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Interpretable AI in Medical Imaging: Enhancing Diagnostic Accuracy through Human-Computer Interaction

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Abstract

This study delves into the realm of Machine Learning (ML) transparency, with the goal of demystifying intricate model operations in terms of interpretability and explainability. Taking a human-centered design approach, transparency is viewed as a relational aspect between algorithms and users rather than an inherent trait of the ML model. The process involves the pivotal elements of prototyping and user evaluations to arrive at effective transparency solutions. In specialized fields such as medical image analysis, applying human-centered design principles encounters challenges due to limited user access and a knowledge gap between users and ML designers. A systematic review spanning from 2017 to 2023 scrutinized 2307 records, ultimately identifying 78 articles that met the inclusion criteria. The findings underscore the prevailing emphasis on computational feasibility in current transparent ML techniques, often at the expense of considering end users, including clinical stakeholders. Notably, a deficiency exists in formative user research guiding the design and development of transparent ML models. In response to these gaps, we put forth the INTRPRT guideline—a design directive for transparent ML in medical image analysis. Anchored in human-centered design, this guideline underscores the importance of formative user research to comprehend user needs and domain requirements. The ultimate aim is to enhance the likelihood that ML algorithms offer transparency, enabling stakeholders to harness its benefits effectively.

Keywords

Explainable AI, Human Cantered Design, Bio-Medical Imaging, Diagnostic Accuracy

1. Introduction

In the domain of healthcare, considerable research efforts have been dedicated to advancing Machine Learning (ML) and Deep Learning (DL) models to support clinical practitioners. However, the translation of these theoretical advancements into practical applications in routine patient care faces substantial challenges. This transition is intricate, given the profound implications associated with decisions impacting human lives. When clinical stakeholders incorporate AI and ML tools into decision-making processes, there is a notable risk of being swayed by machine recommendations that may be inaccurate or inadvertently biased, potentially leading to adverse consequences.

The necessity for reliable ML systems in healthcare has prompted initiatives to delineate specific requirements that ML algorithms must meet. While recent endeavors often focus on achieving task-specific performance, they tend to overlook a critical aspect— in assisted decision-making, it is not solely the ML system's performance that matters, but rather the collaborative performance of the humanoid-AI team, which holds utmost relevance for patient outcomes [1].

The discourse on effective human-machine teaming performance revolves around divergent viewpoints. Some advocate for rigorous algorithmic validation, akin to the evaluation processes for drugs or medical devices, as sufficient for ensuring safe and reliable operation in human-machine collaboration [2]. Conversely, others argue that transparency in AI models, achieved through revealing working mechanisms and providing user-friendly interfaces, is imperative to instill user trust and achieve the desired human-machine teaming performance [3].

Recent studies underscore the growing importance of transparency in ML techniques, emphasizing that neglecting the opacity of these methods could impede their adoption in healthcare, thereby limiting their potential positive impacts. The inability to make the decision-making process transparent may result in the misuse or disuse of ML models in clinical settings, hindering their utility if they do not disclose reasoning processes, limitations, and potential biases [4].

This apparent dichotomy between rigorous validation and transparency is artificial. Rigorous validation and transparency are not mutually exclusive; both approaches aim to augment ML models with additional information to justify recommendations. However, as revealed through a systematic review, current approaches often rely on developers' intuition rather than considering the impact of these mechanisms on users' experiences and their ability to act upon ML model outputs.

Designing ML algorithms with transparency goes beyond computational aspects, introducing complexity related to human factors, particularly the users interacting with the ML algorithm. Transparency is not an inherent property of the algorithm but a dynamic relationship between the transparent ML algorithm and the user processing the information. This relationship is conceptualized as an affordance, a familiar concept in Human-Computer Interactions (HCIs).

- Several implications arise from this conceptualization:
- The development of X-AI algorithms extends beyond computational considerations.
- Design decisions regarding the mechanisms employed to generate explanations or interpretations may be effective for one user group but not necessarily applicable to another.
- Initiating the creation of AI-based systems and models without laying the groundwork to confirm their actual transparency may lead to misallocated resources and efforts.

