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Denoising and segmentation in medical image analysis: A comprehensive review on machine learning and deep learning approaches

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Abstract
Medical imaging plays an essential role in modern healthcare, helping accurate diagnoses and effective treatment strategies. Still, the quality and interpretability of medical images are regularly hindered by various sources of noise. This paper presents a comprehensive exploration of traditional noise reduction techniques in medical imaging, addressing challenges posed by quantum noise, electronic noise, radiation interference, and other factors. The study delves into spatial filtering, frequency domain filtering, statistical methods, probability-based noise reduction, and adaptive filtering techniques. Each method is analyzed for its applicability and effectiveness in mitigating noise while preserving diagnostically relevant information. The comparative analysis provides insights into the strengths and limitations of these techniques, guiding practitioners in selecting appropriate methods based on imaging modalities and noise characteristics. Also, the paper highlights future research directions, emphasizing the potential of advanced Machine Learning (ML) models and the integration of multimodal data for enhanced noise removal.

Keywords Medical imaging · Noise · Reduction · Machine learning · Modalities · Image quality · Diagnostic

1 Introduction

Medical imaging has emerged as an essential aspect of modern healthcare, influencing the detection, treatment, management, and monitoring of a variety of diseases. The field combines modern equipment to develop comprehensive visual models of the human body's internal structure, helping healthcare professionals to investigate and assess both normal

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physiological functioning and abnormal anomalies [1, 2]. The importance of medical imaging in the healthcare system is enormous, with wide-ranging consequences that extend beyond conventional medicine. The primary benefit of this technology is its ability to visualize what was previously undetected, allowing us to peer through the skin and observe the intricate structures of the human body. Medical imaging provides an innovative insight into the intricate structure of an infant's developing heart and the effects of cancer in a patient's lung [3, 4]. Medical imaging is crucial for enabling the early identification and diagnosis of illnesses. Medical experts may diagnose illnesses in their early stages using imaging modalities such as X-rays, Computed Tomography (CT) scans, Magnetic Resonance Imaging (MRI), ultrasounds, and Positron Emission Tomography (PET) scans, commonly before symptoms occur. Mammography plays an important part in detecting breast cancer at an early stage, increasing the chances of successful treatment, and saving lives. Lung cancer screening with CT scans may detect lung cancers in their early stages, providing an opportunity for intervention [5, 6]. Medical imaging supervises the whole healthcare process, from treatment planning to exact implementation. Surgeons may meticulously organize intricate surgeries to minimize damage to healthy tissue. Real-time imaging, including fluoroscopy, assists in directing surgical tools and evaluating progress throughout surgery. Radiation therapy and chemotherapy may be precisely targeted at tumor sites, minimizing side effects, and improving therapeutic effectiveness. Medical imaging is essential for monitoring disease development and analyzing the effectiveness of treatments, as well as playing a significant role in diagnosing, treating, and detecting illnesses [7, 8]. Regular scans are crucial for overseeing chronic conditions like cancer or cardiovascular disease since they enable healthcare providers to track the progression of the illness and assess the efficacy of therapies. Early improvements to treatment protocols according to diagnostic information could improve outcomes for patients.

Also, there is constant research and development in the field of medical imaging. Advanced technologies, including 3D imaging, functional MRI, and molecular imaging, continue to expand the boundaries of medical knowledge. The advancements improve our knowledge of disease processes, help create new medicines, and boost diagnostic procedures. The importance of noise reduction and segmentation in medical image analysis is crucial [9, 10]. Noise from many sources during picture collection might distort crucial features and impede diagnostic accuracy. Reducing such noise is essential not just to achieve visual clarity but also to ensure the effectiveness of automated image analysis techniques. Segmentation, which involves separating an image into important components, is also essential [11, 12]. Segmentation is essential, not only for diagnosing but also for modifying therapies to fit individual patient characteristics. But challenges persist, which include the variation of noise across different imaging techniques, physical variations among people, and the limited availability of accurate data to use for model training [13].

Advanced technologies, such as Deep Learning (DL), provide interesting responses in this dynamic environment. Convolutional Neural Networks (CNNs) are very effective in noise reduction tasks due to their capacity to adapt to the several noise characteristics present across various modalities. DL models like U-Net structures work well for segmentation because they find a good balance between accurate localization and low computational cost [14, 15]. Combining data from multiple domains enhances the overall analysis by incorporating information from various sources. Despite progress, the need for explainable AI is essential to maintaining openness in algorithmic decision-making, particularly in medical fields where trust and comprehension are essential. Real-time segmentation is an innovative factor that improves workflow efficiency and enables dynamic treatment techniques. Processing medical images in real-time speeds up diagnosis, particularly in emergency situations, and helps with adaptive therapies by providing immediate insight into evolving clinical conditions [16, 17].

Finally, the collaboration of medical imaging, noise reduction, and segmentation has advanced healthcare into an innovative era of accuracy and effectiveness. The exploration continues, including historical landmarks and the incorporation of advanced technology. Challenges remain, but each obstacle provides opportunities for innovation and collaboration [18, 19]. As we proceed ahead, it is important to not only emphasize technology developments but also integrate them into clinical processes to ensure that medical imaging can fully enhance patient outcomes. The commitment to creativity, collaboration, and an in-depth knowledge of the intersection of medical imaging, noise reduction, and segmentation remains the main objective in the achievement of excellence in healthcare.

This work aims to improve the efficiency of medical image analysis by overcoming the issues of noise and segmentation. Various sources of noise, such as acquisition techniques and environmental conditions, may cause ambiguities that may prevent an accurate diagnosis [20, 21]. Segmentation, a method of splitting an image into significant parts, is essential for distinguishing specific characteristics or irregularities. Thus, it is crucial to understand and reduce noise while enhancing segmentation methods to progress in medical image analysis.

2 Research objectives

The objectives of the paper are as follows:

- Provide a comprehensive review of modern approaches for noise reduction and segmentation in medical imaging.
- Analyze traditional techniques utilized for noise reduction and image segmentation.
- Compare traditional techniques with modern machine learning (ML) algorithms for noise reduction and segmentation.
- Provide concepts on the suitability and effectiveness of these methods in various medical imaging applications.
- Investigate and evaluate traditional noise reduction methods used in medical imaging.
- Study spatial filtering, frequency domain filtering, statistical approaches, probability-based noise reduction, and adaptive filtering techniques.
- Provide guidance to professionals on choosing suitable methods according to imaging modalities and noise factors.
- Study how advanced ML models and the use of multimodal data may improve noise reduction in medical imaging.
- Identify potential research approaches to enhance noise reduction techniques in medical imaging applications.

2.1 Paper organization

In order to achieve these objectives, the paper is organized in a way that facilitates a comprehensive and systematic analysis of various issues related to the removal of noise and segmentation in medical imaging. The following sections provide an organized structure for this paper, working as an overview for readers to navigate the comprehensive review that is being presented.

- Section 3 provides a basic introduction to essential medical imaging modalities and emphasizes their important role in healthcare.
- Section 4 explores the complexities of noise reduction, including both conventional methods and the recent development of ML-based approaches.
- Section 5 discusses image segmentation, highlighting its importance and providing information on both conventional and advanced ML-based techniques.
- Section 6 discusses the challenges involved in noise reduction and segmentation, recognizing variations across imaging techniques, anatomical changes, and the obstacles of obtaining accurate data for comparison.
- The study in Section 7 discusses future research areas such as improved ML models, multimodal data fusion, explainable artificial intelligence, and real-time segmentation.
- The conclusion in Section 8 summarizes the main findings, emphasizing their impact on medical imaging and emphasizing the need for efficient noise reduction and segmentation in improving healthcare outcomes.

The article provides an overview for readers to help them navigate the intricate area and understand the constantly evolving terrain of medical imaging.

3 Medical imaging in healthcare: A visual revolution

Medical imaging plays an essential role in modern medical treatment by presenting the hidden complexities of the human body with excellent clarity. This overview presents a wide range of imaging techniques, from conventional X-rays to advanced techniques such as MRI and CT scans. We investigate how medical imaging improves diagnosis, optimizes medical treatment, and encourages us toward precision medicine [22, 23]. Simply put, it is a visual revolution that is transforming how medical professionals perceive and improve patient outcomes.

3.1 Types of medical imaging modalities

Medical imaging methods play an important role in providing specialists with novel insights into the human body within the dynamic healthcare sector. This section provides an analysis of several imaging modalities, each with unique features adapted to specific diagnostic requirements [24, 25]. From X-rays showing skeletal structures to CT scans providing cross-sectional imaging and MRIs identifying soft tissue, these modalities collectively give a complete toolset. Recognizing the principles and uses of X-ray, MRI, CT, and other modalities is essential for understanding their significance in diagnostic techniques and therapeutic treatments [26, 27].

