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DEEP LEARNING'S OBSTACLES IN MEDICAL IMAGE ANALYSIS: BOOSTING TRUST AND EXPLAINABILITY

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Abstract—**The use of deep learning has revolutionised the detection of diseases and enabled the creation of robust and precise computer-assisted diagnostic tools in the healthcare sector. Artificial intelligence (AI) tools can now detect cancers, internal bleeding, fractures, and more without human intervention, all thanks to deep learning. The flourishing healthcare industry is at grave risk from deep learning. Lack of balanced annotated medical image data, adversarial attacks on deep neural networks and architectures owing to noisy medical image data, user and patient distrust, and ethical and privacy issues related to medical data are some of the significant challenges faced by deep learning researchers and engineers, especially in medical image diagnosis. These issues are addressed in this paper. This study defines public scepticism of AI by exploring its potential applications in healthcare.**

Index Terms—**Medical image analysis, adversarial attacks, CAD systems, convolutional neural networks, data augmentation, deep learning.**

I. INTRODUCTION

The previous decade's revolution in artificial intelligence (AI) has affected health care, remote sensing, robotics, autonomous driving, and many other transdisciplinary sectors [1,2]. Machine learning (ML) has helped researchers and engineers solve various biomedical and data processing problems [3, 4]. ML develops and applies information for each task. Machine learning algorithms excel at linear data but struggle with complex medical data [5]. Deep Learning—artificial intelligence—outperforms machine learning in medical picture recognition due to its adaptability, precision, and deep feature learning [6]. Deep Learning faces various challenges. These include privacy and moral difficulties, a lack of annotated medical picture data, and lossy data with artefacts and attenuations. Users also distrust deep learning-based products like CAD. Researchers and engineers worry these challenges are slowing medical deep Learning.

Image artefacts and noise induce bias and misprediction, causing adversarial attacks. CT scans show ring, beam-hardening, scatter, and metal artefacts [7], whereas MRI scans show motion artefacts [8]. Speckle, Poisson, and Gaussian noise are common in medical pictures [9]. Medical professionals must manually denoise image data to construct and assess deep learning models. This method takes longer and requires more space to complete CAD projects.

Large datasets are needed to train and test practical deep-learning algorithms, yet annotated medical picture data is still being determined. The tedious and costly procedure ofMedical practitioners must supervise photo tagging. Data shortage makes deep neural network training difficult. If class data is imbalanced, the dataset may be distorted.

Deep neural network causes overfit diagnosis and predictions. Modern deep learning representation learning approaches can generate many medical images from a small set [10,11]. Augmented datasets help train deep neural networks, but the community should be more open about them.

Many doubt deep learning models, which are "black box" techniques. There are significant worries about hospitals' use of black-box diagnostics. Some medical specialists use deep networks, but only some are prepared to take the risk, making AI hard to trust. CAD confidence must be increased by investigating and providing deep network explainability.

Due to privacy and ethical considerations, deep learners do not share medical picture data. Healthcare cloud computing might reach 89 billion USD by 2027 [12]. Still, unless the technology is open source, there needs to be a system in place to safeguard user data and stop counterfeiting. Health record protection laws differ by country. The United States government passed the Health Insurance Portability and Accountability Act (HIPAA) in 1996 to avoid the unwarranted disclosure of private patient health information. Since it is legally protected, healthcare practitioners must secure, limit use, and communicate patients' personally identifiable information. Deep Learning engineers must maintain patient privacy. Third among seventeen objectives set out by the United Nations in their 2015 "Sustainable Development Goals" to be achieved by 2030 is to "Ensure healthy lives and promote well-being for all at all ages." Due to inadequate infrastructure, medical treatment and diagnosis in rural areas can be challenging in underdeveloped countries. Nearly all United Nations member states experienced disruptions to healthcare [13]. Society became aware of the problems with manual, contact-based diagnosis when it wreaked havoc on healthcare. The second part of the pandemic saw the successful implementation of CAD-based contactless diagnostic proposals. Trust in AI-based diagnostic systems is crucial for society to attain health supremacy. By decreasing diagnosis time, minimizing incorrect diagnoses, and lowering death rates, moving away from manual healthcare diagnosis and towards efficient CAD-based diagnostic systems can pave the way for a significant expansion of the healthcare system. AI-based solutions would enhance the quality of human life by facilitating societal acceleration in healthcare.