1.1 Objective of the Study

The broad objective from our research include:

- To review several related works through literature surveys, identifying shortcomings and gaps in research on Explainable AI, Transparent machine learning and Deep Learning techniques.
- To assess the landscape of machine learning and Deep learning techniques used in medical image analysis.
- To investigate potential risks linked to recognized shortcomings, including the potential lack of clarity in ML and DL research for end users and its relevance in clinical applications.

1.2 Motivation for this work

This research is motivated by the critical convergence of machine learning applications within the field of medical imaging and the essential need for transparency and user-cantered design. The intricacy of machine learning models utilized in medical image analysis necessitates a comprehensive exploration to guarantee interpretability and explainability. The lack of focus on end-user perspectives, especially those of clinical stakeholders, in current transparent ML techniques raises concerns about the practical significance of these models. The identified gaps and shortcomings highlight the urgency for an in-depth investigation into the landscape of transparent ML in medical imaging. By comprehending these limitations, our aim is to contribute to the development of more efficient and user-friendly transparent ML models. This research is propelled by a dedication to improving diagnostic accuracy and facilitating the seamless integration of transparent ML systems in medical image analysis, ultimately benefiting both practitioners and patients.

1.3 Imagery processing in Humanized-AI

Humanized AI in medical imagery processing aims to provide more than just automated analysis; it strives to create intelligent tools that augment the capabilities of healthcare professionals, leading to improved diagnostic accuracy. Medical imagery processing in humanized AI refers to the application of artificial intelligence (AI) techniques and tools in the analysis and interpretation of medical images, with a focus on incorporating a human-like understanding and context. This approach aims to create intelligent systems that not only possess advanced image processing capabilities but also emulate human cognition and decision-making processes.

In the context of medical imaging, humanized AI seeks to enhance the collaboration between AI algorithms and healthcare professionals by leveraging machine learning, deep learning, and other AI technologies. This integration enables the development of systems that can not only accurately analyse complex medical images such as X-rays, MRIs, and CT scans but also understand the clinical context, taking into consideration the broader patient information and medical history. Visual information is conveyed through the processing of images, while verbal discursive processing is responsible for delivering textual descriptions [5].

