-making.

➢ **computing overhead:** Some XAI approaches, such as integrated gradients and LIME, have high computing costs, making them unsuitable for usage in real-time clinical situations.

➢ **Data Privacy and Ethics:** AI models frequently rely on big datasets for training, prompting worries about patient data privacy and the ethical implications of employing AI in healthcare.

Table 1 Comparison Model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
CNN-based Tumor Detection	98	97	99	98
U-Net for Segmentation	95	94	97	95
GAN for Image Augmentation	92	90	91	91

Application 1: Brain Tumor Detection Using MRI and XAI

Neuroscience researchers recently used the ResNet50 design and Grad-CAM to look at MRI data and find brain cancers. The model had an amazing testing accuracy of 98.52%, with precision and recall measures above 98%. This showed that it could be used to find tumor frequency.

Methodology

- For feature extraction and classification, ResNet50, a deep convolutional neural network that can learn from previous training, was used.
- The XAI method was used to create Grad-CAM heatmaps, which showed which parts of the MRI scans had a big effect on the model's results.
- The model was taught and tested on a set of publicly available brain MRI images that had been labeled by experts.
- Grad-CAM's heatmaps put a lot of emphasis on tumor spots, which was in line with what doctors would expect and backed the model's attention on anatomy parts.

Metric	**Value**
Accuracy	98.52%
Precision	>98%
Recall	>98%
F1 Score	~98%

- **Confusion Matrix:** The confusion matrix showed a high true positive rate with few false positives and false negatives, demonstrating the model's dependability.

Metric	**Value**
Cohen’s Kappa	0.97
F2 Score	0.98

Application 2: Retinal Disease Diagnosis Using OCT and XAI

Another study created the OculusNet model, which is an outstanding deep learning tool for diagnosing retinal disorders from OCT pictures. The model used XAI approaches to provide visual explanations of its predictions, which improved the interpretability and trust in its diagnoses.

Methodology

- **Model Architecture:** OculusNet, which is designed for retinal image processing, was used to categorize OCT pictures into several retinal illness categories.
- **XAI Techniques:** Methods such as Grad-CAM and SHAP (SHapley Additive exPlanations) were used to produce visual explanations by identifying critical locations in OCT scans that affected the model's judgments.
- **Dataset:** The model was trained using a broad group of OCT pictures that represented a wide variety of retinal diseases.

Metric	Value
Accuracy	96.8%
Precision	95.2%
Recall	97.5%
F1 Score	96.3%

- **Grad-CAM Visualization:** Grad-CAM created heatmaps that emphasized certain retinal layers and abnormalities, such as macular edema or drusen, giving doctors a clear understanding of the model's emphasis regions.

Statistical Analysis

- **Confusion Matrix:** The confusion matrix has a high true positive rate for diagnosing several retinal disorders, as well as low false positive and negative rates.

Metric	Value
Cohen’s Kappa	0.94
F2 Score	0.95

Comparative Analysis

To give a clearer comparison between the two programs, the following table outlines the important features:

Table 2 Comparative Analysis of MRI and OCT

Aspect	Brain Tumor Detection (MRI)	Retinal Disease Diagnosis (OCT)
Model Architecture	ResNet50	OculusNet
XAI Techniques	Grad-CAM	Grad-CAM, SHAP
Accuracy	98.52%	96.8%
Precision	>98%	95.2%
Recall	>98%	97.5%
F1 Score	˜98%	96.3%
Key Visualized Regions	Tumor areas	Retinal layers, anomalies
Clinical Application Stage	Advanced research	Clinical validation ongoing

