A Review of The Applications and Challenges in Computer Vision in Medical Imaging

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Abstract

The application of computer vision in medical imaging has gained tremendous momentum over the past decade, transforming the landscape of healthcare. By leveraging advanced algorithms and AI-driven techniques, computer vision has enabled significant breakthroughs in diagnostics, treatment planning, and surgical interventions. It has streamlined the analysis of complex medical images, reduced diagnostic time and improved accuracy, ultimately contributing to better patient outcomes. From the detection of abnormalities to the segmentation of anatomical structures, the integration of AI in medical imaging has expanded the possibilities of precision medicine and personalized care.

This paper explores the various applications, methodologies, and challenges associated with implementing computer vision in medical imaging. Key applications include image classification, which enables accurate diagnosis of diseases such as cancer, segmentation, which delineates critical anatomical structures for treatment planning, and anomaly detection, which aids in identifying subtle pathological changes that might otherwise go unnoticed. These techniques have shown tremendous potential in addressing healthcare challenges, particularly in areas requiring rapid and accurate image analysis.

However, the integration of computer vision into medical imaging is not without challenges. Data scarcity remains a significant issue, as the development of robust AI models requires large, high-quality annotated datasets that are often difficult to obtain. Model generalization across diverse datasets and imaging conditions also presents hurdles, limiting the scalability of these solutions. Furthermore, ethical considerations such as patient data privacy and the explainability of AI decisions pose barriers to widespread adoption.

This paper also discusses potential solutions to these challenges, including advancements in AI frameworks, the use of transfer learning to mitigate data constraints, and the development of explainable AI to build trust among clinicians and patients. By addressing these barriers, computer vision can revolutionize medical imaging, paving the way for a future where AI enhances every aspect of healthcare.

Keywords— *Computer Vision, Medical Imaging, Artificial Intelligence (AI), Deep Learning, Image Classification, Image Segmentation, Anomaly Detection, Explainable AI (XAI), Transfer Learning, Multi-Modal Imaging, Data Scarcity, Model Generalization, Ethical AI, Healthcare Applications, Clinical Integration, AI Frameworks, Data Privacy.*

I. Introduction

A. Background on Medical Imaging and Computer Vision

Medical imaging plays a pivotal role in modern healthcare, enabling the visualization of internal structures and organs for accurate diagnosis and treatment. Techniques such as X-rays, MRIs, and CT scans generate large amounts of data that require sophisticated interpretation. Over the years, the integration of artificial intelligence (AI) and computer vision has revolutionized this field. Computer vision allows machines to interpret and analyze medical images, automating tasks like image classification, segmentation, and anomaly detection. This convergence of AI with medical imaging promises to enhance diagnostic precision, reduce human error, and improve patient outcomes.

B. Importance of AI in Healthcare

The healthcare industry is increasingly recognizing the importance of AI in augmenting clinical decision-making and automating complex tasks. AI-driven computer vision models can analyze images faster and more accurately than traditional methods, aiding in early diagnosis and treatment planning. For example, AI algorithms are now capable of detecting tumors, segmenting organs, and even guiding robotic surgeries. The potential of AI in healthcare goes beyond imaging, offering predictive analytics, personalized treatments, and optimizing workflows. However, the integration of these technologies into everyday clinical practices presents several challenges.