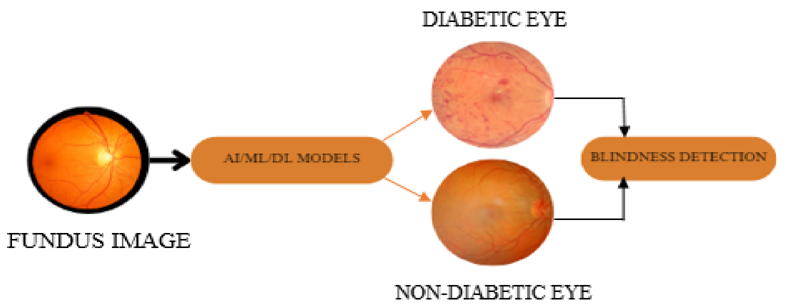

Figure 1. Clinical View of Diabetic Retinopathy

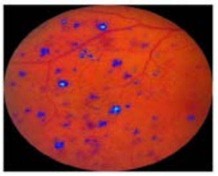

Figure 1.1. AI Interpretable Imaging of DR

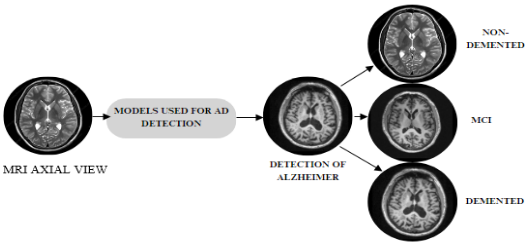

Figure 2. Clinical View of Alzheimer

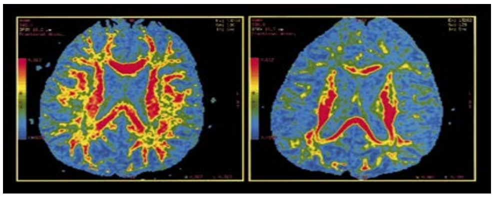

Figure 2.1 AI Interpretable Image of Alzheimer

2. Literature Survey

In surveying the existing body of literature on "Interpretable AI in Medical Imaging: Enhancing Diagnostic Accuracy through Human-Computer Interaction" it becomes evident that diverse perspectives and approaches have shaped the understanding of key issues, prompting a critical examination of the multifaceted nature of this field. In [6], the research assesses the efficacy of Mixed Reality (MR) within the realm of medical education, specifically exploring the pedagogical value of virtual reality methodologies. A survey was conducted among 258 staff members from a medical college, seeking insights into potential applications of MR in the medical curriculum. Respondents completed a comprehensive questionnaire comprising eight questions. The findings indicated a prevailing sentiment among participants favoring the advantages of MR-enhanced education over traditional instructional methods. Notably, the three-dimensional visualization capabilities of MR, particularly in anatomy classes, emerged as highly esteemed. A key takeaway from this study underscores the transformative impact of MR in extending the capabilities and effectiveness of remote learning—an imperative underscored by the normalcy of such modes during the COVID-19 pandemic. MR-based lessons, including specific modules, were identified as offering a distinctive opportunity for knowledge exchange both within and beyond the medical community.

In [7], the study introduces a novel technique for orthopedic surgical training through the creation of a Virtual Surgical Environment (VSE). The educational focus centers on the Less Invasive Stabilization System (LISS) surgery, specifically addressing femur fractures. The methodology involves acquiring requisite knowledge of the

LISS plating procedure through interactions with proficient orthopedic surgeons and leveraging information-centric models to inform the development of an emulator. The incorporation of a haptic interface enhances training activities, enabling users to tactilely experience and interact with surgical tools. This approach aims to bridge the gap between theoretical understanding and practical application in orthopedic surgery education.

Meanwhile, [8] delves into the advancements of Virtual Reality (VR) and Augmented Reality (AR) technologies within the manufacturing industry. Against the backdrop of the fourth industrial revolution, the study underscores the critical role of immersive technologies, particularly in human-machine interaction. Despite the emphasis on progress, the research acknowledges persistent challenges in the implementation of VR/AR technology, spanning both hardware and software domains.

Table 1. Representation of Related Works

AUTHOR / YEAR	AIM OF THE STUDY	PARAMETERS USED	TOOLS USED	FUTURE RESEARCH DIRECTION
Minopoulos et al. [2023] [9]	To address the shortcomings of the current healthcare system exposed during the pandemic.	Virtual Reality, Augmented Reality, Tactile Internet	Haptic technology, Artificial intelligence	Virtual Reality and Augmented Reality need to be explored.
Zhou et al. [2023] [10]	introduces a novel Volumetric Memory Network (VMN) designed for interactive segmentation of 3D medical images	2D interaction network, Bidirectional propagation	Volumetric Memory Network (VMN), Convolutional Network,	Segmentation refinement and optimization of the quality assessment need to be explored.
Alsabhan et al. [2023] [11]	to enhance Speech Emotion Recognition (SER) by using the diversity of human speech	1D CNN, LSTM, 2D CNN	ZCR, RMSE, MFC	Real-world applications and cross-cultural scenarios need to be adopted.
Xu et al. [2023] [12]	to review recent progress in tactile and force sensors for Human-Machine Interface (HMI)	Skin-integrated tactile, Force sensors	Piezoelectric, Triboelectric, Piezoresistive	Potential avenue for HMI need to be improved.
Xue et al. [2022] [13]	To defining bionic strategies of bioinspired sensor systems	Functional Bionic strategies	Bioinspired sensor system	current challenges of bio inspired sensor systems need to be discussed
Nazir et al. [2023] [14]	to address the limited interpretability of deep learning models in medical imaging	Deep learning models	Explainable AI (XAI), Deep Neural Network	Diagnostic accuracy in biomedical imaging need to be improved
Hadjiiski et al [2023] [15]	to address the challenges in the clinical deployment of computer aided design (CAD)	Computer-Aided Image Analysis	Machine Learning	development of most CAD-AI applications, with the goal of improving generalizability and reliability need to be focused

