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A Review of Artificial Intelligence Techniques for Medical Image Enhancement

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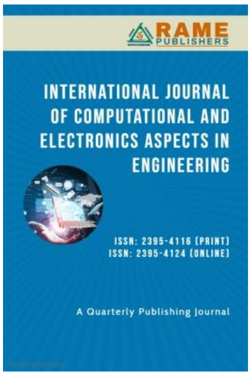

Abstract: Medical imaging plays a crucial role in diagnosis, treatment planning, and monitoring of diseases. However, the quality of medical images is often compromised due to noise, low resolution, and artifacts. Recent advancements in Artificial Intelligence (AI), particularly deep learning techniques, have significantly improved image enhancement capabilities in the medical domain. This paper comprehensively reviews AI-based image enhancement methods applied to medical imaging. We discuss various enhancement techniques, including denoising, super-resolution, contrast enhancement, and artifact removal. Additionally, we provide an overview of commonly used datasets, evaluation metrics, and recent developments in AI models such as convolutional neural networks (CNNs), generative adversarial networks (GANs), and transformer-based architectures. Finally, we highlight current challenges.

Keywords: Medical Imaging, Image Enhancement, Artificial Intelligence, Deep Learning, CNN, GAN.

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1. Introduction

A modern healthcare system relies heavily on diagnostic imaging modalities, including CT scans, ultrasound (US), X-rays, magnetic resonance Imaging (MRI), positron emission tomography (PET) scans, and X-rays. These modalities help clinicians visualize the body's internal structures for diagnostic and therapeutic purposes. However, raw medical images often suffer from poor quality due to factors like sensor limitations, motion artifacts, and noise. Enhancing these images can improve diagnostic accuracy and reduce the likelihood of misinterpretation.

Traditional image enhancement techniques rely on handcrafted filters and mathematical models. While effective in some cases, they often fail to generalize across different imaging modalities and pathologies. The advantages of AI and DL have transformed the discipline by enabling data-driven methods to discover intricate patterns directly from massive datasets.[1].

Medical image processing is a cornerstone in modern healthcare, contributing significantly to accurate diagnosis, faster screening, and enhanced clinical decision-making. AI has the potential to revolutionize medical imaging with its cutting-edge solutions for assessing and improving the quality of X-ray, computed tomography (CT) scans, and MRI.[2].

Anomaly detection, tissue segmentation, convolutional neural networks (CNNs), and contrast enhancement are just a few of the many applications that have seen a meteoric rise in the usage of deep learning and machine learning techniques in the last decade. These technologies provide automated procedures that decrease human interaction and outperform traditional approaches in accuracy.[3].

With the emergence of AI and DL, researchers have developed innovative methods to enhance the intelligence of medical imaging.

AI-based techniques can learn complex patterns from large datasets, enabling superior noise suppression, contrast enhancement, and artifact removal. This review summarizes these advances, focusing on their methodologies, applications, and clinical relevance[4].

2. Overview of Medical Imaging Modalities

Medical imaging involves capturing and analyzing images of the human body to aid in diagnosis and treatment. Nuclear medicine, X-rays, positron emission tomography (PET), ultrasound, computed tomography (CT), magnetic resonance imaging (MRI), and cardiovascular imaging are some of the most used.[5].

2.1 X-rays: X-ray imaging technology, which has been used for a long time and remains prevalent today, utilizes ionizing radiation to quickly visualize structures in bones and certain types of tissue.[6].

2.2 Computed Tomography (CT): This technique produces high-resolution cross-sectional images by combining X-rays and computer processing. CT facilitates the visualization of intricate anatomical structures, although it entails greater radiation exposure than traditional X-rays.[7].

2.3 Magnetic Resonance Imaging (MRI): This technique is ideal for neurological, musculoskeletal, and cardiovascular imaging, as it generates intricate images of soft tissues utilizing potent magnetic fields and radio waves.[5].

2.4 Ultrasound (US): This modality utilizes high-frequency sound waves to create real-time images. Due to its safety and portability, it is frequently used in cardiology, abdominal imaging, and obstetrics.[8].