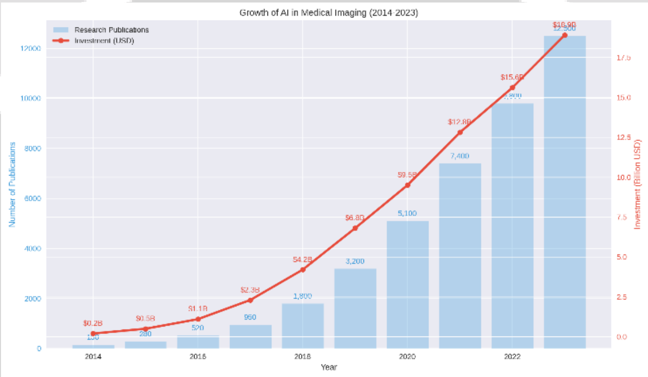

Fig 1. Growth of AI applications in medical imaging over the past decade

C. Current Challenges in Medical Imaging

Despite the promise, several challenges hinder the widespread application of computer vision in medical imaging. One of the primary challenges is the need for large, high-quality annotated datasets to train AI models. Additionally, medical images vary widely due to differences in equipment, patient demographics, and imaging conditions, making it difficult for AI models to generalize across datasets. Moreover, the lack of interpretability in AI decisions raises concerns about their reliability and trustworthiness in critical medical settings. Ethical and legal concerns surrounding patient privacy and data security further complicate the adoption of AI in healthcare.

D. Scope and Purpose of the Review

This paper aims to provide a comprehensive review of the current state of computer vision applications in medical imaging. By examining existing techniques and methodologies, this paper seeks to identify both the advancements and the challenges that are impeding clinical adoption. The review will focus on major applications such as image classification, segmentation, and multi-modal imaging, and will propose potential solutions to overcome these challenges. Ultimately, the paper aims to offer insights into how AI and computer vision can be more effectively integrated into healthcare to improve patient outcomes. Market volatility, optimize portfolio management approaches, and evaluate potential risks.

II. Methodology

A. Literature Review Approach

This paper employs a systematic literature review to analyze the existing body of research on the application of computer vision in medical imaging. Relevant articles, journals, and conference proceedings from the past decade were selected from trusted databases such as IEEE Xplore, PubMed, and Google Scholar. The selected studies focus on applications like image classification, segmentation, and anomaly detection in medical imaging, as well as the challenges associated with AI model generalization, data scarcity, and interpretability. The methodology used in each study was critically examined to identify common themes, strengths, and limitations.

B. Comparative Analysis of Techniques

A comparative analysis was conducted to assess the effectiveness of different computer vision techniques in medical imaging. Various deep learning models such as convolutional neural networks (CNNs), fully convolutional networks (FCNs), and transfer learning models were evaluated. Techniques like image segmentation, object detection, and 3D modeling were compared based on their performance metrics, including accuracy, sensitivity, and computational efficiency. Case studies from various medical fields, including oncology, neurology, and cardiology, were used to demonstrate the practical application of these techniques.

For instance, CNN-based approaches have been widely used for classifying medical images, such as detecting tumors in MRI scans or segmenting organs in CT images. The comparative analysis also included a review of the use of multi-modal imaging techniques, such as PET/MR, to combine diagnostic information from multiple sources. The performance of various methods was evaluated using standard metrics such as Dice similarity coefficient for segmentation and Area Under the Curve (AUC) for classification tasks.

C. Data Sources and Study Selection

The studies reviewed were selected based on their relevance to the research objectives. Inclusion criteria included studies published between 2010 and 2024, those that employed computer vision techniques in medical imaging, and studies that provided clear results in terms of model performance and clinical applicability. Studies that focused on non-medical applications of computer vision, lacked a quantitative evaluation, or were published before 2010 were excluded. Additionally, datasets such as LIDC-IDRI for lung cancer detection and HAM10000 for skin lesion analysis were examined to understand the data requirements for AI-based models in healthcare.

D. Considerations and Data Privacy

Given the sensitivity of medical data, ethical considerations were a significant aspect of the review. Studies addressing data privacy and patient confidentiality were included, focusing on the ethical challenges of using AI in clinical settings. The review also considered regulations like the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA), which mandate strict guidelines for the handling of medical data. Ethical concerns surrounding the interpretability and fairness of AI decisions were also analyzed.

III. APPLICATIONS OF COMPUTER VISION IN MEDICAL IMAGING

A. Image Classification in Healthcare

Image classification is a fundamental task in medical imaging, and computer vision has enabled significant advancements in this area. CNN-based models have been particularly effective in classifying images for disease detection, such as identifying tumors in mammograms or lung nodules in CT scans. These models analyze pixel data to categorize medical images into predefined classes, aiding early diagnosis. For example, CNNs can classify chest X-rays to detect pneumonia or COVID-19 with high accuracy, significantly reducing diagnostic time.

