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# Leveraging Explainable AI to Improve Understanding in Medical Diagnostics

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## ABSTRACT

This study investigates the transformative role of Explainable Artificial Intelligence (XAI) in medical diagnostics, focusing on enhancing the interpretability of AI-driven models. As AI technologies become more prevalent in clinical decision-making, the lack of transparency in traditional black-box models raises critical concerns regarding trust, understanding, and effective application. The research delves into the core principles of XAI, exploring methods for integrating interpretability into machine learning models specifically tailored for medical use. By comparing interpretable models with conventional opaque systems, the study assesses how transparency impacts the diagnostic decisions of healthcare professionals. In addition, it addresses key ethical considerations, patient attitudes, and regulatory frameworks surrounding the deployment of XAI in healthcare settings. Through a comprehensive evaluation of these factors, the study aims to offer actionable insights and propose best practices for the responsible and transparent adoption of XAI in medical diagnostics.

## Introduction:

Explainable Artificial Intelligence (XAI) is revolutionizing medical diagnosis by making complex AI systems more interpretable and transparent. As artificial intelligence becomes increasingly embedded in healthcare—supporting tasks such as disease detection, treatment planning, and risk assessment—the opacity of traditional black-box models presents a major challenge to their acceptance and effectiveness. In a field where decisions can significantly impact patient lives, healthcare professionals must be able to understand and evaluate the reasoning behind AI-driven recommendations. XAI directly addresses this concern by promoting transparency and accountability, enabling clinicians to collaborate with AI systems rather than depend on them blindly. The rapid progress of machine learning, particularly deep learning, has unlocked immense capabilities for analyzing and interpreting complex medical data. However, the exceptional performance of these models often comes at the cost of interpretability. Deep neural networks, while highly accurate, operate in ways that are difficult to decipher. This lack of transparency becomes problematic in clinical environments, where trust, ethical standards, and patient safety are paramount. The core goal of XAI is to bridge this divide—maintaining high predictive accuracy while ensuring that AI outputs are understandable and verifiable by medical professionals.

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## The Significance of Interpretability in AI for Medical Decision-Making

AI has the potential to transform healthcare, yet its successful integration depends heavily on interpretability—the ability to understand how and why a model arrives at a particular decision. For AI systems to gain the trust of clinicians, it is essential that their reasoning be accessible and explainable. Interpretability fosters confidence, ensures safe application, and underpins ethical decision-making in medical practice. Crucially, interpretability ensures that AI serves as an assistant rather than a substitute for human expertise. Medical professionals must be equipped to review AI-generated outputs, validate them against clinical knowledge, and incorporate them into patient care. This collaborative approach enhances both the accuracy and accountability of decision-making processes. Furthermore, interpretable models support clear communication among healthcare teams and with patients, allowing clinicians to explain diagnoses and treatment recommendations with confidence. Interpretability also holds immense value in medical research. As AI models are increasingly used to uncover new biomarkers, analyze disease trajectories, and assist in drug development, researchers need to trace and validate the insights these models provide. Transparent AI systems support reproducibility, enhance scientific integrity, and contribute to the discovery of novel clinical insights. Without interpretability, the role of AI in scientific advancement risks being opaque and unreliable.

## Unraveling the Black Box

The "black box" nature of many AI models refers to their internal complexity and lack of transparency—users often cannot understand how specific outputs are generated. In medicine, this presents a serious concern, as critical decisions must be justifiable and grounded in clinical logic. Unraveling this black box is central to the mission of XAI. To tackle this, XAI incorporates a range of tools and techniques that make AI outputs more interpretable. Model-agnostic methods such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) allow users to understand which input features contribute most to a model's decision. These techniques can be applied even to complex models like deep neural networks, enabling clinicians to assess whether AI recommendations align with established medical reasoning. Additionally, inherently interpretable models—such as decision trees and rule-based systems—offer transparency by design. Their decision-making paths are straightforward, making them especially useful in clinical settings where explanations are needed for both validation and communication. Regulatory bodies have also emphasized the need for explainability. Legislation like the European Union's General Data Protection Regulation (GDPR) and the U.S. Algorithmic Accountability Act mandates transparency in algorithmic decision-making. These policies underscore the right of individuals—patients, in this context—to understand and question automated decisions affecting their health.