The above Table 1 provides a quick overview of diagnostic imaging modalities, summarizing their principles, applications, significance in clinical practice, noise types, distribution characteristics, and radiation sources. This overview serves as a quick reference for medical professionals and scholars seeking a comprehensive understanding of diagnostic imaging techniques.

Table 1 Medical imaging modalities overview

Medical Imaging Modalities	Types of Noise Distribution	Radiation Source	Principle	Applications	Significance
X-ray	Quantum Noise, Electronic Noise, Scintillation Noise	X-Ray Tube	Differential absorption of X-ray photons by tissues	Fracture detection, chest abnormalities, dental examinations	Quick and effective imaging, foundational for bones
MRI	Thermal Noise, System Noise, Motion Artifacts	Magnetic Fields	Interaction of hydrogen nuclei with a magnetic field and RF pulses	Brain, spinal cord, joints, soft tissues imaging	Exceptional soft tissue contrast, crucial for neurology
CT	Electronic Noise, Beam Hardening, Scatter Radiation	X-Ray Tube, Detectors	Combination of X-ray technology with computer processing	Detailed examinations of internal structures, tumor detection	Cross-sectional, 3D images for precise diagnostics
Ultrasound	Speckle Noise, Electronic Noise, Acoustic Noise	Transducer	Utilization of high-frequency sound waves for real-time imaging	Obstetrics, cardiology, abdominal imaging	Non-invasive, real-time imaging, versatile
Nuclear Medicine	Photon Noise, Electronic Noise, Scatter Radiation	Radioactive Tracers	Administration of radioactive tracers emitting gamma rays	Myocardial perfusion imaging, PET for cancer staging, neurological disorders	Functional insights into organ function and metabolism
PET	Coincidence Timing Error, Scatter Radiation	Positron-Emitting Radionuclides	Injection of a radioactive substance emitting positrons	Oncology, cardiology, neurology	Functional images reflecting metabolic activity
Mammography	Quantum Noise, Electronic Noise, Motion Artifacts	X-Ray Tube	Use of X-rays to create detailed images of breast tissue	Breast cancer screening and diagnosis	Primary tool for early detection of breast cancer
Fluoroscopy	Quantum Noise, Electronic Noise, Motion Artifacts	X-Ray Tube	Continuous X-ray imaging for real-time visualization of moving structures	Barium studies, catheter placements, joint injections	Instrumental in interventional procedures, real-time guidance

3.1.1 X-ray imaging

X-ray imaging, a pioneering modality discovered by Wilhelm Roentgen in 1895, relies on the principle of differential absorption of X-ray photons by tissues. This modality excels at visualizing dense structures like bones due to their higher X-ray absorption [28, 29]. Widely employed in diagnostic radiology, X-ray imaging provides a rapid and effective means for detecting fractures, assessing orthopedic conditions, and uncovering abnormalities within the chest, including pneumonia and lung cancer. Its versatility extends to dental examinations, where it aids in the prompt diagnosis and planning of interventions for oral health issues. The enduring significance of X-ray imaging lies in its accessibility, speed, and critical role in providing essential diagnostic information across various medical disciplines.

3.1.2 Magnetic Resonance Imaging (MRI)

MRI, a transformative technology, harnesses the behavior of hydrogen nuclei in response to magnetic fields and radiofrequency pulses. This non-invasive technique captures detailed, high-contrast images of soft tissues by processing the signals generated during the realignment of hydrogen nuclei [30, 31]. Widely acclaimed for its exceptional soft tissue contrast, MRI plays an indispensable role in medical imaging. In neurology, it stands as a key diagnostic tool for conditions such as multiple sclerosis, offering unparalleled insights into the intricacies of the brain and spinal cord. Moreover, its applications extend to musculoskeletal imaging, facilitating precise assessments of ligaments, tendons, and cartilage, essential in orthopedic evaluations. Beyond its neuro and musculoskeletal prowess, MRI's versatility spans various medical disciplines, establishing it as a cornerstone for comprehensive and detailed diagnostic imaging throughout the body [32].

3.1.3 Computed Tomography (CT) Imaging

CT stands at the intersection of X-ray technology and advanced computer processing, facilitating the creation of intricate cross-sectional images with three-dimensional precision. This modality employs a rotating X-ray source and detectors, capturing detailed snapshots of internal structures. CT imaging's versatility is represented in its widespread use for comprehensive examinations of the head, chest, abdomen, and pelvis [33, 34]. Its diagnostic prowess extends to the identification of conditions such as tumors, vascular abnormalities, and traumatic injuries, offering unparalleled clarity in delineating anatomical details. In the realm of vascular imaging, CT angiography plays a pivotal role, providing detailed assessments of blood vessels and enabling the detection of vascular diseases. CT imaging's ability to deliver high-resolution, multi-dimensional images positions it as an indispensable tool in the diagnostic arsenal, contributing significantly to accurate diagnosis and treatment planning across diverse medical specialties.

3.1.4 Ultrasound imaging

Ultrasound imaging, harnessing high-frequency sound waves, offers real-time visualizations of internal structures by processing echoes generated during their interaction. Its non-invasive nature and dynamic imaging capabilities render ultrasound a versatile modality across various medical domains. Widely embraced in obstetrics, it becomes a vital tool for monitoring fetal development, providing expectant parents and healthcare professionals with valuable insights. In cardiology, ultrasound serves as a cornerstone for assessing heart function, capturing detailed images that aid in the diagnosis and management of cardiac conditions [35, 36]. Moreover, abdominal imaging excels at evaluating organs like the liver and kidneys, contributing to the diagnosis of diverse pathologies. The inherent advantages of ultrasound, including portability and the absence of ionizing radiation, underscore its pivotal role in diagnostics, making it an invaluable asset in diverse clinical scenarios.

3.1.5 Nuclear medicine

Nuclear medicine, a dynamic field, revolves around the administration of radioactive tracers emitting gamma rays. In this process, detectors capture emitted gamma rays, and sophisticated computer processing translates this data into images depicting the tracer's distribution within the body. The core strength of nuclear medicine lies in functional imaging, which provides unique insights into organ function and metabolism. Myocardial perfusion imaging, a notable application, provides crucial information about heart function, aiding in the diagnosis and management of cardiovascular conditions [37, 38]. Similarly, PET plays a pivotal role in cancer staging, offering detailed information about tumor activity, and contributing significantly to the evaluation of neurological disorders. The ability of nuclear medicine to unravel physiological processes at a molecular level underscores its importance in personalized medicine, contributing to precise diagnostics and targeted therapeutic approaches.

3.1.6 Positron Emission Tomography (PET)

PET is an advanced imaging technique where a small amount of a radioactive substance, i.e. a glucose analog is introduced into the body. The emitted positrons produce gamma rays, whose detection enables the creation of functional images that vividly reflect metabolic activity. This process is particularly invaluable in oncology, where PET is extensively employed for cancer staging, treatment planning, and monitoring treatment response [39, 40]. Its applications extend to cardiology, facilitating the assessment of myocardial viability, and neurology, providing detailed insights into brain function.

3.1.7 Mammography

Mammography, an essential tool in breast imaging, harnesses X-rays to craft detailed images of breast tissue. The advent of digital mammography has augmented image quality while enhancing the efficiency of image storage and retrieval. Positioned as a primary method for breast cancer screening and diagnosis, mammography plays a crucial role in the early detection of breast cancer [41, 42]. Regular mammographic screenings are instrumental in improving treatment outcomes by facilitating early interventions and contributing to the comprehensive management of breast health.

3.1.8 Fluoroscopy

Fluoroscopy is a continuous X-ray imaging method that allows for the real-time monitoring of moving components within the body. Numerous interventional treatments use its adaptability, providing dynamic, real-time guidance. Conventional procedures include barium studies for assessing contrast agents' movement, catheter insertion, and joint injections [43, 44]. Fluoroscopy's real-time feedback is essential in interventional radiology and other medical fields, providing accuracy and precision in a wide range of operations, from diagnostics to treatments.

Overall, the variety of medical imaging modalities plays an important role in healthcare, providing professionals with an extensive range of tools for diagnosis and treatment. Each modality has distinct benefits, enabling an extensive knowledge of anatomical structures and clinical circumstances. Advancements in these technologies are continuously improving their capabilities, leading to better patient care, early illness identification, and progress in medical research [45]. Combining these modalities into clinical workflows emphasizes their importance in contemporary healthcare, influencing the diagnostic and treatment processes and eventually enhancing the results achieved for patients.