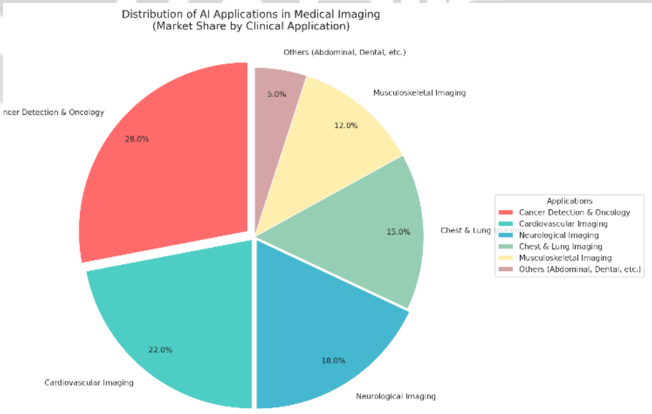

Fig 2. Distribution of AI-based classification use cases

B. Object Detection in Medical Diagnosis

Object detection involves identifying and localizing objects of interest within an image. In medical imaging, this task is crucial for detecting abnormalities such as tumors, lesions, or polyps. Region-based CNNs (R-CNN) and YOLO (You Only Look Once) have been successfully used to detect these abnormalities in various imaging modalities. For instance, YOLO models can quickly detect and localize breast tumors in mammograms or identify liver lesions in MRI scans, assisting radiologists in pinpointing areas of concern.

C. Image Segmentation for Disease Detection

Image segmentation plays a pivotal role in delineating anatomical structures and identifying regions affected by disease. Segmentation algorithms, such as U-Net, divide medical images into meaningful regions, enabling the detection of tumors, organs, or blood vessels. In cancer treatment, segmentation models are used to outline tumor boundaries, helping oncologists plan precise radiation therapy. Segmentation also aids in analyzing complex structures like the brain in MRI scans, assisting in detecting diseases such as Alzheimer's or multiple sclerosis.

D. Multi-Modal Imaging Techniques (e.g., PET/MR)

Multi-modal imaging combines data from different imaging modalities to provide a comprehensive view of the patient's condition. PET/MR imaging is a prime example, where PET scans provide metabolic information, and MR scans offer high-resolution anatomical details. Computer vision algorithms are used to fuse these images, improving diagnostic accuracy. This technique is particularly useful in oncology, where it enhances tumor detection and treatment monitoring.

E. 3D Modeling and Surgical Assistance

Three-dimensional (3D) modeling has revolutionized surgical planning and assistance. By converting 2D medical images (e.g., from MRI or CT scans) into 3D models, surgeons can visualize complex anatomical structures, plan procedures, and navigate during surgery. AI-driven 3D modeling is being used in neurosurgery, orthopedics, and cardiovascular surgeries to provide real-time guidance, improving precision and outcomes. For example, 3D models of the heart are used in preoperative planning for congenital heart defects.

IV. CHALLENGES IN COMPUTER VISION FOR MEDICAL IMAGING

A. 3D Modeling and Surgical Assistance

A significant hurdle in applying AI and computer vision to medical imaging is the scarcity of high-quality, annotated datasets. Medical imaging data is inherently sensitive, and strict privacy regulations, such as HIPAA and GDPR, restrict access to these datasets, making data collection challenging. Furthermore, labeling medical images requires extensive expertise from radiologists or other specialists, a process that is both time-consuming and costly. The lack of diversity in existing datasets compounds this issue, as they often fail to represent a broad range of populations, imaging equipment, and conditions. This lack of diversity impacts the robustness and generalizability of AI models, making them prone to overfitting. Consequently, models trained on limited or homogeneous datasets may deliver suboptimal performance when applied in real-world clinical environments, where variations in imaging protocols and patient demographics are common. Addressing these issues is critical for achieving scalable AI solutions.