3. Research Hypothesis and Guidelines

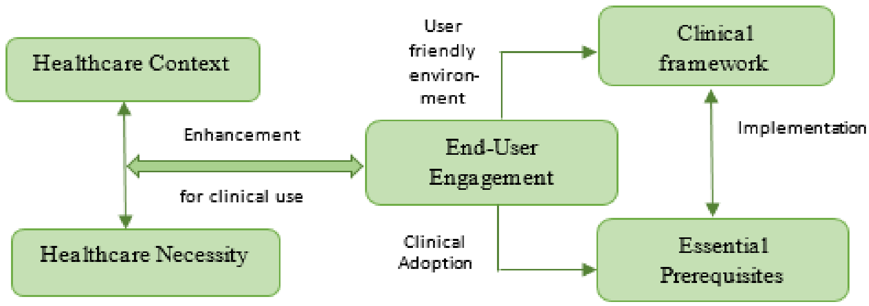

Figure 3. Methodology for Working Concept of HCI applications in Medical Imaging for Users

The implementation of interpretable artificial intelligence models in medical imaging, characterized by user-centric design, enhanced transparency, and continuous refinement mechanisms, will significantly enhance diagnostic accuracy through improved human-computer interaction in clinical settings. Within this investigation, we delve into various research papers concerning applications of man-machine interaction in the context of medical imaging, exploring its diverse uses across different sectors within the healthcare industry. Our focus encompasses an examination of a contemporary methodology, widely employed across various research domains, known as X-AI, which involves the utilization of Machine Learning Algorithms. Furthermore, through the course of this study, we identify specific research questions, as outlined below:

H1: Does the integration of interpretable AI models in medical imaging have a significant impact on diagnostic accuracy through enhanced human-computer interaction in clinical settings?

The research aims to investigate whether the implementation of interpretable AI models significantly improves diagnostic accuracy in medical imaging by fostering improved human-computer interaction within clinical settings.

H2: To what extent does the expandability of AI models in healthcare impact the decision-making process and user experience?

The research investigates whether expandability of AI models within healthcare significantly contributes to influencing the decision-making process and positively enhancing the overall user experience by using ML and DL techniques.

We have devised a framework outlining principles for the development of interpretable artificial intelligence (AI) models. These guidelines are centered on fostering seamless interaction between the system and the user, prioritizing

comprehensibility and ensuring straightforward access to clinical systems.
The above structured approach delineates the process into five distinct levels, schemes, or steps, as elaborated below:

3.1 User-Centric Definition of Requirements

Initiate a comprehensive engagement process with healthcare professionals, radiologists, and end-users to discern their specific needs and anticipated outcomes from the artificial intelligence (AI) model. Delve into the nuances of the medical imaging workflow to pinpoint elements requiring interpretability, ensuring alignment with practical clinical processes.

3.2 Enhanced Feature Transparency and Explanation Mechanisms

Integrate features that augment transparency within the AI model. Develop sophisticated mechanisms to deliver lucid and succinct explanations for the model's predictions and decisions. This encompasses the application of interpretable algorithms, visualization of feature importance, and the creation of intelligible summaries elucidating the outcomes of image analyses.

3.3 Intuitive Design of User Interface

Craft an intuitive and user-friendly interface tailored to accommodate the diverse needs of healthcare professionals possessing varying degrees of technical expertise. Emphasize simplicity and clarity in presenting the results of AI-assisted medical imaging. Ensure seamless navigability of the interface, fostering integration with existing clinical systems.

3.4 Thorough Validation and Collaborative Evaluation

Execute meticulous validation and testing protocols for the interpretable AI model in collaboration with esteemed medical experts. This includes a robust evaluation of the model's performance across diverse datasets, encompassing cases that pose challenges or are less conventional. Actively engage healthcare professionals in the evaluation process, seeking their feedback on usability, interpretability, and clinical significance.