3.2 Significance of medical imaging in healthcare

Medical imaging has importance beyond collecting visual data, ranging beyond technical complexities. This section explores the important impact of medical imaging on the diagnostic and therapeutic components of healthcare. Medical imaging provides a crucial role in early illness detection and treatment planning, which makes it a key instrument for healthcare providers. The study continues throughout how imaging technologies help in precision medicine, monitoring treatment responses, and non-invasive assessments of both anatomy and function [46, 47]. The predominant theme throughout every application is the significant impact of medical imaging on patient outcomes, medical research, and the ongoing development of healthcare methods.

3.2.1 Early diagnosis and disease detection

One of the paramount contributions of medical imaging is its unparalleled ability to facilitate early diagnosis and the detection of diseases. Technologies such as X-ray, MRI, CT, and ultrasound empower clinicians to visualize internal structures, identify abnormalities, and detect diseases at their nascent stages [48, 49]. In the realm of oncology, early detection through modalities like mammography and PET-CT significantly enhances the chances of successful treatment, underscoring the critical role of medical imaging in the fight against cancer.

3.2.2 Treatment planning and precision medicine

Medical imaging serves as a linchpin in treatment planning, enabling clinicians to formulate precise and personalized intervention strategies. In orthopedics, imaging modalities like MRI and CT guide surgical planning for joint replacements or spinal surgeries. Similarly, in cardiology, imaging techniques such as echocardiography and coronary angiography aid in planning interventions like angioplasty or heart surgeries [50, 51]. The integration of imaging into treatment planning not only enhances precision but also minimizes the invasiveness of procedures, contributing to improved patient outcomes.

3.2.3 Monitoring disease progression and treatment response

The significance of medical imaging extends beyond diagnosis and initial treatment planning to the continuous monitoring of disease progression and treatment response. Sequential imaging studies, involving modalities like MRI or CT, provide clinicians with real-time insights into changes in tumor size, tissue healing, or the efficacy of therapeutic interventions [52, 53]. This real-time monitoring is crucial in oncology, neurology, and various other specialties, guiding adjustments in treatment protocols and ensuring timely interventions.

3.2.4 Non-invasive assessment of anatomy and function

Medical imaging facilitates a non-invasive assessment of both anatomical structures and physiological functions. Modalities like functional MRI (fMRI) and nuclear medicine techniques offer insights into brain activity, metabolism, and organ function. This non-invasiveness is particularly crucial in pediatrics and geriatrics, where traditional invasive diagnostic procedures may pose additional risks [54, 55]. Imaging's ability to unveil both structural and functional aspects of the body provides a comprehensive understanding, laying the foundation for informed clinical decision-making.

3.2.5 Image-guided interventions

The integration of medical imaging and interventional procedures has revolutionized medical practice. Techniques like fluoroscopy and ultrasound-guided interventions allow clinicians to perform procedures with unprecedented precision [56]. From guided biopsies in oncology to catheter placements in cardiology, image-guided interventions enhance accuracy, reduce complications, and offer minimally invasive alternatives to traditional surgical procedures.

3.2.6 Advancements in research and medical knowledge

Medical imaging contributes significantly to advancements in research and the expansion of medical knowledge. Imaging studies generate data that fuels research endeavors, enabling scientists and clinicians to explore disease mechanisms, evaluate treatment efficacy, and develop innovative diagnostic tools [57]. Medical imaging provides a wealth of information that deepens our understanding of disease processes, paving the way for groundbreaking discoveries and advancements in medical science.

3.2.7 Improved patient outcomes and quality of care

Ultimately, the overarching significance of medical imaging lies in its profound impact on patient outcomes and the overall quality of healthcare. Early diagnosis, precise treatment planning, and continuous monitoring facilitated by medical imaging contribute to improved survival rates, reduced morbidity, and enhanced patient well-being [58, 59].

The non-invasive nature of imaging procedures also aligns with patient-centric care, emphasizing safety and comfort.

3.2.8 Training and education

Medical imaging plays a vital role in medical education and training. From anatomy classes to specialized radiology training, medical imaging provides a tangible and visual representation of the human body. Interactive simulations and virtual reality applications based on imaging data enhance the educational experience for medical students and practitioners [60]. Understanding the nuances of medical imaging becomes an integral part of the skill set for healthcare professionals across various specialties.

3.2.9 Technological advancements and innovation

The relentless pursuit of excellence in medical imaging has led to continuous technological advancements and innovation. From the advent of digital imaging to the integration of artificial intelligence (AI) in image analysis, these innovations enhance the capabilities of imaging modalities [61, 62]. AI algorithms aid in rapid image interpretation, improving diagnostic accuracy and efficiency. Moreover, developments in imaging technologies, such as 3D imaging and functional imaging, open new frontiers in diagnostics and research.

3.2.10 Multimodal approaches for comprehensive assessment

The emergence of multimodal approaches, which integrate information from multiple imaging modalities for a comprehensive assessment, further underscores the significance of medical imaging [63]. Managing multimodal medical imaging data involves various issues and possibilities for reducing noise and enhancing images. Researchers may enhance image quality and diagnosis accuracy by combining data from several imaging modalities or modalities with varied noise characteristics to use their complementary strengths. Integrating methods like data fusion from MRI, CT scans, PET scans, and other imaging modalities enables an extensive assessment of anatomical structures and physiological processes. Improved signal processing techniques designed for multimodal data, such as multi-sensor fusion and joint estimation algorithms, allow for extracting more information while reducing noise and artifacts present in each modality. ML methods, such as DL structures, provide powerful ways to combine multimodal data and understand the connections between various imaging techniques and biological processes. Further study in this field is essential to fully using the capabilities of multimodal medical imaging, resulting in enhanced diagnostic precision, personalized medical approaches, and improved treatments for patients.

An overview of essential components in the domain of medical imaging is effectively and meticulously presented in Table 2. Multimodal integration, point-of-care imaging, precision oncology, interventional imaging, early disease monitoring, treatment guidance, functional neuroimaging, and non-invasive assessment are among the numerous contributions explored. Each contribution comprises a brief description, key metrics, modalities involved, and impact on healthcare. The data provided in Table 2 is very useful in realizing the diverse and nuanced ways in which medical imaging contributes to the enhancement of treatment accuracy, patient outcomes, and diagnostic capabilities. In conclusion, the significance of medical imaging in healthcare is profound and far-reaching. From the

Table 2 Comprehensive overview of medical imaging contributions

Contribution	Modalities	Key Metrics	Impact on Healthcare	Description
Early Diagnosis	X-ray, MRI, CT, Ultrasound	Sensitivity, Specificity, False-Positive Rate	Improves treatment outcomes, reduces morbidity, and enhances the potential for successful interventions	Enables early detection of diseases and abnormalities, providing a crucial head start in treatment
Treatment Guidance	X-ray, MRI, CT	Accuracy, Precision, Navigational Accuracy	Enhances treatment precision, minimizes invasiveness, and contributes to personalized medicine approaches	Guides healthcare professionals in planning and executing precise treatment strategies
Disease Monitoring	MRI, CT	Temporal Resolution, Spatial Resolution, Monitoring Duration	Facilitates adaptive treatment strategies, aids in timely adjustments, and provides insights into overall patient progress	Enables real-time monitoring of illness progression, therapy effectiveness, and recovery after treatment
Non-Invasive Assessment	X-ray, MRI, CT, Ultrasound	Patient Comfort, Repeatability, Non-Ionizing Radiation	Enhances patient safety, allows for repeated assessments without significant risk, and contributes to a more patient-friendly approach	Provides a non-invasive means of assessing anatomical structures and physiological functions
Multimodal Integration	PET-MRI, SPECT-CT, PET-CT	Fusion Accuracy, Information Coherence, Diagnostic Synergy	Enables a more holistic understanding of complex medical conditions	Combines data obtained from various imaging techniques to provide an in-depth review of a patient's health
Point-of-Care Imaging	Portable ultrasound, handheld X-ray, mobile MRI	Speed, Accessibility, Real-Time Imaging Capabilities	Facilitates rapid decision-making and treatment initiation	Brings imaging capabilities directly to the patient's bedside for quick and efficient diagnostic assessments
Precision Oncology	PET, CT, MRI	Molecular Imaging, Tumor Heterogeneity Assessment	Optimizes cancer treatment outcomes and minimizes side effects	Utilizes imaging to adapt treatments for cancer based to specific patient features and tumor biology
Interventional Imaging	Fluoroscopy, MRI-guided interventions, CT angiography	Real-Time Imaging, Accuracy of Needle Guidance	Improves procedural success rates and patient outcomes	Guides minimally invasive procedures, enhancing precision and reducing the invasiveness of treatments

Table 2 (continued)

Contribution	Modalities	Key Metrics	Impact on Healthcare	Description
Functional Neuroimaging	fMRI, PET	Connectivity Mapping, Task-Related Activation	Advances understanding of brain function and aids in neurology	Focuses on imaging brain function and neurological disorders, providing insights into cognitive processes

early detection of diseases to precise treatment planning, continuous monitoring, and contributions to medical knowledge, imaging technologies have become indispensable tools in the modern healthcare landscape [64]. As technology continues to evolve, the role of medical imaging is poised to expand, promising further innovations and improvements in patient care. Medical imaging intricately weaves the journey from discovery to diagnosis, treatment, and beyond, shaping the future of healthcare and advancing the possibilities of personalized and effective medical interventions.