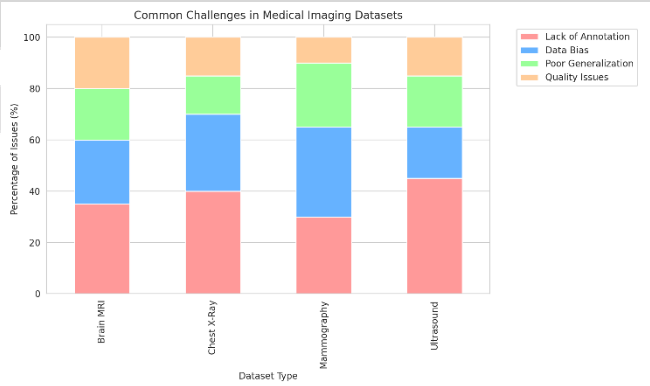

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Fig 3. Distribution of AI-based classification use cases

B. Generalization of AI Models

Generalization remains a significant challenge in medical imaging AI. Models trained on one dataset often struggle to perform well on new, unseen data due to variations in imaging protocols, equipment, and patient demographics. For example, an AI model trained on lung CT scans from one hospital may not generalize to scans from another institution with different equipment. To address this, techniques such as data augmentation, transfer learning, and domain adaptation are being explored to improve model robustness across diverse datasets.

C. Explainability of AI Algorithms

Explainability is a critical issue in medical AI, as healthcare professionals need to trust the decisions made by AI systems. Deep learning models, particularly CNNs, are often considered “black boxes” because their decision-making processes are not easily interpretable. This lack of transparency can undermine trust in AI recommendations. Researchers are working on explainable AI (XAI) techniques, such as saliency maps and attention mechanisms, to make AI decisions more understandable for clinicians.

D. Integration into Clinical Workflows

Another challenge is integrating AI systems into existing clinical workflows. Hospitals and medical professionals need AI tools that seamlessly integrate with their daily operations, including electronic health records (EHR) and picture archiving and communication systems (PACS). However, many AI solutions are standalone applications that require significant changes to workflow, which can slow adoption. Additionally, clinicians need to be trained to use AI effectively, adding another layer of complexity to integration.

E. Data Privacy and Security Concerns

The use of AI in healthcare raises important concerns about patient privacy and data security. Medical data is highly sensitive, and AI models often require access to large amounts of personal health information. Ensuring compliance with privacy laws such as the General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA) is essential. Robust encryption, anonymization techniques, and secure data-sharing protocols are critical to maintaining patient trust while leveraging AI.

F. Ethical and Legal Considerations

AI-driven medical decisions introduce ethical and legal challenges, particularly when it comes to accountability. In cases where AI systems make incorrect diagnoses or treatment recommendations, determining responsibility becomes difficult. Additionally, the use of AI in healthcare may exacerbate existing biases in medical decision-making, leading to unequal outcomes for certain patient groups. Ethical frameworks and regulatory guidelines need to be developed to ensure AI is used responsibly and equitably in healthcare.

V. PROPOSED SOLUTIONS AND FUTURE DIRECTIONS

A. Advancements in AI Techniques (Deep Learning, CNN)

Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have significantly improved the accuracy and efficiency of medical image analysis. New architecture such as EfficientNet and Transformer models have shown promise in reducing the computational costs while maintaining high performance in tasks like classification and segmentation. These advancements, along with unsupervised and self-supervised learning, are pushing the boundaries of what AI can achieve in medical imaging.