2.5 PET and SPECT: Molecular imaging techniques based on nuclear medicine that produce three-dimensional (3D) representations of the biodistribution of exogenous radiotracers include Positron Emission Tomography (PET) and Single-Photon Emission Computed Tomography (SPECT). Diagnostics, staging, treatment planning, and therapy evaluation of various diseases, including cancer, rely heavily on the functional and physiological information these modalities provide.[9].

3. Image Processing Techniques for Medical Images

Digital image processing is becoming increasingly essential in healthcare, driven by the growing adoption of direct digital imaging systems for diagnostics, including CT, MRI, and endoscopy.

3.1 Enhancement of Images

The main objective of image enhancement is to process a particular image so that it works better for a specific application than it initially was. It sharpens image elements, such as borders, boundaries, and contrast, to enhance the visual display's usefulness for study and display. Quantifying the enhancement criterion is the most challenging aspect of picture enhancement, and to achieve satisfactory results, a wide range of image enhancement techniques must be employed. Techniques for improving images may be based on frequency domain or spatial methods.[10].

Image processing is crucial, particularly when enhancing brightness, contrast, and image quality. Contrast enhancement is widely used in various industries, including medical imaging systems and satellite imaging systems, as it enhances the visibility of features.[11].

3.2 Segmentation of Images

Medical segmentation of images is a critical task of imaging for medical purposes, enabling the precise identification and delineation of entities, such as organs, tissues, and lesions, within medical images. These split zones are crucial for diagnostics, treatment planning, and disease surveillance. Medical image segmentation has progressed significantly over the years, driven by advancements in imaging technologies and technology. Traditional methods, including thresholding, region growth, and active contouring, have been enhanced and, in some cases, replaced by deep learning (DL) and advanced machine learning (ML) techniques.[12].

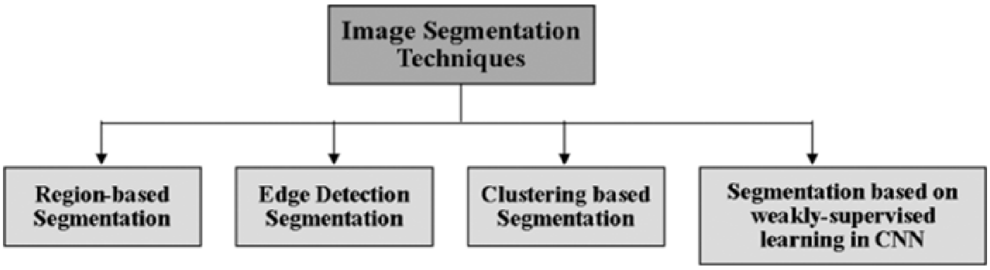

Figure 1: Image Segmentation Techniques

3.3 Image Detection

Detecting edges is fundamental to imaging and computer vision, with numerous applications in parallel. Due to its ability to extract critical structural information, edge detection is a powerful tool in applications that require understanding and interpreting visual data. Thus, edge detection approaches enhance medical imaging, facilitate autonomous navigation, and aid in object identification, leading to incremental technological advancements.[13].

3.4 Image Classification

A fundamental classification system entails a dataset of recorded and concurrently analyzed photos. Image classification categorizes images into distinct groups based on their similarities and characteristics. It can yield inaccurate or false results, particularly when the images are noisy, blurry, contain background clutter, or have poor quality. Datasets, which have predetermined sample patterns of an object, are essential to the classification process. To assign the test object to the correct category, these patterns are compared with it[14][15].