Ethically, unraveling the black box is crucial for addressing bias, fairness, and equity in AI systems. Interpretable models can help identify potential biases in training data or algorithmic behavior, ensuring that AI tools do not reinforce existing disparities in healthcare. In this way, explainability becomes a tool for promoting ethical responsibility and equitable treatment.

## Interpretable Models in Medical AI

Interpretable models are designed with human understanding in mind, allowing

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users to grasp how predictions are made. Common examples include linear regression, decision trees, and rule-based classifiers—models that are transparent by nature and well-suited to domains where clarity and trust are vital. In healthcare, interpretable models enable clinicians to see which clinical features (e.g., symptoms, test results, patient history) most influenced a diagnosis. This visibility reinforces confidence in AI systems and helps practitioners make informed decisions in collaboration with machine intelligence. Post hoc explanation techniques such as LIME and SHAP have become increasingly popular for interpreting complex models. These methods explain how inputs influence predictions both locally (on a case-by-case basis) and globally (across all predictions), making black-box models more accessible without changing their underlying structure. Beyond healthcare, interpretable models are widely used in finance, legal systems, and public policy—domains where algorithmic accountability is equally critical. Their cross-disciplinary adoption underscores a shared recognition of the importance of transparency wherever human lives and rights are affected by automated decisions. Still, a key challenge remains: balancing accuracy and interpretability. Simple models may fall short in performance when faced with complex medical datasets, while advanced models may sacrifice explainability for accuracy. Research is now focused on developing hybrid models and layered explanations that preserve both precision and transparency, ensuring that AI systems are both effective and understandable.

## Explainability and Accountability in Healthcare

## Literature Review

Explainability forms the backbone of accountability in AI-assisted healthcare. When an AI model generates a diagnosis or treatment recommendation, it must be able to justify its conclusions. Without this transparency, healthcare providers cannot fully evaluate the reliability of AI outputs, nor can they responsibly integrate them into clinical workflows. In cases of AI error or misjudgment, explainability allows for root-cause analysis and system improvement. Clinicians must be able to trace and understand what went wrong to refine decision-making and prevent future errors. Transparent systems thus enable a continuous learning loop between humans and machines, supporting safer and more responsive healthcare delivery. Regulatory approval of AI technologies also depends heavily on explainability. Health authorities require developers to demonstrate the safety, reliability, and rationale of AI systems before deployment. Transparent models simplify this process, enabling more rigorous validation and easing the path to clinical integration. From a patient perspective, explainability fosters trust and informed consent. As patients become active participants in their care, they expect to understand how AI contributes to diagnosis or treatment decisions. Explainable AI supports this by enabling clinicians to clearly communicate the logic behind automated recommendations, reinforcing the therapeutic alliance and promoting shared decision-making. Finally, explainability enhances collaboration among healthcare professionals. When radiologists, pathologists, and physicians understand AI outputs, they can more effectively work together, leveraging AI insights to support holistic and personalized care. Explainable AI thus strengthens not only individual decision-making but also the broader healthcare ecosystem.

1. **Adadi et al. (2018)** highlight XAI as a critical solution to the black-box nature of AI systems, emphasizing its role in improving

trust and transparency in AI adoption.