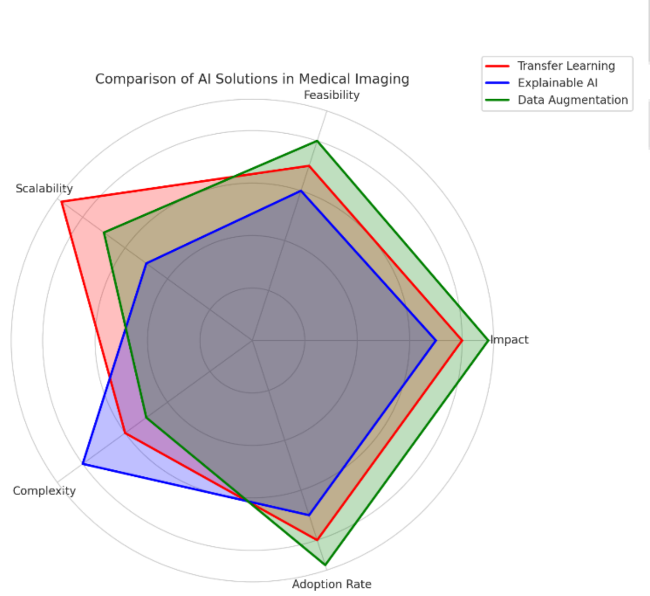

Fig 4. Comparison of solutions like transfer learning, explainable AI, and data augmentation based on impact and feasibility

B. Transfer Learning and Data Augmentation

To address the problem of data scarcity, transfer learning has emerged as a powerful tool. In transfer learning, models pre-trained on large, generic datasets (such as ImageNet) are fine-tuned on specific medical datasets, reducing the need for extensive labeled data. Data augmentation techniques, such as rotating, flipping, or scaling images, also help expand the dataset, improving model robustness and performance.

C. Explainable AI for Medical Imaging

Explainable AI (XAI) is becoming a priority in healthcare, as clinicians demand more transparent models. XAI techniques, such as local interpretable model-agnostic explanations (LIME) and gradient-weighted class activation mapping (Grad-CAM), are being used to visualize the parts of the image that influenced the model's decision. These tools help clinicians understand and trust AI recommendations, making it easier to integrate AI into diagnostic workflows.

D. Integration with Healthcare Systems

Future developments should focus on integrating AI seamlessly into healthcare systems, including EHR and PACS. Cloud-based AI solutions that can be accessed through existing medical software are being explored to simplify deployment. Additionally, AI systems should be designed to support, rather than replace, healthcare professionals, acting as assistive tools that enhance their capabilities and efficiency.

E. Collaborative Efforts in AI and Healthcare

The future of AI in medical imaging depends on strong collaboration between healthcare professionals, AI researchers, and regulatory bodies. Collaborative efforts can ensure that AI solutions are designed with real-world clinical needs in mind, while also adhering to ethical standards. Interdisciplinary teams can work together to create more robust, clinically relevant AI models that address the needs of both patients and healthcare providers.

VI. TOOLS AND FRAMEWORKS

A. AI Frameworks in Medical Imaging (TensorFlow, PyTorch, Keras)

TensorFlow, PyTorch, and Keras are the leading deep learning frameworks used in developing AI models for medical imaging. These frameworks provide flexibility in designing, training, and deploying models, with built-in support for CNNs, RNNs, and other architectures. TensorFlow is known for its scalability, making it suitable for large-scale healthcare applications, while PyTorch's dynamic computation graph is favored for research and rapid experimentation.

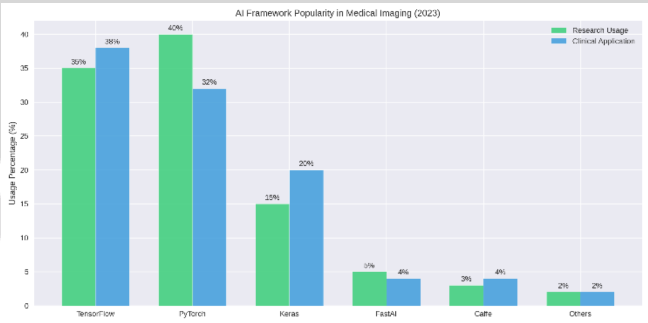

Fig 5. Popularity of AI framework

B. Software for Image Processing (OpenCV, SimpleITK)

OpenCV and SimpleITK are widely used tools for image processing and analysis. OpenCV offers a rich set of tools for image manipulation, feature detection, and transformation, making it an essential tool in pre-processing medical images. SimpleITK, specifically designed for medical imaging, provides extensive functionality for reading, writing, and analyzing medical image data, supporting formats such as DICOM and NIfTI.