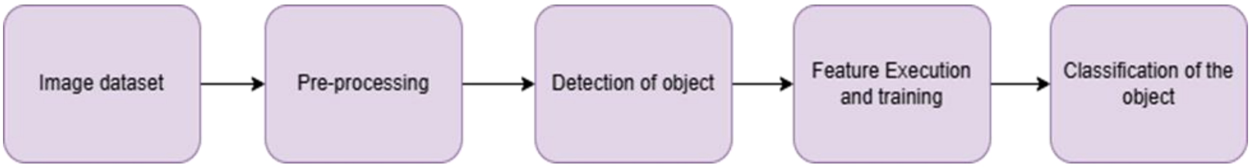

Figure 2: Image classification process

4. Artificial Intelligence (AI)

AI is the development of smart devices by utilizing giant data sets. These machines obtain information from prior experiences and perform tasks similar to those executed by humans. AI improves the efficiency, precision, and effectiveness of human activities. Looking at AI from a higher vantage point, we can divide it into two main groups according to their functions: capability-based AI and functionality-based AI (Figure 3). Machine learning, deep learning, and natural language processing are other technical disciplines that make up AI.[16].

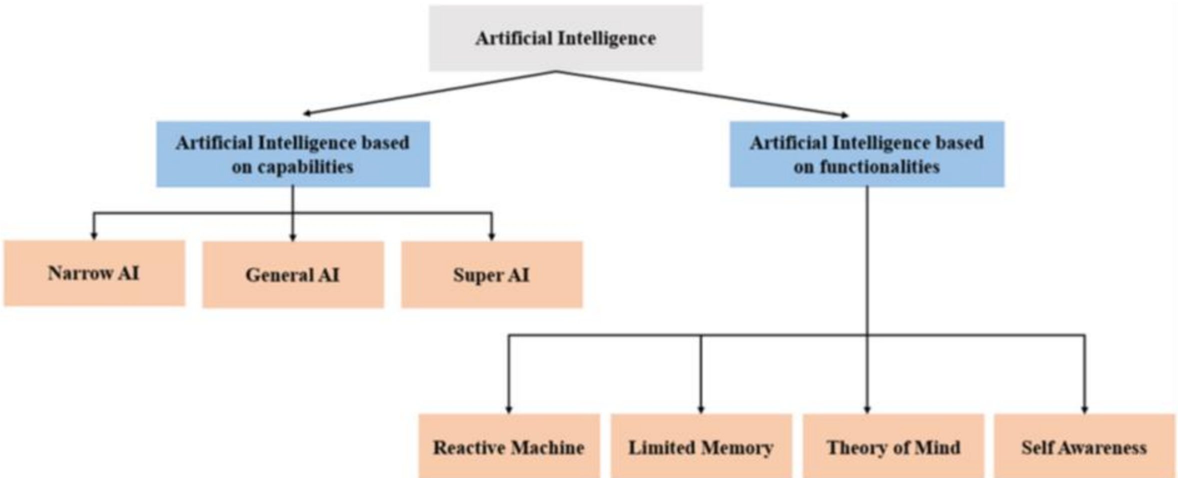

Figure 3: Hierarchy of Artificial Intelligence

Artificial Intelligence (AI) is a branch of computer science that develops systems that can do things that usually require human intelligence. It includes several different methods. Machine learning (ML), first introduced by Arthur Samuel in 1959, is a branch of artificial intelligence that enables computers to learn autonomously. ML has found extensive application in medical imaging. Among the many approaches to machine learning (ML), deep learning (DL) stands out as particularly promising. Actually, DL is a subfield of ML, which is itself a subfield of AI (Figure 4). [17].