2. **Holzinger et al. (2019)** argue that explainability alone is insufficient in healthcare; they introduce the concept of "causability" to evaluate the quality of explanations in medical AI.
3. **Das et al. (2019)** propose SHIMR, an interpretable model with a rejection option for uncertain cases, offering a cost-effective diagnosis method tailored to patients.
4. **Xie et al. (2019)** emphasize aligning XAI systems with clinical reasoning by mimicking how doctors prioritize data during diagnosis.
5. **Tsiknakis et al. (2020)** demonstrate a COVID-19 diagnostic model using interpretable attention maps validated by radiologists, achieving high accuracy.
6. **Vellido (2020)** calls for involving medical experts in designing interpretable models and stresses the role of data visualization for effective XAI in healthcare.
7. **Reyes et al. (2020)** review interpretability methods in radiology and underline the need for clinician trust in complex models.
8. **Stiglic et al. (2020)** classify interpretability techniques into local/global and model-specific/agnostic approaches, highlighting their application in various healthcare domains.
9. **Ploug et al. (2020)** introduce "effective contestability," advocating that patients should be able to challenge AI decisions with access to explanation-relevant data.
10. **Farkhadov et al. (2020)** identify lack of transparency and poor training data as reasons for mistrust in AI, proposing human-AI collaborative systems.
11. **Mi et al. (2020)** categorize interpretable models and methods (e.g., SHAP, clustering, knowledge graphs), helping researchers choose the right XAI approach.
12. **Cutillo et al. (2020)** summarize challenges in integrating AI into healthcare, such as bias, data quality, and system transparency, emphasizing ethical implementation.
13. **Kourou et al. (2021)** review AI/ML in oncology, stressing the need for transparent and robust models for accurate diagnosis and prognosis.
14. **Khodabandehloo et al. (2021)** present an XAI system for detecting early cognitive decline in smart homes, using clinical indicators and interactive clinician interfaces.
15. **Kinger et al. (2021)** apply Grad-CAM++ for plant disease detection and highlight the need for human-interpretable AI in agriculture.
16. **Ong et al. (2021)** compare LIME and SHAP in interpreting COVID-19 diagnoses from X-ray images, improving trust in deep learning outputs.
17. **Wang et al. (2021)** introduce a multimodal CNN with interpretable outputs for skin cancer diagnosis, improving accuracy and clinician confidence.
18. **Banegas-Luna et al. (2021)** examine ML models in cancer diagnostics, stressing the need for interpretability in deep learning to aid clinical decision-making.
19. **Joshi et al. (2021)** provide a survey on explainability in multimodal deep learning systems, focusing on language and vision-based tasks.
20. **Oh et al. (2021)** develop an explainable system for glaucoma diagnosis using SHAP and statistical charts to interpret XGBoost predictions.
21. **Mathews et al. (2021)** use LIME to interpret deep learning in medical and cybersecurity domains,

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improving user understanding of model predictions.

22. **Linardatos et al. (2021)** present a taxonomy of interpretability methods and tools, serving as a reference for developers and practitioners.
23. **Tjoa et al. (2021)** review interpretability research across disciplines and its importance in medical applications, promoting responsible AI use.
24. **Angelov et al. (2021)** provide a critical overview of explainability principles and recent methods, offering guidelines for future XAI research.

## The Foundation of Explainable AI in Healthcare

As Artificial Intelligence (AI) becomes increasingly embedded in healthcare—from diagnostic tools to treatment recommendations—ensuring transparency and interpretability is more important than ever. **Explainable AI (XAI)** serves as the cornerstone for building ethical, transparent, and trustworthy medical AI systems. By making complex algorithms understandable to both clinicians and patients, XAI enhances accountability, supports informed decision-making, and builds the confidence required for wide-scale adoption in clinical environments.

## Building Trust through Transparent AI Models

Trust is essential in healthcare, where decisions can have life-altering consequences. Yet, many modern AI systems—especially those using deep learning—operate as "black boxes," producing results without offering insight into their reasoning. This lack of transparency hinders clinical trust and makes it difficult for practitioners to rely on AI-driven insights.Explainable AI techniques such as LIME (Local Interpretable Model-agnostic Explanations), SHAP (SHapley Additive exPlanations), and decision trees aim to overcome this opacity by providing interpretable, human-understandable justifications for algorithmic decisions. These tools help clinicians verify that AI outputs are sound and relevant, empowering them to confidently incorporate AI into diagnosis and treatment workflows. Furthermore, transparent models support legal and ethical mandates, such as the GDPR**'s "**right to explanation**,"** by enabling accountability and traceability.

## Overcoming the Black-Box Challenge in Clinical Settings

In the medical field, decisions must be explainable—not only for regulatory reasons but also to uphold professional and ethical standards. Healthcare providers are obligated to explain the rationale behind diagnoses and treatment plans to patients and colleagues. However, black-box AI systems undermine this duty by producing results without a clear chain of reasoning.Explainable AI addresses this challenge by shedding light on how algorithms arrive at specific outcomes. By clarifying which features influenced a diagnosis or recommendation, XAI enables clinicians to critically assess AI-generated insights. This not only promotes better clinical judgment but also fosters trust and collaboration between humans and machines in the decision-making process.