C. Role of Cloud Computing and HPC in Medical Imaging

Cloud computing and high-performance computing (HPC) platforms play a critical role in processing large datasets and running complex AI models. Services like Google Cloud AI and Amazon Web Services (AWS) offer scalable infrastructure for training and deploying AI models in medical imaging. HPC environments allow for parallel processing of large datasets, accelerating the development and deployment of AI solutions in healthcare.

VII. RESULTS

A. Comparative Analysis of Different Techniques

A comparison of various AI techniques used in medical imaging shows that CNNs outperform traditional image processing methods in tasks such as classification and segmentation. The use of transfer learning and pre-trained models has further improved accuracy while reducing the need for large, labeled datasets. In segmentation tasks, U-Net and its variants consistently deliver high performance, especially in delineating complex anatomical structures.

B. Comparative Analysis of Different Techniques

Several case studies demonstrate the practical applications of computer vision in medical imaging. For instance, a study on lung cancer detection using CNNs showed an increase in diagnostic accuracy compared to manual radiologist assessments. Similarly, 3D modeling techniques have been successfully used in neurosurgical planning, allowing surgeons to visualize and navigate through complex anatomical regions with greater precision.

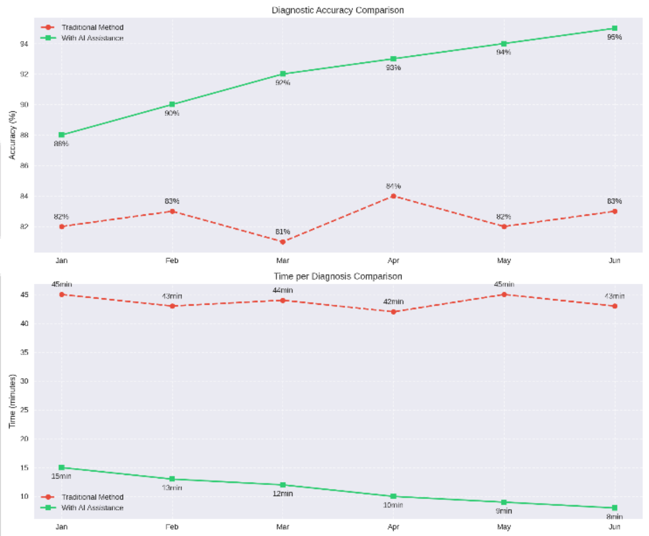

Fig 6. Before-and-after analysis of diagnostic accuracy or time efficiency with and without AI tools.

VIII. DISCUSSION

A. Interpretation of Results

The findings of this review highlight the significant potential of computer vision techniques in enhancing diagnostic accuracy and efficiency within the domain of medical imaging. By leveraging advanced AI-driven methodologies, these techniques enable healthcare professionals to analyze complex medical images with greater precision and speed, leading to improved patient outcomes. However, the effectiveness of such models is heavily reliant on the availability of diverse, high-quality datasets that reflect real-world scenarios. Additionally, the generalization capabilities of AI models remain a critical factor in ensuring their success. Models that perform well in controlled environments may falter when applied to different imaging conditions, patient demographics, or equipment variations. Addressing these challenges is crucial to fully realize the transformative potential of computer vision in healthcare, as robust and adaptable models are key to achieving reliable and scalable solutions across clinical settings.