3.5 Establishment of Continuous Improvement Mechanisms and Educational Initiatives

Institute mechanisms for continual refinement and learning. Monitor the model's performance within authentic clinical settings and actively solicit feedback from users to inform ongoing improvements. Additionally, institute educational resources and training programs aimed at empowering healthcare professionals to proficiently leverage and interpret the results of the AI model in their daily clinical practice.

4. Reviewed Methodologies

In the pursuit of refining diagnostic accuracy in medical imaging, diverse methodologies have been applied in prior research endeavors. Most approaches have predominantly concentrated on utilizing advanced image analysis techniques, including deep learning methodologies and convolutional neural networks (CNNs). While these methods have displayed promise, there persists a necessity for a more nuanced understanding of the challenges related to interpreting these intricate models. This paper conducts a critical examination and analysis of the methodologies employed in past studies, shedding light on both their strengths and limitations. Drawing from the insights gained through this review, the research proposes an innovative approach that integrates human-computer interaction, aiming to enhance the interpretability of AI models in medical imaging. The overarching objective is to foster more dependable and clinically relevant diagnostic outcomes.

Table 2. Shows some methodologies and models used in related previous works

CITATION	USED MODELS	METHODOLOGY PROPOSED	STRENGTH	LIMITATIONS
[23]	Explainable AI in Medical Imaging	Integrating interpretable models or generating heatmaps to explain the decision-making process of deep learning models.	• Interpretability • Clinical Validation	• Simplification • Loss of Expressiveness
[24]	Human-in-the-loop (HITL) Systems:	Incorporating user feedback into the training process, making AI models more aligned with the preferences and expertise of medical professionals.	• Continuous Learning • Adaptibility	• Subjectivity • Training Overhead
[25]	Virtual Reality (VR) for Medical Imaging Interpretation using Deep Learning	Using VR technologies to provide an immersive environment for medical professionals to visualize and interpret medical images.	• Immersive Visualization • Collaborative diagnosis	• Cost and Accessibility • Learning Curve
[26]	Natural Language Processing (NLP) for Radiology Reports	Extracting structured information from unstructured radiology reports using NLP techniques.	• Structured Information Extraction • Time Efficiency	• Ambiguity and Context • Variability in Reports
[27]	Face Region Tracking and Emotion Classification using intensity of Region of Interest (RoIs).	Facial region detection using R-CNN and tracking RoIs through MIL and classify the emotions by using Dynamic Time Warping (DTW).	• Non-invasive Monitoring • Real Time Analysis	• Limited to Surface-level Emotions • Dependency on Visibility

To examine the influence of patients' responsibility attribution following AI service failure on human-computer trust, and subsequently, to assess how personality traits moderate the relationship between human-computer trust and the acceptance of medical AI for both independent and assistive diagnosis and treatment [28].

Participants paid to use the algorithm, varying information about its performance, and were monitored for peripheral neurophysiology. Results showed that adoption was influenced more by information about previous adoption by others than algorithm accuracy, and neurophysiologic measurements revealed improved cognitive engagement and task performance with information about others' use [29].

5. Research Gap and Analysis

In the field of medical imaging, notable progress has been made through the integration of advanced technologies. Nevertheless, a critical gap exists in comprehending and making artificial intelligence (AI) in medical imaging more interpretable. Despite the heightened importance of precise diagnostics, there's a notable absence of in-depth studies addressing the challenges associated with interpreting AI models. This research endeavors to fill this void by exploring the role of human-computer interaction in enhancing the interpretability of AI algorithms within medical imaging, with the ultimate goal of advancing diagnostic accuracy. By pinpointing and addressing this research gap, the study makes a significant contribution to the ever-evolving landscape of applications in healthcare.

5.1 User-Centric Evaluation of Interpretability

There might be a gap in studies that rigorously evaluate the effectiveness of interpretable AI models from a user-centric perspective. This involves understanding how healthcare professionals interact with these models, perceive their interpretability, and whether these models truly enhance their decision-making processes.