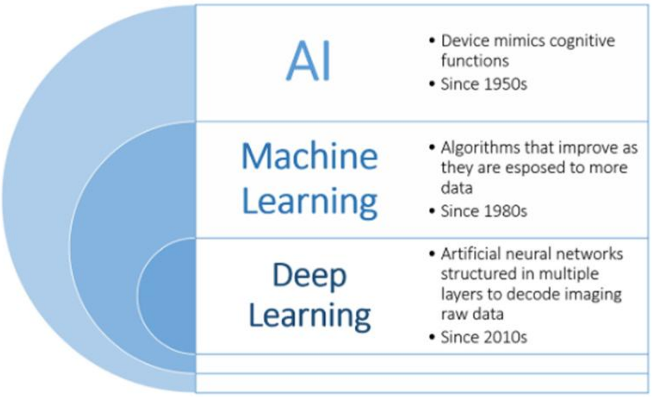

Figure 4: Broader AI Family

5. Machine Learning (ML)

A subfield of AI, machine learning (ML), has rapidly expanded into a game-changing industry, reshaping many more and radically transforming how we tackle complex, real-world problems. The subject of machine learning has grown exponentially in the last several decades, and its influence on our culture is apparent. Recommendation systems, autonomous vehicles, healthcare, finance, engineering, and manufacturing are just a few of the many fields that have grown to rely on machine learning (ML) algorithms and the methods used to apply them.[18].

Classification using KNN and SVM, components include histogram extraction, training image encoding using the generated vocabulary, of conventional machine learning (ML) methods widely used in academia and industry. These methods include detecting points of interest and extracting features (descriptions for each image in the trained dataset), creating a visual vocabulary using the Bag-of-Vocabulary (BOVW) model, and implementing the K-means algorithm.[19][20].

6. Deep learning (DL)

DL is an evolving domain of ML that attains human-level or even better performance on intricate cognitive tasks. Originating from Artificial Neural Networks (ANNs), deep learning proficiently identifies patterns within extensive datasets, constituting one of its primary advantages.

Over the past few years, DL has experienced rapid growth and has been successfully applied across multiple areas, including natural language processing, cybersecurity, bioinformatics, robotics, and medical informatics, where it often outperforms traditional machine learning methods.[21].

The notion of deep learning (DL) emerged in 2006 as a novel area of inquiry within ML. Initially, it was referred to as hierarchical learning, typically encompassing various research domains associated with pattern recognition. Deep learning primarily focuses on two fundamental aspects: nonlinear processing over numerous layers or stages and applying unsupervised or supervised learning.[22].

Deep learning implies an analysis of the mental framework and techniques at many stages. In almost all cases, it remains used for many of its original applications. For example, in preparing computer images, shading the dark-scale image was physically done by customers who had to choose each shade based on their criteria. By applying an in-depth learning calculation, shading can be performed naturally from a PC [23].

Recurrent Neural Networks (RNN) and deep learning techniques can incorporate audio into a silent drumming movie.[24].

Many application areas have successfully applied deep learning to numerous problems. These involve sentiment analysis,natural language processing, business, virtual assistants, healthcare cybersecurity, visual recognition, medical systems, robotics, IoT applications, smart cities, and many more [25].

6.1 Deep Learning Applications

AI, ML, and DL have garnered significant attention for an extended period. Deep learning is transforming how we view advancements. Much enthusiasm surrounds AI and its subdivisions, particularly ML and DL. Numerous deep-learning applications are expected to impact your life shortly. They are now exerting an influence. In the next 5 to 10 years, deep learning frameworks, tools, and languages will be essential elements of any software development toolbox. Deep learning can be understood as optimizing outcomes and reducing processing times in specific computational models. Deep learning techniques have been associated with the image captioning era in standard dialect preparation.[26].

6.1.1 Image processing

Integrating deep learning (DL) into image processing has enabled transformative improvements, providing capabilities surpassing conventional methodologies. The advent of deep learning has revolutionized image processing, a branch of artificial intelligence that emulates the structure and operations of the human brain to analyze and understand complex data patterns. Historically, image processing has relied heavily on human feature extraction and conventional machine learning techniques, requiring considerable domain expertise and often encountering challenges due to visual data's inherent variety and complexity. Although effective for narrow, well-defined tasks, these solutions lacked the adaptability and scalability required to manage real-world photographs' various and high-dimensional characteristics.[27].

Deep learning models can capture complex information that conventional approaches may overlook by directly extracting feature representations from data. In denoising, methodologies such as MPR-CNN, Self2Self NN, denoising CNNs, and DFT-Net are prominent. They provide diminished noise while addressing the complexities of data augmentation and parameter tuning. [28].

6.1.2 Medical and Healthcare

The advent of deep learning has caused a sea change in medical imaging analysis. The medical imaging community has recently become increasingly interested in this technology, to the point where a specialist conference, "Medical Imaging with Deep Learning," was held in 2018. [29].