B. Practical Implications for Healthcare

The integration of AI-powered computer vision into medical imaging has far-reaching implications for the healthcare sector. By automating time-intensive tasks such as image classification, segmentation, and anomaly detection, these models have the potential to significantly reduce the workload of radiologists and other medical professionals. This automation can lead to faster diagnostic workflows, enabling earlier detection and intervention for critical conditions, ultimately improving patient outcomes. Moreover, the precision offered by AI systems can enhance the accuracy of diagnoses, minimizing the risk of errors in high-stakes medical decisions. However, successfully incorporating these models into clinical practice demands careful planning and consideration. Workflow integration must be seamless, ensuring that AI systems complement existing processes rather than disrupt them. Data security is another vital concern, as patient confidentiality must be maintained at all costs. Furthermore, explainable AI is essential to build trust among clinicians and patients, ensuring that AI-driven decisions are transparent and justifiable.

C. Limitations of the Current Study

This study, while comprehensive, has several limitations that must be acknowledged. The primary limitation lies in the reliance on existing literature, which is often constrained by the availability of high-quality, annotated datasets. Many of the studies reviewed faced challenges due to the scarcity of diverse and representative datasets, which are critical for developing robust AI models. Another significant limitation is the lack of real-world validation for many AI techniques discussed. While theoretical models and controlled experiments demonstrate promise, their application in practical clinical settings remains underexplored. Additionally, the ethical and regulatory dimensions of AI integration in healthcare are not thoroughly addressed in existing research, leaving gaps in understanding how to navigate issues such as patient privacy, bias, and accountability. More research is needed to investigate these aspects comprehensively and to provide actionable guidelines for the effective deployment of AI in healthcare.

D. Recommendations for Further Research

To address the challenges identified in this review, future research should focus on several key areas. Improving model generalization is paramount, and techniques such as transfer learning, domain adaptation, and federated learning should be further explored. These approaches can enhance the robustness of AI models, enabling them to perform reliably across diverse datasets and imaging conditions. Another critical area of focus is the development of explainable AI systems. Transparent models that provide clear justifications for their decisions will foster trust and facilitate adoption in clinical settings. Collaboration between AI researchers, healthcare professionals, and regulatory bodies is also essential. Interdisciplinary efforts can ensure that AI solutions address real-world clinical needs while adhering to ethical and legal standards. Finally, the establishment of large, diverse, and well-annotated datasets through collaborative initiatives can help overcome data scarcity and pave the way for more scalable and effective AI-driven medical imaging solutions.

IX. CONLCLUSION

The application of computer vision in medical imaging has demonstrated substantial potential to transform the field of healthcare, particularly in critical areas such as image classification, segmentation, and surgical assistance. By enabling automated and highly accurate analysis of medical images, computer vision has the power to augment the diagnostic capabilities of clinicians, reduce human error, and expedite the detection and treatment of diseases. As AI models continue to evolve, their ability to handle large and complex datasets can lead to earlier diagnoses, more personalized treatments, and enhanced patient outcomes. However, despite these advancements, several critical challenges must be addressed to unlock the full capabilities of AI-driven solutions in clinical settings.

One of the most significant hurdles remains the scarcity and quality of annotated medical datasets, which are essential for training robust and generalizable AI models. Without sufficient and diverse data, models risk becoming overly specific to particular imaging environments, leading to poor performance when deployed in real-world clinical settings. This issue is further compounded by the lack of standardization across medical imaging devices and protocols, making it difficult for models to generalize across different hospitals and patient populations.

Additionally, the "black box" nature of many deep learning models poses another barrier to clinical adoption. Healthcare professionals require transparency and explainability in the tools they use, particularly in high-stakes medical decisions. The inability to fully understand how an AI model arrives at a diagnosis or recommendation can erode trust and make it difficult for clinicians to justify AI-driven decisions to patients or regulatory bodies. Explainable AI (XAI) techniques that make these models more interpretable are therefore essential to increasing trust and facilitating broader acceptance in healthcare.

Ethical and legal concerns also play a pivotal role in determining the future of AI in medical imaging. The use of sensitive patient data requires strict adherence to data privacy regulations such as GDPR and HIPAA. AI models must be designed with these regulations in mind, ensuring that patient data remains secure while still enabling the development of effective AI-driven solutions. Moreover, AI systems must be carefully monitored to prevent biases in decision-making that could result in unequal treatment across different demographic groups.