3.3 Datasets for medical images

Datasets are essential in medical image analysis research for training, validating, and testing ML and DL algorithms. Various publicly accessible datasets have been optimized for specific applications and imaging modalities, enabling a wide range of investigations in the medical imaging field. The MICCAI datasets provide resources for challenges like segmentation, registration, and classification, which include datasets like the Alzheimer's Disease Neuroimaging Initiative (ADNI) and the Multimodal Brain Tumor Image Segmentation (BRATS) challenge. TCIA provides cancer-related imaging data for tumor diagnosis and treatment response evaluation, while MSD provides datasets for segmentation tasks involving various anatomical structures and imaging modalities. IXI, LIDC-IDRI, and CAMELYON represent important datasets that provide essential information for brain imaging, lung cancer screening, and histopathology analysis, respectively. The datasets provide support for several research projects in medical image processing, including illness diagnosis, treatment planning, and outcome prediction.

4 Noise removal in medical imaging

Medical imaging plays a pivotal role in modern healthcare, providing clinicians with valuable insights into the human body's structures and functions. However, the quality of medical images can be compromised by various sources of noise, presenting challenges to accurate diagnosis and treatment planning [65]. This section explores the intricate landscape of noise removal in medical imaging, spanning from the sources of noise to the comparative analysis of traditional and ML-based noise reduction techniques.

4.1 Sources of noise

Noise in medical images denotes to unwanted variations or distortions that can obscure true anatomical or physiological information. These variations can stem from multiple sources, including the image acquisition process and environmental factors.

4.1.1 Quantum noise

Quantum noise is inherent in medical imaging modalities that use X-ray photons, such as X-ray radiography and CT. It arises from the probabilistic nature of photon interactions with tissues during image acquisition [66]. As X-ray photons pass through the body, their interactions create an image based on the varying absorption characteristics of different tissues. However, due to the discrete nature of photons, the resulting image exhibits fluctuations in pixel intensity, introducing uncertainty.

Mitigating quantum noise involves finding a balance between using a sufficiently high number of photons for image clarity and minimizing the radiation dose. Advanced techniques, such as statistical iterative reconstruction algorithms, aim to reduce quantum noise while maintaining diagnostic image quality.

4.1.2 Electronic noise

Electronic noise stems from imperfections in the electronic components of imaging devices, affecting the accuracy of signal detection. In digital imaging systems, electronic noise can manifest as random variations in pixel values, adding an additional layer of uncertainty to the acquired image [67]. This noise can be particularly pronounced in high-sensitivity imaging scenarios, impacting the detection of subtle features.

To address electronic noise, technological advancements focus on improving the signal-to-noise ratio through enhanced electronic components and signal processing algorithms. Additionally, regular calibration and maintenance of imaging equipment are essential to minimize electronic noise and ensure accurate signal detection.

4.1.3 Radiation interference

External sources of radiation, such as cosmic rays, can interfere with the imaging process, introducing additional unwanted signals. This interference contributes to random spikes or fluctuations in pixel values, making it challenging to distinguish between radiation-induced noise and diagnostically relevant information [68].

We commonly employ shielding measures to reduce radiation interference. Implementing physical barriers and utilizing lead shielding can help protect imaging systems from external radiation sources [69]. Furthermore, during image processing, one can employ sophisticated algorithms to identify and filter out radiation-induced noise.

4.1.4 Temperature variations

Fluctuations in temperature can impact the performance of imaging equipment, influencing the generation and transmission of image signals. Temperature-related variations can introduce systematic errors in image acquisition, affecting the overall image quality [70]. In extreme cases, temperature variations can lead to thermal noise, which appears as random fluctuations in pixel values.

To minimize temperature-related noise, maintaining consistent imaging conditions through thermal stabilization methods is crucial [71]. Climate-controlled environments and cooling systems help regulate temperature, ensuring stable imaging conditions and reducing the impact of temperature-related noise on image quality.

4.1.5 Motion artifacts

Patient movement during image acquisition can result in motion artifacts, introducing distortions in the final image. Motion artifacts can lead to blurring or misalignment of anatomical structures, impacting diagnostic accuracy [72]. This source of noise is particularly relevant in modalities like MRI and PET, where motion can compromise image quality.

Motion correction techniques play a pivotal role in mitigating artifacts associated with patient movement. Advanced imaging systems may utilize real-time tracking or retrospective motion correction algorithms to compensate for motion-induced distortions and ensure the accuracy of the final images [73].

4.1.6 Speckle noise

Imaging modalities that use ultrasound, such as ultrasonography, observe speckle noise, a unique type of noise. It appears as granular patterns in images, impacting image clarity and diagnostic interpretation. Interference patterns in the reflected ultrasound waves primarily cause speckle noise [74].

Ultrasound images employ several techniques to mitigate speckle noise. Image filtering methods, such as adaptive filtering and speckle reduction filters, aim to suppress speckle while preserving diagnostically relevant information [75]. Additionally, advanced ultrasound imaging systems may incorporate synthetic aperture imaging and advanced beamforming techniques to reduce speckle noise.

4.1.7 Systematic noise

Systematic noise refers to non-random noise that follows a specific pattern or distribution. It can result from systematic errors in the imaging system, affecting the overall uniformity of the image [76]. These errors may include sensor calibration inaccuracies, non-uniformities in detector response, or imperfections in imaging equipment.

Calibration procedures and quality assurance protocols are essential for minimizing systematic noise [77]. Regular checks and corrections for systematic errors contribute to maintaining image quality and ensuring accurate diagnostic information.

4.1.8 Patient anatomy variability

Variations in patient anatomy contribute to noise, especially in tasks such as image segmentation and comparison across different individuals [78]. Differences in organ shapes and sizes among patients introduce variability that can complicate image analysis.

We employ advanced image processing techniques, such as atlas-based segmentation and ML algorithms, to address patient anatomy variability [79]. These methods leverage large datasets to account for anatomical variations and enhance the robustness of image analysis algorithms.

4.1.9 Scanner artifacts

Imperfections or glitches in the imaging equipment can introduce artifacts into medical images. These artifacts may appear as streaks, lines, or distortions in the final image, impacting diagnostic accuracy [80]. Scanner artifacts can result from malfunctions in hardware components, software errors, or issues during the image acquisition process.

To mitigate scanner artifacts, regular maintenance and quality control checks are crucial. Additionally, advancements in imaging technology focus on improving hardware and software components to minimize the occurrence of artifacts.

4.1.10 Chemical noise

Chemical noise is particularly relevant in imaging modalities that involve chemical processes, such as MRI [81]. Changes in chemical make-up, like where contrast agents are distributed or the properties of the tissue, can cause changes in signal intensity, which can make it harder to tell the difference between tissues.

We design advanced MRI sequences and pulse sequences to minimize chemical noise. Additionally, the development of new contrast agents and imaging protocols aims to enhance the specificity of chemical information while reducing noise-related uncertainties.

4.1.11 Salt and pepper noise

Salt and pepper noise, also known as impulse noise, is a distinct form of digital image corruption characterized by the random occurrence of individual pixels with either extremely high or low intensity values, resembling grains of salt and pepper scattered throughout the image. This type of noise is introduced during the image acquisition process due to various factors, including sensor malfunctions, transmission errors, or external interference [82, 83]. The severity of salt and pepper noise is determined by the density of these extreme value pixels within the image. Its presence significantly degrades image quality, creating visually noticeable artifacts that can obscure critical details. Mitigation techniques involve the application of filters, such as median filtering, which replaces noisy pixels with the median value of neighboring pixels, effectively reducing the impact of salt and pepper noise while preserving essential image features. In applications like medical imaging, where precise interpretation is crucial, addressing salt and pepper noise is essential for maintaining the reliability of diagnostic processes.