Recently, deep learning has had a profound impact on several scientific fields. Deep learning algorithms have outperformed other state-of-the-art technologies in picture processing and analysis. There is also considerable hope for deep learning in the healthcare industry. A tremendous need for trustworthy automated processing and analysis of health information has arisen due to the growing trend towards individualized therapies and the massive amounts of patient records and data being collected.[30].

7. AI Technique used in Imaging for Medicine

Artificial intelligence has primarily advanced in medical image identification applications, especially in diagnosing image data. Numerous papers have illustrated the remarkable precision of AI in diagnostics, including diabetic retinopathy, head computed tomography (CT) scans, and skin cancer. Nonetheless, its potential extends beyond diagnosis to encompass the prediction of the clinical trajectory. Furthermore, precise medical forecasts are seen as effective in diagnostics and therapies.[31].

AI enhances the analysis of medical pictures, refines image reconstruction, and aids in illness identification across multiple imaging modalities, including X-ray, CT, and MRI. Deep learning and machine learning algorithms facilitate the automation of everyday diagnostic activities, enhance image quality, and detect intricate patterns associated with diseases.[32].

7.1 Convolutional Neural Networks (CNNs)

CNNs have emerged as the foundation of image improvement tasks. They are skilled at learning various levels of features and have been used to reduce noise, improve image quality, and correct errors in medical imaging techniques such as computed tomography (CT), magnetic resonance imaging (MRI), and functional magnetic resonance imaging (fMRI). Examples include U-Net architectures tailored for segmentation and enhancement, and residual networks designed to improve image sharpness.[33][34].

A CNN was employed to extract features from medical images, thereby enhancing the medical image fusion process. Pre-trained CNN models were used to compute weight maps based on pixel visibility, temporal consistency, and exposure adjustment without requiring labelled or ground-truth data. The results showed that using CNN features improves the quality of fused images compared to traditional methods, making it suitable for accurate medical diagnosis systems.[35][36].

7.2 Generative Adversarial Networks (GANs)

GANs can produce deep learning representations with minimal reliance on manually annotated training data. They employ a competitive methodology, leveraging two networks to generate backpropagation signals. Applications of the representations learned by GANs include semantic image editing, image synthesis, image super-resolution, classification, and style transfer.[37].

The GAN, a kind of CNN used for synthesis, competes with a discriminator CNN to distinguish between synthetic and genuine CT images. The discriminator CNN offers feedback to the synthesis CNN regarding the overall quality of the generated CT images.[38].

7.3 Autoencoders and Variational Autoencoders (VAEs)

Among the most often used methods in medical picture production is a variational autoencoder (VAE). Data augmentation operates with VAE, which offers benefits. This set includes improved datasets with unequal class representation, as well as smaller datasets.[39].

The VAE paradigm helps provide reasonable synthetic data, removes intense noise and artefacts, and simulates intricate disease progression. In many medical contexts, VAEs are preferred over more traditional approaches due to their advantages. VAEs could significantly accelerate the development of new biological therapies, enhance diagnostic accuracy, and inform tailored treatment.[40].

7.4 Vision Transformers (ViT)

In computer vision, Vision Transformer (ViT) is a recently developed image identification system. It recognizes photos using a Transformer structure and performs exceptionally well in natural language processing.[41].

Requiring far fewer computer resources to train, Vision Transformer (ViT) achieves outstanding performance relative to state-of-the-art convolutional networks.[42].

7.5 Reinforcement Learning and Hybrid Approaches

Hybrid methods can be beneficial when interpreting challenging data or results. They combine statistical models, expert knowledge, and traditional machine learning techniques to understand the data comprehensively. Bringing together various types of data, such as written reports, body signals, and other relevant information, helps to understand the medical condition better and improves decision-making.[43][44].