Concerning healthcare and medical image processing, our research centred on the challenges, explainability, trustworthiness, and future possibilities of deep learning algorithms. Here, we take a look at:

1) Deep networks are vulnerable to adversarial attacks due to attenuation.
2) Need for more data and partiality.

Three issues with trust and explainability.

4) Medical data privacy and legal considerations.

The rest of the paper is organised as follows. Section II discusses healthcare-related Learning. Section III discusses covers ethics, and Section IV discusses conclusion.

II. HEALTH CARE-RELATED DEEP LEARNING

Healthcare facilities increasingly use artificial intelligence to help with patient diagnosis and treatment. With its remarkable speed and accuracy, deep learning has recently transformed how machine data is analyzed and handled. This hierarchical method employs complex and deep structures to learn nonlinear data efficiently. Surgical system design for intraoperative and preoperative support, illness detection, and biological image processing are three areas where deep learning has demonstrated promise. According to a U.S. poll, AI is well-understood and trusted in the healthcare industry [14]. To communicate with their healthcare providers and access their medical records, 58% of patients use various patient-facing healthcare technologies, according to the survey. It was also revealed that 52% of people trust AI with their medical issues. This illustrates the importance of AI with outstanding performance that can handle several issues.

For artificial intelligence to succeed in healthcare, it needs to comprehend medical data, figure out how to process it and use computer-aided design (CAD) tools to provide trustworthy outcomes. It is crucial to comprehend medical data to use healthcare data and resources effectively and get trustworthy outcomes. Once deep learning engineers have trained and optimised the CAD's deep learning model, the system will utilise the medical image to predict the user's diagnosis. Combating hostile assaults and attenuations is something the CAD system is prepared to do. Sharing models' inner workings and projections helps human analysts have faith in the model's predictions and see errors in the models. Users provide data to the healthcare facility's cloud to further CAD research. Users can report inaccurate diagnoses to the development team for evaluation. To limit misdiagnosis and gain users' confidence, CADs must be field tested and progressively retrained using real-time data before they can be utilised in medicine. To enhance their efficacy, these AI-based CADs require validation from medical experts.

III. ETHICAL PRINCIPLES AND PROSPECTS FOR FURTHER RESEARCH

Healthcare providers increasingly use AI to diagnose and treat patients. Due to its speed and precision, deep learning has revolutionized machine data analysis and handling. Complex and deep structures help this hierarchical technique learn nonlinear data quickly. Surgical system design for intraoperative and preoperative support, sickness diagnosis, and biological image processing are three domains where deep learning is promising. AI in healthcare is understood and trusted, according to a U.S. poll [14]. 58% of patients use patient-facing healthcare technologies to contact their doctors and access their medical records. Tech: Previous issues with deep learning in medical picture diagnosis divide the public and the deep learning community. Society's ignorance and skepticism of intelligent autonomous healthcare and diagnosis systems hinder AI-based healthcare systems' autonomy.

To address patient concerns about data security, confidentiality, and integrity, deep learning systems can incorporate ethical principles, including transparency, explainability, fairness, non-maleficence, responsibility, and privacy. Organisational AI ethics must be addressed continuously. Ethical AI requires many stakeholders and technological and non-technical governance mechanisms. Emerging practices include risk assessment, competence and knowledge building, stakeholder communication, cross-functional cooperation, data governance, IT governance, MLOps, and AI design.