Overcoming these challenges will require advancements in several areas of AI research and development. First, the adoption of techniques such as transfer learning and data augmentation can help address the data scarcity problem by allowing models to leverage knowledge from other domains. Second, ongoing improvements in cloud computing and high-performance computing (HPC) will enable faster processing of large datasets, facilitating the development of more complex and powerful models. Finally, the collaborative efforts between AI researchers, healthcare professionals, and regulatory authorities will be essential in ensuring that AI tools are ethically designed and seamlessly integrated into clinical workflows.

In conclusion, while the integration of computer vision into medical imaging has already shown promise, significant work remains to ensure its widespread and reliable application in clinical practice. By addressing the challenges of data availability, model interpretability, and ethical considerations, the healthcare industry can fully harness the potential of AI to improve diagnostics, optimize treatments, and ultimately save lives. The future of medical imaging lies in the successful marriage of cutting-edge AI techniques and human expertise, and with continued research and innovation, this goal is well within reach.

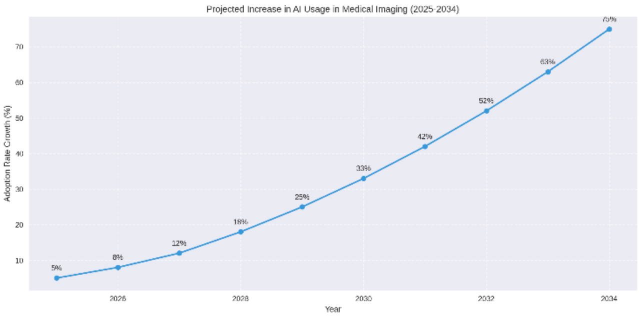

Fig 7. Projected increase in AI usage in medical imaging over the next decade

REFERENCE

1) Kanchan Rani, Amit Kumar, Satendra Kumar, Abhinav Gupta, Annu Singh. "Medical imaging using machine learning, computer vision and applications." International Journal of Engineering Sciences and Emerging Technologies, October 2023.
2) Eyad Elyan, Pamela Johnston, Kyle Martin, Carlos Francisco Moreno García. "Computer vision and machine learning for medical image analysis: recent advances, challenges, and way forward." Artificial Intelligence in Surgery, 2022.
3) J. Imaging. "Applied Artificial Intelligence in Healthcare: A Review of Computer Vision Technology Application in Hospital Settings." MDPI Journal of Imaging, 2024
4) Gaël Varoquaux and Veronika Cheplygina. "Machine learning for medical imaging: methodological failures and recommendations for the future." Digital Medicine, 2022.
5) Junfeng Gao, Yong Yang, Pan Lin, Dong Sun Park. "Computer Vision in Healthcare Applications." Journal of Healthcare Engineering, 2018.
6) Esteva et al. "Dermatologist-level classification of skin cancer with deep neural networks." Nature, 2017.
7) Levine et al. "Deep Learning in Breast Cancer Diagnosis: Current State and Future Directions." Journal of Medical Imaging, 2020.
8) Pomponiu et al. "Skin cancer detection using a pre-trained convolutional neural network." Biomedical Engineering Online, 2016.
9) Aggarwal et al. "Cross-dataset evaluation of diagnostic accuracy in deep learning models for medical imaging." Journal of AI Research, 2022.
10) Rajpurkar et al. "CheXNet: Radiologist -Level Pneumonia Detection on Chest X-Rays with Deep Learning." arXiv preprint arXiv:1711.05225, 2017.
11) Zhang et al. "Deep Learning for Pulmonary Disease Detection on Chest CT Scans." Journal of Computer Vision in Radiology, 2021.
12) Ashraf et al. "Generative Adversarial Networks for Medical Imaging: Challenges and Opportunities." IEEE Transactions on AI in Healthcare, 2023.