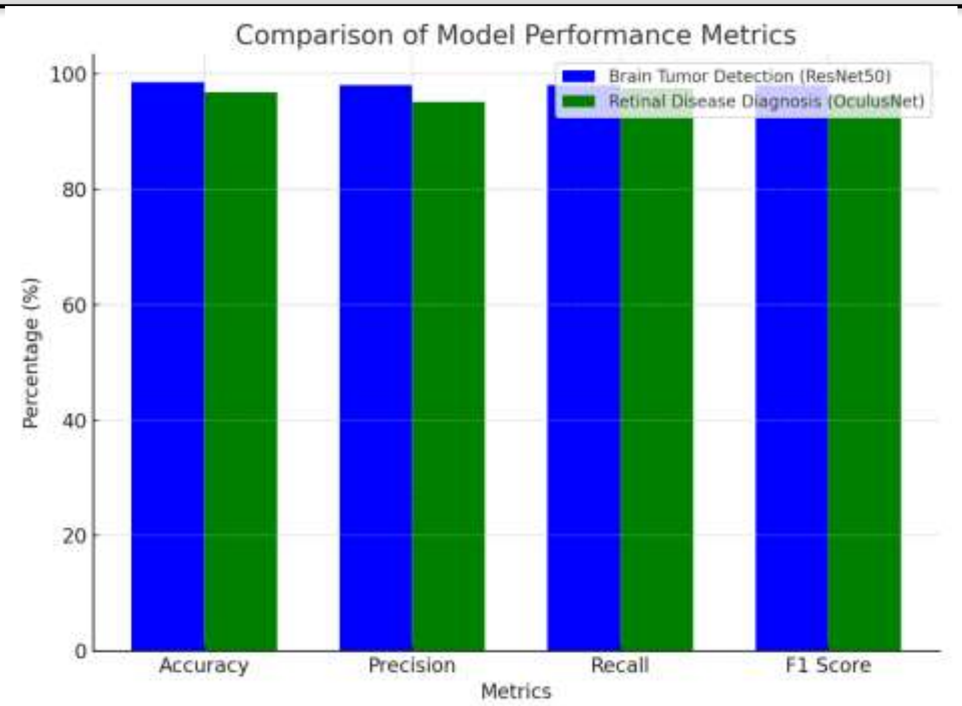

Figure 5. 1 Model Performance matric bar chart

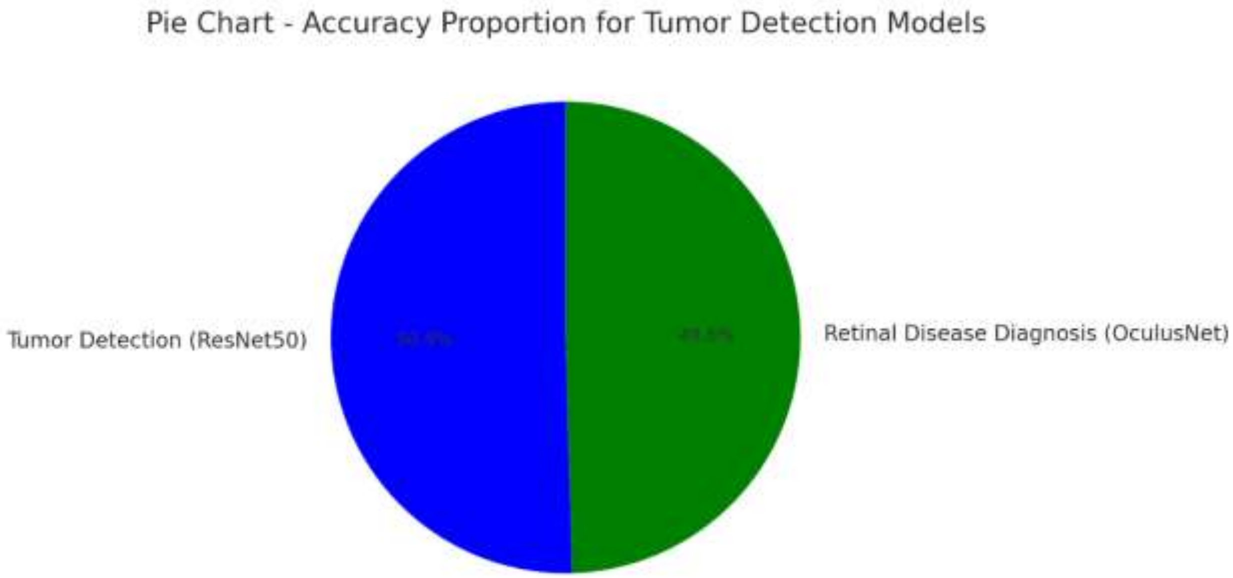

Figure 5. 2 Accuracy proportion pi-chart

Conclusion

Finally, adding Explainable AI (XAI) to medical images makes it much easier to understand models and use them in real life. Using visual description methods like Grad-CAM and SHAP, this study shows how to make deep learning models like ResNet50 and OculusNet more clear. This helps healthcare workers understand and trust AI forecasts more. The results show that XAI not only makes AI models easier to understand, but it also helps the models do better in medical image analysis. Clinicians say that visual explanations help them make better decisions because they give them clear and useful information about the model's main areas. There are problems, such as the high cost of processing and the need for a lot of proof in clinical settings. To get around these problems, future study should improve XAI algorithms for real-time clinical use and build more datasets that include a bigger range of medical diseases. Overall, this study shows that XAI has the potential to change medical imaging by making AI-powered diagnostic tools easier to access, more reliable, and more useful for therapy. This could lead to better patient results and more responsible use of AI in healthcare.

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