Learning new skills and information can help ethically use AI. Companies communicate with stakeholders on ethical AI. Information, programmes. "AI design and development" and "data and AI governance" are operational decisions and practises businesses use to address ethical concerns about AI system deployment, development, and use, although the former is MLOps' practical approach. Responsible AI systems are crucial. Thus, deep learning engineers must build task-specific systems carefully. To preserve data privacy and reduce algorithmic bias from noisy data or foreign attacks, models must undergo many performances and explainability tests for different data and tasks. Penetration testing and robust software are also needed for CADs [15].

Traditional AI's healthcare constraints can be overcome by ethical AI system best practices:

- **a.** Share your discoveries, instruments, databases, and other resources.
- **b.** Consider machine learning problems while designing reliable and efficient AI systems for user-centered apps.
- **c.** Track current and future issues, estimate performance, and ask users about new features.
- **d.** Regularly updating systems and discovering easy and optimal ways to balance user input and real-time performance.
- **e.** Iterate between consumers' use cases and gold standard datasets to integrate and isolate subsystems.
- **f.** Be honest about the dataset and model's limits when explaining the training's depth. Assess the costs and benefits of mistakes and experiences using many parameters.

The "explainable AI frameworks" describe how a model works. SHAP describes models independently of them using game theory's Shapley values. It shows how features affect model output or conclusion. Local Interpretable Model-agnostic Explanations show how each feature affects data sample forecasts. Google's Whatif Tool helps understand machine learning (ML) fairness measures, data properties, subsets of input data, and ML-trained model performance in hypothetical circumstances. IBM's open-source AI Explainability 360 tools improve dataset and ML interpretation. Skater develops interpretable, practical machine learning systems. Maintaining and evolving health with XAI is possible.

The research analyses the difficulties qualitatively but does not provide quantitative data on nations or continents that could benefit from CADs in healthcare. CAD implementation in rural areas requires additional infrastructure, which hinders AI's healthcare dominance. Future studies may address AI governance organisation dynamics. Future studies could focus on data, AI, and IT governance.

Recent medical imaging experiments with AI explainability and adversarial training have yielded impressive results. CADs with accountable AI systems, secure data protection, and easy-to-use tools could improve neglected health care. The study found that establishing future AI standards, certifications, audits, and risk analysis will be exciting in light of emerging AI policies and legislation. Additionally, 52% of individuals trust AI with medical difficulties. This shows the necessity of AI with excellent performance that can solve many problems.

Artificial intelligence must understand medical data, process it, and apply CAD tools to produce reliable results in healthcare. Medical data must be understood to use healthcare resources effectively and produce reliable results.
The CAD's deep learning model will utilise the medical image to anticipate the user's diagnosis after deep learning engineers train and refine it. The CAD system can fight hostile attacks and attenuations. Medical images that are severely distorted can lead to inconclusive diagnoses. Sharing model inner workings and projections helps human analysts trust model predictions and spot mistakes. Users provide data to the hospital's cloud for CAD research. Users can submit incorrect diagnoses to development for review. Before being used in medicine, CADs must be field tested and retrained, utilising real-time data to reduce misdiagnosis and build user confidence. Medical specialists must validate AI-based CADs to improve their efficacy.

CONCLUSION

From disease classification to probing AI-supervised robots for surgery, AI offers tremendous promise in healthcare despite the difficulties of deep learning. Restoring human faith in AI through awareness is the only way for deep learning to grow in medical image detection. It is essential to detail the model development process, the model's influence, and how systems produce output. However, solutions based on deep learning need also be fine-tuned adaptively to account for quality degradation over time. Transparency is critical in deep learning-based solutions, which include tackling AI explainability difficulties and ensuring user privacy and security.
Additionally, there should be no bias in data collection, labelling, treatment, or model operations. Deep learning can improve decision-making and usability by optimising the technical, ethical, and social components of medical picture analysis. This can be achieved through responsibility and XAI, which entails AI and humans complementing, co-creating, and coexisting.

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