A REVIEW ON ADVANCEMENTS IN BIOMEDICAL IMAGE PROCESSING: 2015–2025

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Abstract

In the last decade, biomedical image processing has made substantial progress. It could be largely attributed to the development of deep learning and artificial intelligence (AI) and innovative ways it is incorporated to biomedical image processing. This paper examines major advancements in the field from 2015 to 2025, with a broad focus on three areas: deep tomographic reconstruction, AI-powered diagnostic tools, and cutting-edge methods for medical image segmentation. These innovations have significantly enhanced the precision and effectiveness of medical imaging, offering promising possibilities for more individualized and prompt healthcare. The objective of this paper is to review these developments, identify ongoing challenges, and explore the potential for AI technologies to continue transforming the landscape of biomedical imaging.

1. Introduction

Our human body is a complex, well organized system that consists of several other component systems like cardiovascular system, nervous system to name a few. And each of the major systems in our body is made up of subsystems that help carry various physiological processes. All these systems work in cohesion to maintain homeostasis, loosely translated to what is known as equilibrium. The inputs for the systems in our body could be neurotransmitters or information, physical material and corresponding outputs may be mechanical signals, electrical or biochemical in nature. Any ailment in the body causes alterations to these signals and subsequently affects the well being of the body. Observing and analysing these systems, thus could help understand the system better and provide better pathways to treatment of the ailment [1].

Biomedical image processing plays a vital role in modern healthcare, enabling precise diagnostics and improving the planning of treatments. Over the past decade, from 2015 to 2025, this field has experienced significant advancements, primarily driven by the integration of deep learning and artificial intelligence (AI) technologies. These innovations have revolutionized how medical images are analyzed, leading to better detection of diseases, more accurate interpretation of imaging data, and enhanced decision-making processes. AI algorithms, particularly those based on deep learning, have shown remarkable performance in tasks such as image segmentation, feature extraction, and pattern recognition. As a result, healthcare providers are now able to identify abnormalities with greater accuracy and speed, ultimately improving patient outcomes. Additionally, AI-driven advancements in imaging techniques have facilitated the development of more personalized treatment plans, tailored to individual patient needs. This ongoing transformation marks a critical shift toward more efficient, automated, and effective healthcare solutions [2-4].

In this paper, a review of these developments has been presented alongside the ongoing challenges, and the potential for AI technologies that to continue transform the landscape of biomedical imaging has been discussed.

2. Deep Tomographic Reconstruction

The novel method of Deep Tomographic Reconstruction leverages deep learning techniques to enhance image quality across various medical imaging modalities such as MRI, CT, SPECT, PET, Optical Imaging and Ultrasound Imaging, and it addresses challenges like measurement noise, data sparsity, image artifacts, and computational inefficiency. Significant advancements include:

- *Computed Tomography (CT):* In Computed Tomography (CT), deep learning models have successfully minimized radiation exposure while preserving image quality. One example is the use of residual encoder-decoder convolutional neural networks for low-dose CT imaging, which significantly reduces the radiation dose without compromising the quality of the images.
- *Magnetic Resonance Imaging (MRI):* In Magnetic Resonance Imaging (MRI), deep learning has enhanced acquisition speeds, referred to as fast MRI, and helped reduce motion artifacts. Methods like domain-transform manifold learning have been applied to reconstruct high-quality images from under-sampled data, leading to a notable decrease in scan durations.
- *Positron Emission Tomography (PET) & Single Photon Emission CT (SPECT):* In Positron Emission Tomography (PET) and Single Photon Emission CT (SPECT), deep learning models have enhanced low-dose imaging and corrected motion artifacts. The use of multimodal networks that incorporate MRI data

has improved PET image quality by utilizing anatomical details. For example, deep neural networks optimized for denoising PET images have led to significant improvements in image clarity.

These advancements highlight the profound effect of deep learning on tomographic image reconstruction, resulting in improved diagnostic accuracy and more tailored patient care [5-10].