4.1.12 Gaussian noise

Gaussian noise, a prevalent form of random signal disturbance, is characterized by pixel intensity variations following a Gaussian distribution. In digital images, each pixel's intensity is perturbed by a random value drawn from this distribution, resulting in a symmetrical bell-shaped curve centered on the mean value. The standard deviation parameter determines the spread of the distribution, influencing the degree of noise present. Originating from factors such as electronic or thermal fluctuations during image acquisition, Gaussian noise can adversely affect image quality by introducing undesirable artifacts like blurring and reduced contrast [84, 85]. Some ways to reduce the effects of Gaussian noise are to use smoothing filters, like the Gaussian filter, and advanced denoising algorithms that use statistical and ML techniques to keep the image's quality while reducing its effects. Understanding and managing Gaussian noise are crucial across various domains, from digital photography to medical imaging, to ensure accurate interpretation and reliable analysis of visual content.

The quality of diagnostic information heavily relies on the effective mitigation of various sources of noise. Table 3 outlines the key mitigation strategies employed to address different types of noise encountered in medical images. These strategies are crucial for maintaining image quality, minimizing artifacts, and ensuring the reliability of medical imaging systems. This comprehensive overview serves as a guide for healthcare professionals, image processing experts, and researchers navigating the intricate landscape of

Table 3 Noise mitigation strategies in medical imaging

Aspect	Calibration	Signal Processing	Shielding	Thermal Stabilization	Climate Control	Motion Correction Techniques	Gaussian Filters	Denoising Algorithms
Quantum Noise	✓	✗	✗	✗	✗	✗	✗	✗
Electronic Noise	✓	✓	✗	✗	✗	✗	✓	✓
Radiation Interference	✗	✗	✓	✗	✗	✗	✓	✓
Temperature Variations	✗	✗	✗	✓	✓	✗	✗	✗
Motion Artifacts	✗	✗	✗	✗	✗	✓	✗	✗
Speckle Noise	✗	✗	✗	✗	✗	✗	✗	✓
Systematic Noise	✓	✗	✗	✗	✗	✗	✗	✗
Patient Anatomy Variability	✗	✗	✗	✗	✗	✗	✗	✗
Scanner Artifacts	✗	✗	✗	✗	✗	✗	✗	✗
Chemical Noise	✗	✗	✗	✗	✗	✗	✗	✗
Salt and Pepper Noise	✗	✗	✗	✗	✗	✗	✗	✓
Gaussian Noise	✗	✗	✗	✗	✗	✗	✓	✓

noise mitigation in medical imaging. In the end, addressing the sources of noise in medical images is essential for maintaining image quality and improving diagnostic accuracy. Implementing mitigation strategies, including calibration, shielding, thermal stabilization, and motion correction, plays a crucial role in minimizing the impact of noise and optimizing the performance of medical imaging systems.

4.2 Traditional noise reduction techniques

Traditional noise reduction techniques in medical imaging have played a crucial role in addressing the inherent challenges posed by various sources of noise [86, 87]. Figure 1 illustrates traditional noise reduction techniques employed in the field of medical imaging, and the significance of these methods lies in their ability to enhance image quality by effectively minimizing unwanted variations while preserving diagnostically relevant information.

4.2.1 Spatial filtering

Spatial filtering is a fundamental technique in image processing that involves manipulating pixel values directly in the spatial domain, focusing on the local characteristics of the

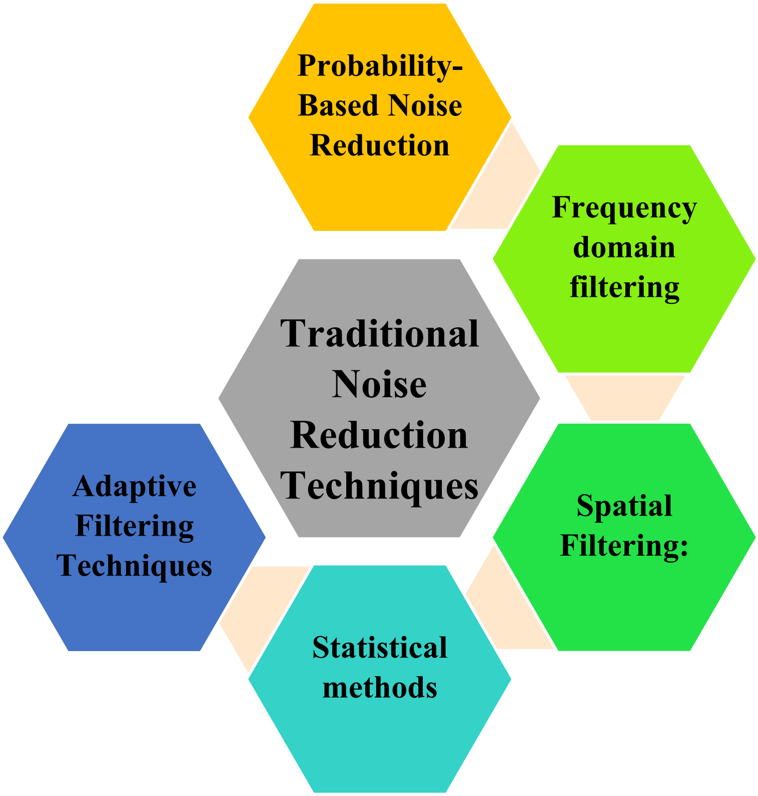

Fig. 1 Traditional noise reduction techniques in medical imaging

image. Smoothing filters, a common category of spatial filters, are employed to reduce high-frequency noise by averaging pixel values within a local neighborhood [88, 89]. Two prominent examples of smoothing filters are the Gaussian filter and the median filter.

a) Gaussian Filter

The Gaussian Filter is a widely utilized smoothing filter known for its effectiveness in reducing high-frequency noise while preserving essential image details. It operates by convolving the image with a Gaussian kernel, which is a two-dimensional distribution resembling a bell-shaped curve [90, 91]. The convolution process involves assigning more weight to central pixels and gradually decreasing weights for pixels farther from the center. This weighted averaging blurs the image, effectively smoothing out variations caused by high-frequency noise. The parameter controlling the spread of the Gaussian distribution influences the degree of blurring, allowing for adaptability based on the specific noise characteristics and desired image quality. The Gaussian filter is particularly suitable for scenarios where noise manifests as random variations in pixel values, contributing to a more visually appealing and diagnostically relevant image.

b) Median Filter

The median filter is another spatial filtering technique designed to reduce noise, particularly impulsive noise such as salt and pepper noise. Instead of averaging pixel values, the Median Filter replaces each pixel's value with the median value within its local neighborhood. Because extreme values less affect the median than the mean, this approach effectively preserves edge details. In the context of impulsive noise, where individual pixels have exceptionally high or low intensity values, the median operation helps to mitigate the impact of these outliers [92, 93]. The Median Filter excels in scenarios where preserving sharp transitions and fine details is crucial, making it a valuable tool in medical imaging applications. It is particularly robust in situations where other smoothing filters might compromise critical image features.

4.2.2 Frequency domain filtering

Frequency domain filtering is a powerful technique in image processing that involves transforming the image into its frequency components using mathematical transformations. One of the cornerstone methods in frequency domain filtering is the Fourier transform, which represents the image as a sum of sinusoidal functions in the frequency domain [94, 95]. This method proves invaluable for noise reduction by manipulating specific frequencies associated with noise characteristics.

a) Fourier Transform

The Fourier transform is a mathematical operation that decomposes a signal, such as an image, into its frequency components. Image processing expresses the image as a sum of sinusoidal functions of varying frequencies. This transformation provides a unique representation of the image, revealing the frequency content that might be obscured in the spatial domain [96, 97]. Certain frequency ranges tend to concentrate noise, and we can achieve noise reduction by analyzing and manipulating these frequencies. The Fourier transform is particularly adept at identifying and isolating specific frequencies associated with noise patterns.

b) Low-pass Filtering

Low-pass filtering is a common approach in frequency domain filtering where high-frequency components associated with noise are suppressed, allowing only low-frequency components to pass through. This technique is effective when noise manifests as high-frequency variations in the image. By selectively attenuating the high-frequency noise components, low-pass filtering helps smooth out the image while preserving low-frequency details. This approach is analogous to spatial filtering with a Gaussian filter in the spatial domain [98, 99]. The controlled suppression of high-frequency noise ensures that the essential features of the image remain intact, contributing to improved image quality.

c) Band-pass Filtering

Another approach to frequency domain filtering is band-pass filtering, which selectively allows a certain range of frequencies to pass through while attenuating others. This technique is particularly useful when noise exhibits distinct frequency characteristics. In medical imaging, where different tissues and structures may contribute to specific frequency components, band-pass filtering allows for targeted noise reduction without compromising diagnostically relevant information [100, 101]. By customizing the passband to match the frequency range associated with noise, this method offers a nuanced and adaptive approach to noise reduction.