5.2 Optimization of HCI Designs for Medical Professionals

While there's acknowledgment of the importance of HCI in the context of interpretable AI, there may be a gap in research that focuses on the optimization of user interfaces and interaction designs tailored specifically for medical professionals. This could include studies on the usability of interpretability features and the development of HCI standards in medical imaging.

5.3 Longitudinal Studies on Clinical Impact

There could be a gap in research that conducts longitudinal studies to assess the sustained impact of interpretable AI on clinical outcomes. Understanding how these models influence long-term diagnostic accuracy and patient care is crucial for widespread adoption in the medical field.

5.4 Ethical Considerations in HCI-Driven Interpretable AI

The ethical implications of incorporating interpretable AI into medical imaging, particularly concerning HCI, may not have been thoroughly explored. Future research could delve into ethical frameworks specific to the user interaction aspect, addressing issues of trust, transparency, and accountability.

5.5 Integration of User Feedback into Model Improvement

Research might explore methodologies for effectively integrating user feedback from medical professionals into the improvement of interpretable AI models. This could involve iterative user-centered design cycles to ensure that the models align with the preferences and needs of healthcare practitioners.

The research reveals a potential gap in understanding the intricate dynamics among user proficiency levels, the fine-tuning of decision-making algorithms, and users' perceptions of algorithmic performance across various decision-making tasks. There is a need for further exploration into the interaction of these factors and their influence on collaborative decision-making between humans, which could offer valuable insights for refining decision-making processes across diverse contexts. A more comprehensive investigation in this direction would contribute to the improvement of decision-making strategies, accommodating individuals with diverse levels of expertise [30].

6. Challenges & Discussion

In this section of our research, our paramount objective is to explore the novel challenges faced by Human-Computer Interaction (HCI) professionals in the development of human-centered systems during the transition from conventional non-AI systems to AI systems. Our high-level literature review and analysis focused on two key aspects:

- The existing research and application efforts in human interaction with AI systems.

- Distinct issues related to AI systems that HCI professionals did not encounter in conventional HCI work, specifically human interaction with non-AI systems.

To conduct this investigation, we utilized prominent electronic databases, including IEEE Xplore Digital Library, Google Scholar, and ResearchGate, to identify pertinent papers published over the past decade. The result of our search yielded approximately 550 relevant papers. We systematically categorized the issues discussed in these papers into ten groups. Subsequently, through a comprehensive analysis involving primary references cited in this paper, we further refined these issues into seven main groups.

We contend that these categorized seven main issues, as outlined in Table 2, effectively encapsulate the primary HCI challenges that underscore significant disparities between the familiar HCI concerns associated with human interaction with non-AI systems and the emerging HCI challenges intrinsic to human interaction with AI systems.

Table 3. Represents the categorization between AI and Non-AI System

ISSUES WITH NON-AI SYSTEM	HCI CHALLENGES WITH NON-AI SYSTEM	HCI CHALLENGES WITH AI SYSTEM	PRIMARY HCAI DESIGN GOALS
Autonomous Attributes of Systems	Conventional systems lack autonomous characteristics. HCI emphasizes user interface (UI) and awareness.	AI systems may manifest autonomous characteristics (learning, self-adaptation). Addressing unforeseen circumstances and managing non-deterministic outputs pose challenges (Kaber, 2018; Xu, 2021). [16]	Human-Guided Automation
Collaborative Interaction between Humans and Machines	Users engage with traditional systems; machines provide assistance.	AI systems can act as collaborators with humans, establishing human-AI cooperative relationships. Disputes arise regarding the depth of collaboration (Brill et al., 2018; O'Neill et al., 2020). [17]	Humanized Decision Making system
System Behaviour	Traditional systems operate as designed.	AI systems can display distinctive and potentially biased behaviors. The system's behavior evolves through the learning process (Rahwan et al., 2019). [18]	Human-controlled AI
Ethical Framework	User requirements centre on usability, functionality, and security.	Ethical considerations become more pronounced in the context of AI, encompassing privacy, ethics, fairness, skill development, and decision-making authority [19].	Ethical Automation System
Clarity of System Output	System output is explicable with a user-friendly UI in traditional systems.	AI systems may introduce an "opaque box" effect, rendering the output obscure. Users may lack insight into AI decision-making, thereby challenging the establishment of trust [20]	Transparent AI
Interface Design	Design for usability of traditional UI.	AI necessitates sophisticated UI design for interactions that are both natural and user-friendly. Emphasis is placed on adapting AI to human capabilities. The establishment of HCI standards specifically tailored for AI systems is deemed essential [21]	Interpretable AI