## Explainability as a Catalyst for AI Adoption

Explainability is not a luxury—it's a prerequisite for the effective adoption of AI in high-stakes, human-centered environments like healthcare. Without interpretability, even the most accurate model may be underutilized or misapplied due to fear, uncertainty, or lack of trust.XAI

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promotes wider acceptance and integration of AI by bridging the gap between data scientists, regulators, clinicians, and patients. It encourages collaboration during model development, enables transparent performance evaluation, and ensures alignment with clinical goals. Moreover, XAI helps uncover hidden biases within AI systems—enabling fairer, more inclusive decision-making that resonates with diverse patient populations.

## Bridging the Gap Between Technical Experts and Medical Professionals

Effective deployment of AI in healthcare demands interdisciplinary collaboration. Yet, AI developers and healthcare practitioners often operate in distinct spheres, using different languages and frameworks. Explainable AI serves as a common ground, translating complex algorithmic behavior into terms that clinicians can understand and critique.This shared understanding fosters deeper collaboration and co-design of AI systems tailored to specific domains such as cardiology, radiology, or oncology. Feedback loops between developers and clinicians enable iterative improvements and ensure that AI tools are aligned with real-world clinical needs. Ultimately, explainability transforms AI from a static solution into a dynamic partner in care.

## Ethical Foundations of Patient-Centered Explainable AI

Healthcare is an inherently ethical discipline, and AI must align with its foundational values transparency, fairness, privacy, and accountability. XAI supports these principles by uncovering hidden biases, validating the fairness of decisions, and enabling scrutiny of training data and model behavior. Moreover, XAI ensures that patients are treated not merely as data points, but as individuals with unique needs and concerns. By clearly explaining how AI systems contribute to medical decisions, XAI promotes transparency and shared understanding, which are essential for ethical patient engagement. It also enables safeguards for patient privacy by revealing where and how data is being used—reinforcing public trust.

## Informed Consent in the Age of AI

Traditional models of informed consent must evolve to reflect the realities of AI-assisted healthcare. It's no longer enough for patients to know what decisions have been made—they must also understand how those decisions were reached and what role AI played in the process. Explainable AI supports this shift by making algorithmic reasoning accessible and understandable to non-experts. When patients comprehend the logic behind a diagnosis or treatment suggestion, they are better equipped to make informed decisions about their care. This transparency strengthens patient autonomy, promotes trust in medical AI, and ensures compliance with legal and ethical standards.

## User Feedback Integration in AI Medical Systems

The integration of Artificial Intelligence (AI) into modern healthcare systems has opened new avenues for improved diagnostics, personalized treatments, and streamlined operations. However, the effectiveness of these AI applications hinges not only on their computational accuracy but also on how well they incorporate and respond to the experiences and feedback of their primary users—healthcare professionals and patients. User feedback plays a pivotal role in shaping AI systems that are not only intelligent but also contextually relevant, ethically sound, and human-centered. Healthcare professionals interact directly with AI tools during clinical decision-making, relying on these systems to support diagnoses, predict