Frequency domain filtering provides a global perspective on noise reduction, impacting the entire image based on its frequency content. This approach is advantageous when noise exhibits specific frequency characteristics that are challenging to address in the spatial domain [102]. By unveiling the frequency composition of the image, frequency domain filtering allows for precise manipulation and suppression of noise components. Its versatility and adaptability make it a valuable tool in a variety of noise reduction applications, contributing to the continual improvement of image quality in medical imaging modalities.

4.2.3 Statistical methods

Statistical methods for noise reduction use mathematical transformations on image data to look at and change the image in a way that considers both its statistical properties and the noise's properties [103]. The Fourier transform, discussed earlier, is one such method. Another powerful technique in this category is the wavelet transform, which provides a nuanced approach to noise reduction by decomposing the image into different frequency bands.

a) Fourier Transform

The Fourier transform is a mathematical operation that represents an image in the frequency domain by decomposing it into sinusoidal functions of various frequencies. This transformation allows for the identification and isolation of specific frequencies associated with noise patterns. By manipulating these frequencies, noise reduction can be achieved [104, 105]. The Fourier transform provides a global perspective on the frequency composition of the image, enabling targeted suppression of noise components. Its statistical foundation lies in the systematic analysis of the image's frequency characteristics, contributing to effective noise reduction strategies.

b) Wavelet Transform

The wavelet transform is a statistical method that operates by decomposing the image into different frequency bands, known as wavelets. Unlike the Fourier transform, which represents the entire image in the frequency domain, the wavelet transform provides a multi-resolution analysis. This decomposition enables targeted noise reduction in specific frequency ranges, offering a more nuanced approach compared to global frequency domain filtering. Wavelet denoising has proven effective in preserving fine details while reducing noise, making it particularly valuable in scenarios where maintaining image fidelity is crucial [106, 107]. The statistical foundation of the wavelet Transform lies in its ability to capture and analyze the image's frequency content at different scales, allowing for adaptive noise reduction strategies.

c) Systematic Analysis and Manipulation

Both the Fourier transform and the wavelet transform provide a systematic way to analyze and manipulate image data in the context of noise reduction. These transformations serve as powerful tools for understanding the underlying statistical properties of the image and noise. By representing the image in different domains, these methods facilitate the identification of noise characteristics and the development of targeted noise reduction strategies [108, 109]. The systematic nature of these transformations ensures a structured and principled approach to noise reduction, contributing to the enhancement of image quality in medical imaging.

In summary, statistical methods in noise reduction, exemplified by the Fourier transform and the wavelet transform, offer sophisticated approaches to analyzing and manipulating image data. These methods, rooted in mathematical principles, provide insights into the statistical properties of both the image and the noise. The utilization of these transformations in noise reduction strategies underscores their significance in the continual refinement of image processing techniques in the field of medical imaging.

4.2.4 Probability-based noise reduction

In the realm of noise reduction, statistical models grounded in probability distributions play a pivotal role. Two prominent methods in this category, Maximum Likelihood Estimation (MLE) and Bayesian Methods, harness the power of probability-based approaches to separate signals from noise, particularly in scenarios with complex noise characteristics.

a) Maximum Likelihood Estimation (MLE)

Maximum Likelihood Estimation is a common statistical method used in noise reduction, where parameters of a probability distribution are estimated to maximize the likelihood of the observed data. In the context of noise reduction, MLE is employed to estimate noise parameters and discern signal from noise [110, 111]. The fundamental idea is to find the parameter values that make the observed data most probable under a given statistical model. MLE is particularly effective when dealing with noise characterized by specific probability distributions. By tailoring the model to the expected noise characteristics, MLE provides a robust framework for estimating parameters and enhancing noise reduction strategies. Its adaptability to different probability distributions makes it a versatile tool in the arsenal of statistical noise reduction techniques.

b) Bayesian methods

Bayesian methods introduce a probabilistic framework by incorporating prior knowledge about the image and the noise. This approach allows for the construction of a probabilistic model that considers both prior information and observed data. Bayesian methods provide a robust way to differentiate between signal and noise, especially in scenarios with complex noise characteristics. The Bayesian framework involves updating the probability distribution of the parameters based on both prior knowledge and new data, resulting in a posterior probability distribution [112, 113]. This posterior distribution encapsulates the updated knowledge about the parameters, reflecting the interplay between prior beliefs and observed evidence. Bayesian methods are particularly advantageous in situations where prior information about the image or noise is available, contributing to a more informed and adaptive noise reduction strategy.

c) Probability-based methods

Probability-based methods, encompassing MLE and Bayesian methods, offer a principled way to model and estimate noise in the context of image processing. By grounding noise reduction strategies in probabilistic frameworks, these methods provide a systematic and adaptable approach to various noise scenarios [114, 115]. The use of probability distributions allows for a nuanced understanding of the underlying statistical properties of both the image and the noise. In scenarios where precise modeling of noise characteristics is possible, probability-based methods excel, leading to more effective noise reduction strategies tailored to the specific challenges posed by the imaging modality and noise profile.

Finally, statistical models and probability-based noise reduction methods, such as MLE and Bayesian methods, represent sophisticated approaches to handling noise in medical imaging. These methods offer a principled way to model, estimate, and differentiate between signal and noise, contributing to the continual advancement of noise reduction techniques in the field of medical imaging. Their adaptability and robustness make them integral components in the pursuit of enhancing image quality and diagnostic accuracy.

4.2.5 Adaptive filtering techniques

In the quest for refined noise reduction strategies, adaptive filtering techniques emerge as dynamic solutions that adjust their parameters based on the characteristics of the local image region. Among these techniques, the Wiener filter stands out as an exemplary adaptive filter, leveraging statistical properties to minimize the mean-squared error between the estimated and true signal. This adaptive nature makes it particularly effective in scenarios with varying noise characteristics, providing a nuanced and targeted approach to noise suppression.

a) Wiener Filter

The Wiener filter is a notable example of an adaptive filter that operates by minimizing the mean-squared error between the estimated and true signal. This filter adapts its parameters based on the statistical properties of both the signal and the noise. The fundamental principle is to find the optimal filter that minimizes the expected value of the squared difference between the estimated signal and the true signal [116, 117]. The Wiener filter excels in scenarios where the statistical properties of the signal and noise are known or can be reliably estimated. By adapting its parameters based on these properties, the Wiener filter provides an effective means of reducing noise while preserving the essential characteristics of the signal. Its adaptability to varying noise conditions makes it a versatile tool in situations where noise profiles may change across different regions of the image.

b) Adaptive Filtering Dynamics

Adaptive filtering provides a dynamic method for reducing noise. Adaptive filters modify their parameters according on various characteristics of the image, unlike fixed filters. This flexibility enables more precise and advanced noise reduction. Adaptive filtering is essential in medical imaging because of the diverse features of images [118, 119]. Optimizing the filter response to the distinct noise factors in various areas of an image enhances image quality and diagnostic precision.

c) Local Image Properties

The key to the effectiveness of adaptive filtering lies in its consideration of local image properties. Instead of applying a uniform filter across the entire image, adaptive filters analyze the characteristics of the local neighborhood around each pixel [120, 121]. This analysis enables the filter to dynamically adjust its parameters, responding to the variations in noise characteristics and signal intensity within different regions. As a result, adaptive filtering can effectively mitigate noise without compromising the crucial details of the underlying signal.