AI can enhance the detection of tuberculosis-related abnormalities, potentially leading to substantial progress toward alleviating this global health crisis. To tackle this, an AI hybrid model integrates a neural network (CNN) architecture and a vision transformer (ViT). This model efficiently classifies 14 TB-related anomalies in CXR photos using multi-class and multi-label methods.[45][46].

8. Comparative Analysis of AI Techniques for Medical Image Enhancement

To provide a comprehensive understanding of the AI techniques discussed, this section compares Convo -lutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), Vision Transformers (ViTs), and hybrid approaches based on their applications, performance metrics, strengths, and limitations in medical image enhancement. The comparison is summarised in Table 1.

Table 1: Comparison of AI Techniques for Medical Image Enhancement

Technique	Applications	Performance Metrics	Strengths	Limitations
CNNs	Denoising, super resolution, segmen tation	High PSNR, SSIM, DSC	Robust, versatile	Requires datasets, large limited generalization
GANs	Image synthesis, super-resolution, artefact removal	High SSIM, low MSE	High-quality ages, im minimal labeled data	Training instability, mode collapse
VAEs	Data augmentation, noise removal	Moderate IoU SSIM,	Effective for small datasets	Blurry outputs
ViTs	Image recognition, classification	High accuracy, F1 score	Efficient training, scalable	Less explored in medical imaging
Hybrid approaches	Multi-label classification, multi-modal integration	High accuracy, ro bustness	Combines strengths of multiple models	High complexity, computational cost

9. Challenges and Limitations

Despite the progress, several challenges hinder the widespread adoption of AI techniques in clinical settings:

1. Data Quality and Availability

One of the significant obstacles in training robust AI models for diagnostic imaging is the scarcity of quality datasets. Medical data is often scarce, sensitive, and challenging to annotate due to the need for expert clinicians.[47][48].

2. Human and Clinical Variability

Significant variability among human experts when interpreting medical images makes defining "ground truth" labels for training an AI system a challenging task.[49].

3. Combination with the current medical systems

A clear plan is necessary to address the new and complex problems arising from the mixed reactions to the use of AI in clinical radiology. Reliable software and robust hardware are critical for managing the massive amounts of data generated by medical imaging equipment. Artificial intelligence (AI)-enabled applications can leverage vast amounts of underutilized hospital data, significantly enhancing the prediction of illness trajectories and the optimization of treatment regimens.[50].

4. Privacy of patient data and security

The incorporation of artificial intelligence in medical imaging presents a risk to patient privacy. Mandates providers exercise vigilance regarding patient care. Mandates that no unauthorized individual access a patient's data. Nevertheless, the ongoing increase in digitalization has rendered the issue of cybersecurity pervasive. Artificial intelligence electrical instruments, including telemedicine and remote patient monitoring. Elevate the likelihood of unauthorized entities accessing data. It must be monitored to avert unauthorized access by third parties.[51].

5. Regulatory and ethical issues

AI technologies can enhance healthcare. Integrating AI into decision-making processes clarifies and constrains the array of choices, facilitating clinicians' ability to achieve precise diagnoses. Future medical practitioners must be proficient in machine learning technologies and aware of the ethical implications of employing this technology in patient care.[51][52] .

10. Conclusion

Artificial intelligence-based Image enhancement has become a pivotal influence in medical imaging, markedly enhancing clinical workflow efficiency, picture quality, and diagnostic precision. Leveraging advanced techniques such as Generative Adversarial Networks (GANs), autoencoders, Convolutional Neural Networks (CNNs), transformers, and reinforcement learning, these models enable radiologists to detect and analyze pathologies with greater precision and consistency.

Medical image processing has seen remarkable development due to advancements in artificial intelligence and deep learning techniques. These technologies have enhanced diagnostic capabilities, accelerated examination processes, and reduced human errors. However, despite the promising progress, several challenges remain in deploying these models widely in clinical environments. Key issues include data scarcity, lack of transparency and interpretability, generalization across diverse patient populations, and integration with existing healthcare systems and workflows.

Addressing these issues ensures the ethical, safe, and efficient application of AI-driven image enhancement technologies in real-world medical settings.

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