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outcomes, or recommend treatments. Their feedback is essential in identifying inconsistencies, validating recommendations, and enhancing the clinical utility of AI models. Medical professionals bring invaluable contextual knowledge that AI systems often lack, allowing for critical refinement and adaptation of algorithms to real-world clinical workflows. Over time, this collaborative feedback loop fosters confidence, accountability, and a deeper trust in AI-assisted care. Equally important is the voice of the patient. As the ultimate recipients of healthcare services, patients offer a perspective that goes beyond clinical data. Their feedback can reveal whether AI-generated decisions feel understandable, empathetic, and appropriate for their personal and cultural contexts. When patients feel that technology respects their values and communicates transparently, it not only builds trust but also empowers them to take a more active role in their health journey. A key element that enables effective feedback integration is Explainable AI (XAI). Many AI models, especially deep learning systems, are often perceived as "black boxes" due to their complexity. XAI seeks to bridge this gap by offering interpretable outputs that help users—both clinicians and patients—understand the rationale behind AI decisions. This transparency is essential for validating AI outputs, supporting shared decision-making, and encouraging meaningful feedback that can further improve system performance. Despite its importance, integrating user feedback into medical AI systems presents notable challenges. Feedback mechanisms must be secure, intuitive, and accessible to users across a range of technical proficiencies. Healthcare environments are often fast-paced and resource-constrained, making it crucial that feedback processes are efficient and non-disruptive. Moreover, developers must have systems in place to analyze feedback systematically and translate it into practical updates and enhancements. Ethical considerations are equally vital. Any feedback integration process must ensure data privacy, informed consent, and secure handling of sensitive health information. Trust can only be sustained if users are assured that their insights will be respected, protected, and used constructively. To be truly effective, feedback integration must be iterative and continuous. AI systems should be designed to evolve with clinical practices, medical advancements, and user expectations. This involves establishing a responsive feedback loop in which data is regularly collected, assessed, and used to retrain and optimize the AI model. Beyond the technical infrastructure, creating a culture of collaboration is essential. Both clinicians and patients must be recognized not merely as users but as co-creators of AI systems. This shift in perspective can be achieved through inclusive design practices, open communication, and ongoing education that emphasizes the value of human insight in shaping technological progress.

## REFERENCES

1. Valdes et al., Scientific Reports, 2016.
2. Lakkaraju et al., arXiv:1707.01154, 2017.
3. Arrieta et al., Information Fusion, 2020.
4. Tosun et al., in AI & ML for Digital Pathology, Springer, 2020.
5. Das & Rad, arXiv:2006.11371, 2020.
6. Gomolin et al., Frontiers in Medicine, 2020.
7. Gupta et al., Array, 2021.
8. Holzinger et al., WIREs: DMKD, 2019.
9. Khamparia et al., MDSSP, 2020.
10. Polino et al., arXiv:1802.05668, 2018.
11. Rajkomar et al., NPJ Digital Medicine, 2018.
12. Rajkomar et al., NEJM, 2019.

13. Adadi & Berrada, IEEE Access, 2018.
14. Alicioglu & Sun, Computers & Graphics, 2022.
15. Angelov et al., WIREs: DMKD, 2021.
16. Ayano et al., Diagnostics, 2022.
17. Letham et al., Ann. Appl. Stats., 2015.
18. Mahbooba et al., Complexity, 2021.
19. Patro et al., ICCV, 2019.
20. Banegas-Luna et al., IJMS, 2021.
21. Molnar et al., 2019.
22. Roggeman et al., NeuroImage, 2010.
23. Sudlow et al., PLoS Med, 2015.
24. Xiao et al., PLoS One, 2018.
25. Zucco et al., IEEE BIBM, 2018.
26. Cutillo et al., NPJ Digital Medicine, 2020.
27. Somers & Sheremata, WIREs: Cognitive Science, 2013.
28. Gunning et al., Science Robotics, 2019.
29. Higgins & Madai, Advanced Intelligent Systems, 2020.
30. Li et al., SIGIR, 2021.
31. Schönberger, IJLIT, 2019.
32. Shen et al., ARBE, 2017.
33. Slack et al., arXiv:1902.03501, 2019.
34. Carvalho et al., Electronics, 2019.
35. Das et al., PeerJ, 2019.
36. Peterson, JAMA, 2019.
37. Hwang et al., JAMA Netw Open, 2019.
38. Topol, Nature Med., 2019.
39. Jabason et al., IEEE ISCAS, 2022.
40. Khodabandehloo et al., FGCS, 2021.
41. Strickland, IEEE Spectrum, 2019.
42. Tjoa & Guan, IEEE TNNLS, 2020.
43. Williams et al., Nature Methods, 2017.
44. Ennab & Mcheick, Diagnostics, 2022.
45. Esteva et al., Nature Med., 2019.
46. Poursabzi-Sangdeh et al., CHI, 2021.
47. Doshi-Velez & Kim, in Springer Book, 2018.
48. Doshi-Velez & Kim, arXiv:1702.08608, 2017.
49. Jiang et al., Stroke & Vascular Neurology, 2017.
50. Farkhadov et al., IEEE AICT, 2020.
51. Fuhrman et al., Medical Physics, 2022.
52. Hinton et al., arXiv:1503.02531, 2015.
53. Litjens et al., Medical Image Analysis, 2017.
54. Montavon et al., Pattern Recognition, 2017.
55. Montavon et al., Digital Signal Processing, 2018.
56. Stiglic et al., PLoS One, 2012.
57. Yang et al., Magnetic Resonance in Medicine, 2015.
58. Yang et al., Information Fusion, 2022.
59. Lee et al., in Springer MICCAI, 2019.
60. Hassija et al., Cognitive Computation, 2023.
61. Holzinger et al., arXiv:1712.09923, 2017.
62. Doroniewicz et al., in Springer ITB, 2021.
63. Goodfellow et al., Deep Learning, MIT Press, 2016.
64. Lage et al., arXiv:1902.00006, 2019.
65. Burrell, Big Data & Society, 2016.
66. Nam et al., Radiology, 2019.
67. Hao et al., BMC Bioinformatics, 2018.
68. He et al., Nature Med., 2019.
69. Huysmans et al., DSS, 2011.
70. Ker et al., IEEE Access, 2017.
71. England & Cheng, AJR, 2019.
72. Joshi et al., IEEE Access, 2021.
73. Yu & Snyder, MCP, 2016.
74. Yu et al., Nature Biomed Eng., 2018.
75. Geras et al., arXiv:1703.07047, 2017.
76. Kallianos et al., Clinical Radiology, 2019.