System Intelligence	Traditional systems lack artificial intelligence (AI).	AI systems can attain intelligence levels analogous to human cognition. Augmenting human cognitive capabilities presents challenges. The integration of human roles is deemed imperative [22].	Human Guided Automation

6.1 Discussion

In our comprehensive exploration of challenges within Human-Computer Interaction (HCI), specifically focusing on medical imaging, several distinct observations emerge. In traditional imaging systems, which lack autonomous features, the primary emphasis lies on user interface (UI) and awareness. This aligns with a user-centric approach that is crucial for efficient interpretation of medical data. On the contrary, the incorporation of advanced technologies, excluding Artificial Intelligence (AI), initiates a shift in perspective. Although not AI-driven, these systems require adept handling of unforeseen clinical scenarios and outputs, which inherently possess non-deterministic complexities. Collaborative efforts between medical professionals and these systems prompt debates regarding the extent and nature of cooperation, molding the ongoing evolution in medical image diagnostics. Ethical considerations, particularly related to privacy, fairness, and decision-making authority, gain prominence in this domain. The concept of a "black box" effect in these systems raises transparency concerns, influencing user trust in diagnostic outcomes. Intelligent UI design becomes paramount in fostering natural interactions in medical imaging, necessitating adaptation to the unique cognitive capabilities of healthcare practitioners. Finally, without venturing into AI territory, the pursuit of human-like intelligence levels introduces challenges in enhancing the cognitive capabilities of medical professionals and seamlessly integrating technological advancements into the healthcare workflow. This discussion underscores the dynamic challenges within the HCI domain in medical imaging, underscoring the critical need for nuanced approaches to navigate the intricate interplay between medical professionals and evolving imaging technologies, both conventional and technologically advanced.

7. Conclusion and Future Research Direction

In exploring the realm of Human-Computer Interaction (HCI) within the context of medical imaging and interpretable systems, our study sheds light on the intricate dynamics where technology converges with healthcare. Traditional imaging systems, emphasizing user-centric design principles like UI and awareness, establish a robust framework for effective interpretation of medical data. However, the incorporation of interpretable systems marks a transformative shift, demanding adept navigation of unpredictable intricacies in unexpected clinical scenarios. The collaborative partnership between medical professionals and interpretable systems emerges as a pivotal element, influencing the ongoing evolution of medical image diagnostics. Ethical considerations, spanning privacy, fairness, and decision-making authority, attain heightened significance in the context of medical imaging bolstered by technological enhancements. The transparency challenges presented by the intricacies of these systems underscore the imperative for instilling user confidence in diagnostic outcomes, mitigating uncertainties associated with technology in healthcare.

7.1 Future Research Direction

Looking forward, future research direction should prioritize the refinement and optimization of models that facilitate interpretability in medical imaging. The objective is to seamlessly integrate these systems into medical workflows, enhancing their efficiency and efficacy. A critical research focus involves delving into the impact of interpretability on diagnostic accuracy and its implications for clinical decision-making. Moreover, there is a need for extensive exploration into the development of ethical frameworks and specific guidelines tailored to the application of interpretability in medical imaging. This will ensure the responsible and patient-centered deployment of these technologies. Essentially, our research lays the groundwork for a comprehensive understanding of challenges and opportunities in the domain of interpretable systems in medical imaging, viewed through the lens of Human-Computer Interaction. The identified areas of concern serve as a cornerstone for future initiatives aimed at fully realizing the potential of interpretability to elevate diagnostic precision and enhance patient outcomes within the dynamic landscape of medical imaging.

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Conflicts of Interest

The authors declare no conflict of interest.

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