3. AI-Enhanced Diagnostic Systems

There has been a significant improvement in detection of a disease and treatment planning with the integration of AI into diagnostic systems. Remarkable ones include:

Cancer Diagnosis: AI models like the "Chief" foundation model, created by Harvard Medical School, have shown impressive accuracy in identifying various types of cancer, evaluating treatments, and forecasting survival outcomes. Trained on millions of unlabeled whole-slide tissue images, Chief has achieved a cancer detection accuracy of up to 94%, surpassing previous AI approaches by as much as 36%.

Coronary Imaging: AI algorithms have significantly improved coronary imaging by providing real-time evaluations of heart health, which supports preventive care and tailored treatment plans. Researchers at institutions such as the University of Texas at San Antonio (UTSA) are working on AI-based methods to increase the precision and effectiveness of coronary imaging.

There is a huge potential for AI in diagnostic systems by reducing human error and reducing the time involved for assessment. Personalised treatment strategies for patients can be achieved at a rapid pace [11-17].

4. Medical Image Segmentation Techniques

Recent advancements in medical image segmentation have significantly enhanced the precision and speed of medical image analysis, leading to more accurate diagnoses and more effective treatment strategies. By leveraging deep learning technologies, these advancements have minimized the reliance on manual efforts, automating the process of segmenting complex anatomical structures in medical images. This has not only improved efficiency but also reduced the risk of human error. A prominent example of this progress is the use of convolutional neural networks (CNNs) in segmenting brain tumors in MRI scans. These AI-driven methods have demonstrated remarkable accuracy, thus enabled earlier detection of tumors and provided clinicians with more detailed information to guide treatment planning. Moreover, such advancements have contributed to faster turnaround times for medical imaging, allowing healthcare providers to make quicker decisions and ultimately improving patient outcomes [18-21].

5. Conclusion

From 2015 to 2025, significant progress has been made in biomedical image processing, largely due to the incorporation of deep learning and AI technologies. These advancements have improved image reconstruction, increased diagnostic precision, and refined segmentation methods, ultimately resulting in better patient outcomes and more streamlined healthcare delivery. Medical image analysis has become far more accurate, efficient with betterment in stability and scalability. In this paper, a review of the major advancements in biomedical image processing in the decade 2015 to 2025 has been presented. The primary focus was on the areas of deep tomographic reconstruction, AI-powered diagnostic tools, and cutting-edge methods for medical image segmentation. These innovations have significantly enhanced the precision and effectiveness of medical imaging, offering promising possibilities for more individualized and prompt healthcare.

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About the Author

Prashanthi Govindarajan is an Electronics Engineer with the best of technical and analytical skills. She received her MSc. Electronic Engineering (Sept 2010 – Feb 2012) from Staffordshire University with Distinction and Overall Average Grade Point - 12.17. Her project title was Signal Sparsification with Discrete Rajan Transform (DRT): Principles, Properties and Applications. This study aimed at introducing Generalized Discrete Rajan Transform (DRT) as a potential sparsifying transform. The results point towards the success of DRT in achieving higher degree of sparsity. Her Industrial Project Overview titled Speaker Recognition Using Mel-Frequency Cepstrum Coefficients (MFCCS) aims to enable machines to understand and identify a human speaker using feature extraction and feature matching techniques. From a wide range of algorithms available for such processing, the algorithm using Mel-Frequency Cepstrum Coefficients (MFCC) is considered for feature extraction. She has published research papers (i) "A Unified Framework to Measure Sparsity for Uncorrelated Random Signal", Transactions on Emerging Telecommunications Technologies (ETT), Wiley

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Mrs. Prashanthi Govindarajan has been rcognized as a 'Distinguished Scientist' by the steering committee members of the international conference on science, spirituality for global peace and harmony (IAPIC 2025). This citation was awarded to her in absentia and the PDF version sent to her. The organizing and steering committee members congratulate him for her innovative contribution in the field of 'Signal and Image Processing'.