ISSN 2454-9940

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77. Roberts et al., JAMIA, 2017.
78. Tomczak et al., Contemporary Oncology, 2015.
79. Kinger & Kulkarni, IEEE IC3, 2021.
80. Kourou et al., CSBJ, 2021.
81. Arras et al., arXiv:1904.11829, 2019.
82. Zhao & Bolouri, JBI, 2016.
83. Lim et al., MBEC, 2022.
84. Linardatos et al., Entropy, 2020.
85. Loh et al., Comp. Meth. Biomed., 2022.
86. Lötsch et al., BioMedInformatics, 2021.
87. Pocevičiūtė et al., in Springer Pathology Book, 2020.
88. Aminu et al., AEJ, 2021.
89. Ancona et al., arXiv:1711.06104, 2017.
90. Barandas et al., Electronics, 2022.
91. Belkin & Niyogi, NIPS, 2001.
92. DeCamp & Lindvall, JAMIA, 2020.
93. Graber et al., Arch. Intern. Med., 2005.
94. Nazar et al., IEEE Access, 2021.
95. Mondal et al., PLOS One, Curr. Med. Imaging, Inf. Med. Unlocked, 2020–21.
96. Hossain et al., IEEE Network, 2020.
97. Sundararajan et al., PMLR, 2017.
98. Ribeiro et al., KDD, 2016.
99. Wu et al., AAAI, 2018.
100. Mathews, in Springer Intelligent Computing, 2019.
101. Mi et al., IEEE Access, 2020.
102. Minh et al., AI Review, 2022.
103. Frosst & Hinton, arXiv:1711.09784, 2017.
104. Prentzas et al., IEEE BIBE, 2019.
105. Weingart et al., BMJ, 2000.
106. Oh et al., Diagnostics, 2021.
107. Ong et al., IEEE ICSIPA, 2021.
108. Comon, Signal Processing, 1994.
109. Croskerry et al., Diagnosis: Interpreting the Shadows, 2017.
110. Esmaeilzadeh, BMC Med. Informatics, 2020.
111. Podder et al., in Data Science for COVID-19, Elsevier, 2021.
112. Peng et al., Journal of Medical Systems, 2021.
113. Ploug & Holm, AI in Medicine, 2020.
114. Bro & Smilde, Analytical Methods, 2014.
115. Basnet et al., Biomed. Signal Process. Control, 2021.
**116.** Caruana et al., KDD, 2015.