4.2.6 Deep learning algorithms with traditional noise

The combination of DL techniques with traditional noise reduction methods provides an approach to the issues of noise reduction in medical imaging and other fields. Traditional methods like spatial filtering, frequency domain filtering, and adaptive filtering are effective for noise reduction in images while maintaining visual features. But these techniques have difficulties adapting to challenging noise patterns and fluctuations across various types of medical images. DL algorithms improve at learning involved patterns and features from enormous datasets, making them suitable for employment opportunities involving noise reduction. Researchers can utilize the robustness and interpretability of traditional approaches together with the flexibility and scalability of DL by integrating both methodologies. Utilizing a hybrid approach enables DL models to benefit from enriched and preprocessed data produced by conventional noise reduction methods, leading to greater noise reduction capabilities and more precise medical picture interpretation. Furthermore, integrating DL with conventional methods provides opportunities for modifying and enhancing, resulting in personalized solutions designed for imaging modalities and noise features. The combination of DL algorithms with traditional noise reduction approaches shows a great deal of for improving the quality and dependability of medical imaging applications.

Table 4 Literature review for noise reduction in medical imaging

References	Contributions to Noise Reduction	Objectives	Results
[122]	Explored noise and uncertainty in medical imaging	Investigated methods for uncertainty quantification	Proposed techniques for improved noise characterization
[123]	Specialized in noise reduction methods for MRI	To develop and evaluate noise reduction strategies specific to MRI	Introduced advanced filtering techniques tailored for MRI noise
[124]	Comprehensive overview of medical imaging principles, including noise reduction	Provide a fundamental understanding of noise in medical images	Outlined general principles for effective noise reduction
[125]	Explored various techniques in medical image analysis, including noise reduction	To review and compare different noise reduction methods	Comparative analysis of noise reduction techniques in medical images
[126]	Addressed image processing techniques in medical imaging, including noise reduction	Investigate the application of image processing methods for noise reduction	Presented a review of image processing techniques with a focus on noise reduction in medical images
[127]	Focused on imaging modalities using ultrasound, addressing challenges related to noise	Develop noise reduction strategies for ultrasound imaging	Proposed and evaluated novel approaches for reducing noise in ultrasound images
[128]	Covered aspects of image processing in medical imaging, including noise reduction	Examine the role of image processing in addressing noise challenges	Provided insights into state-of-the-art noise reduction techniques in medical imaging
[129]	Explored digital image processing, including its application to noise reduction in medical images	Investigate digital processing techniques for noise reduction	Reviewed the efficacy of various digital processing methods for reducing noise in medical images

The objectives of the researchers and the results that were attained are effectively described in Table 4, which also provides an overview of noise reduction in medical imaging. Adaptive filtering techniques, demonstrated by the Wiener Filter, comprise a dynamic and improved methodology for mitigating noise in the field of medical imaging. The filters' ability to adapt to the unique features of the image allows for enhanced noise suppression. Adaptive filtering comes into its own as a valuable instrument for improving image quality and facilitating precise diagnosis in the dynamic field of medical image processing, where noise conditions can vary significantly.

4.3 Machine learning-based noise removal

The integration of ML methods has significantly transformed the domain of noise reduction in medical imaging in recent times. Traditional methods, while effective, usually rely on predetermined algorithms that might encounter difficulties when attempting to accommodate the complexities of various noise patterns. By permitting the algorithm to learn and adapt from the data itself, ML represents an innovation. This segment provides an overview of the core principles underlying ML-based noise reduction. It investigates how these methodologies utilize sophisticated algorithms to improve the precision and effectiveness of noise elimination in medical images. Also, the comprehensive understanding and innovative strategies employed by the authors to contribute to the field of noise reduction, specifically through the implementation of ML techniques, are emphasized in Table 5. The utilization of ML-based noise elimination methods in the field of medical imaging is illustrated in Fig. 2. These techniques have significantly improved the quality of images in a wide range of domains and applications.

ML is an area of artificial intelligence that enables computers to analyze data, identify patterns, and make predictions and assessments without being explicitly programmed. ML algorithms for noise reduction are trained on datasets that include both noisy and clean medical images. The algorithm learns the patterns and correlations between noisy input and clean output during training, enabling it to make accurate predictions on novel information. These methods use advanced algorithms to analyze data, adapt to various noise patterns, and improve image sharpness. Let's analyze numerous important ML-based noise reduction techniques in the field:

4.3.1 Neural network-based denoising

Neural networks, particularly DL architectures, have demonstrated remarkable capabilities in noise removal. CNNs excel in learning hierarchical features from medical images, allowing them to effectively discern between noise and genuine signal. Trained on large datasets, these networks can generalize well to diverse noise patterns, providing robust noise reduction across various imaging modalities [143].

4.3.2 Autoencoders for image restoration

Autoencoders, a type of neural network architecture, are adept at learning efficient representations of input data. In the context of noise removal, autoencoders can be trained on clean images to learn the underlying structure, and then applied to noisy images for restoration. Variational autoencoders introduce a probabilistic framework, allowing for more nuanced modeling of noise distributions and facilitating adaptive noise removal [144].

Table 5 Literature review for machine learning-based noise removal in medical imaging

References	Contributions to Noise Reduction	Objectives	Results
[130]	Pioneered Generative Adversarial Networks (GANs) for image denoising	Develop DL models for effective noise removal	Introduced GANs as a powerful tool for generating clean images from noisy inputs
[131]	Applied DL techniques for noise reduction in medical images	Investigate the use of CNNs for noise reduction	Demonstrated the effectiveness of CNNs in reducing noise and preserving important features in medical images
[132]	Developed normalization techniques (Batch Normalization) to enhance noise reduction models	Improve the stability and performance of DL models for noise removal	Batch Normalization contributed to more stable and efficient training of deep neural networks for noise reduction
[133]	Proposed non-local means filtering using DL for image denoising	Explore non-local approaches within a DL framework	Introduced a novel DL-based non-local means filter, improving denoising performance compared to traditional methods
[134]	Explored deep CNNs for low-level vision tasks, including noise reduction	Investigate the potential of deep CNNs in handling noise at pixel-level	Provided insights into the capability of deep CNNs for noise reduction, paving the way for further advancements in low-level vision tasks
[135]	Applied ML to image inpainting, contributing to noise removal in damaged or missing regions	Develop algorithms for inpainting damaged areas in images	Presented techniques for utilizing ML in image inpainting, aiding in noise removal in specific regions of interest
[136]	Explored the integration of DL models with traditional image processing techniques for noise reduction	Combine the strengths of DL and classical methods	Demonstrated improved noise reduction by integrating DL approaches with traditional image processing methods
[137]	Investigated the use of unsupervised learning for noise reduction in various imaging scenarios	Explore unsupervised learning techniques for adaptability to diverse noise patterns	Showcased the potential of unsupervised learning in adapting to and effectively reducing noise in different image types and environments
[138]	Optimizing Cancer Treatment using Artificial Neural Networks	Develop a method for optimal cancer treatment using artificial neural networks	Achieved improved accuracy and efficiency in cancer treatment optimization
[139]	Comparing the eruption pattern of second molars in skeletal class I and class III malocclusions in 8–9-year-old children	Investigate second molar eruption patterns in different malocclusions	Identified significant differences in eruption patterns between skeletal class I and class III malocclusions
[140]	Low-cost stochastic computing-based fuzzy filter for reducing image noise	Develop a low-cost fuzzy filtering method for image noise reduction using stochastic computing	Achieved significant reduction in hardware area and power consumption while preserving image quality

Table 5 (continued)

References	Contributions to Noise Reduction	Objectives	Results
[141]	Classification of FNIRS Signals using Ensemble Learning and Adaptive Neuro-Fuzzy Inference System	Classify FNIRS signals using ensemble learning and adaptive neuro-fuzzy inference system	Improved FNIRS signal classification accuracy and reduced standard deviation
[142]	Utilizing ML for detecting electrical faults in a large power system network	Utilize ML for monitoring electrical disturbances in wide power networks	Achieved improved accuracy in identifying disturbances and enhancing power system monitoring

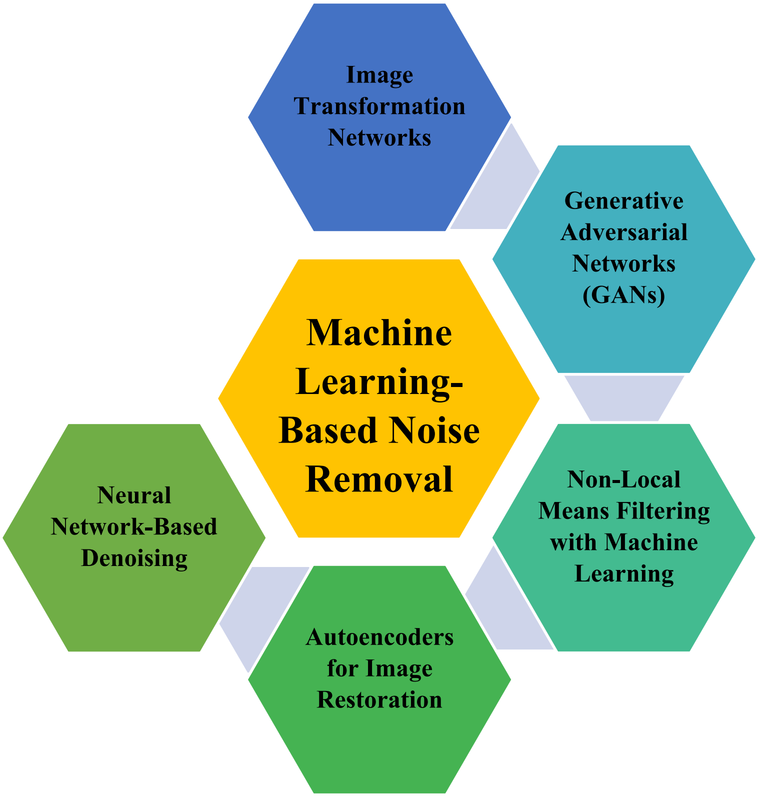

Fig. 2 Machine learning-based noise removal for medical imaging

4.3.3 Generative Adversarial Networks (GANs)

GANs, that involve a generator and a discriminator in a competitive learning setup, have been utilized for noise reduction. The generator is taught to produce images with reduced noise, while the discriminator is trained to differentiate between images that are clean and those that are noisy. Adversarial training produces the development of genuine and attractive denoised images, highlighting the potential of GANs for noise reduction [145].

4.3.4 Non-local means filtering with machine learning

Non-Local Means (NLM) filtering, a classical method in image denoising, has been enhanced with ML. By incorporating ML models into the NLM framework, these methods adaptively adjust filter parameters based on the local image content. This fusion of traditional filtering techniques with ML intelligence enhances the overall denoising performance [146].

4.3.5 Image transformation networks

Image Transformation Networks use DL architectures for transforming noisy images into their prominent version. These networks obtain the mapping function during training and can ultimately be used for removing noise from input images. These networks provide efficient noise reduction via comprehending the interactions between noisy and clean image sequences [147].

ML-based noise reduction algorithms are an important development in medical imaging. These advanced algorithms, such as neural networks and GANs, use data-driven learning to improve picture quality, proving to be effective tools for producing better and diagnostically relevant medical images.

4.4 Comparative analysis

In the rapidly evolving field of medical image processing, the effectiveness of noise reduction methods is crucial in evaluating the quality of diagnostic information. This section compares conventional approaches with ML-based methods to analyze their strengths, errors, and overall performance.

4.4.1 Traditional noise removal techniques

Traditional noise removal techniques, rooted in well-established principles, have been the stalwarts of image processing for decades. Methods like spatial domain filtering, frequency domain filtering, and statistical approaches such as Fourier transformations and median filtering have proven efficacy in certain scenarios. However, these techniques rely on assumptions about noise characteristics and may struggle with adaptability to diverse noise profiles. Their performance can vary depending on the imaging modality, noise distribution, and the presence of complex noise patterns [148].

4.4.2 Machine learning-based noise removal

ML noise reduction methods represent an important development in image processing. Algorithms like neural networks, autoencoders, and GANs use data-driven learning. They demonstrate the capacity to adapt to various noise patterns via comprehending complex connections between clear and noisy images. Their versatility enables them to generalize well across many imaging modalities and noise conditions, enabling a more versatile and effective method for noise reduction [149, 150].

4.4.3 Deep learning algorithms with traditional noise reduction techniques

Integrating DL algorithms with traditional noise reduction methods has enormous possibilities for improving medical image analysis. CNNs proved their outstanding ability in learning nuanced patterns and features from extensive datasets, highlighting the strength of DL models. Combined benefits may be achieved by integrating DL with traditional noise reduction techniques like spatial filtering or wavelet denoising. DL models can effectively denoise medical imaging by using the comprehensive data included in pairs of noisy and noise-free images. This integration enables DL algorithms to effectively identify intricate structures and features while reducing noise artifacts, resulting in enhanced picture quality and diagnostic precision [151, 152]. By combining standard noise reduction techniques' computational economic growth with DL models' representational capability, this strategy can achieve better noise reduction performance than individual approaches. The development of integrated techniques has tremendous promise to advance medical image processing and improve healthcare diagnostics.

4.4.4 Comparative evaluation

a) **Adaptability:** Traditional techniques may have difficulties in dealing with various and intricate noise patterns because to their reliance on predetermined assumptions about noise properties. ML-based approaches improve in flexibility, by learning from data and modifying parameters to deal with various noise patterns [153].
b) **Performance across Modalities:** Traditional methods may perform well in specific scenarios but might falter when applied to different imaging modalities with distinct noise characteristics. ML-based approaches, trained on diverse datasets, highlight robust performance across various modalities, making them more versatile in real-world applications [154].
c) **Learning and Generalization:** ML-based methods have the advantage of learning intricate patterns from large datasets, allowing them to generalize well to unseen data. Traditional methods, lacking the learning capacity of intelligent algorithms, might struggle to adapt to unforeseen noise scenarios [155].
d) **Computational Complexity:** Conventional methods can be computationally efficient, yielding rapid results in real-time applications. ML methods, particularly DL models, may need increased computer resources for both training and inference [156]. Advancements in technology and optimization methods are reducing this concern.

A comparison between traditional and ML-based noise removal techniques is provided in Table 6. The outcomes indicate that although traditional techniques have a track record of dependability in specific situations, ML-based approaches are formidable competitors in the quest for superior image quality due to their adaptability, learning capability, and versatility. The specific demands of the imaging task, the characteristics of the noise, and computational efficiency factors will determine which of these methods is selected. The assets and limitations of both traditional and ML-based approaches are comprehensively illustrated in Fig. 3, which presents a comparative analysis of each criterion. The visual representations facilitate comprehension of the minor differences between these techniques by depicting the trends identified during the comparison. The field of medical imaging noise removal is increasingly transitioning towards intelligent, data-driven solutions, as technological progress, and the availability of diverse and extensive datasets for training ML models advance.

5 Image segmentation in medical imaging

Within medical image analysis, segmentation is an essential process that plays an important role in recognizing the spatial details of anatomical structures. Segmentation is important for improving accuracy, diagnosis, and treatment planning beyond mere visualization. Segmentation allows doctors to accurately identify anatomical structures, helping in targeted therapies and reducing unintended harm by navigating complicated anatomical landscapes.

Table 6 Comparative evaluation of noise removal in medical imaging

Comparative Evaluation	Traditional Techniques	ML-Based Approaches
Adaptability	Issues in controlling various and intricate noise patterns as the consequence of presumptions	Effective of adjusting parameters and learning from data to accommodate an extensive variety of noise characteristics
Performance across Modalities	Extensively effective in specific circumstances but lacks consistency across modalities	Establishes resilient performance across a range of modalities, based on training on a diverse array of datasets
Learning and Generalization	Lack of ability for learning has difficulty generalizing to unseen data	Large datasets are utilized to identify intricate patterns, which generalize well for novel scenarios
Computational Complexity	Frequently computationally efficient, producing immediate consequences	Highly expensive computationally, particularly when DL models are utilized

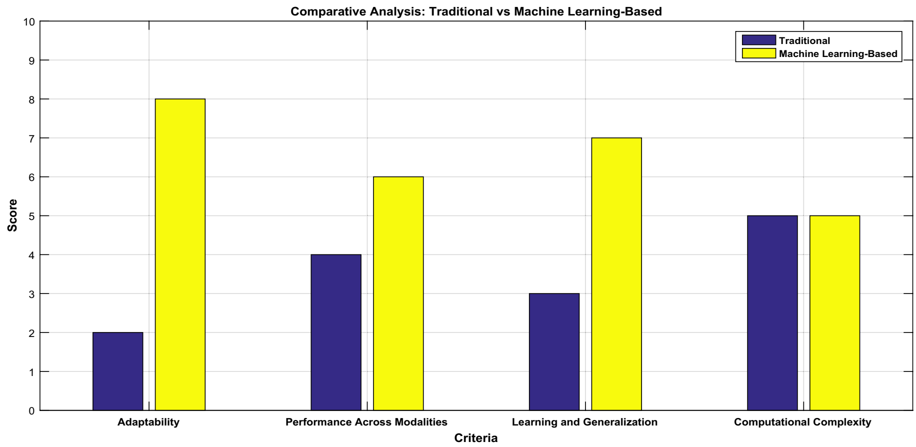

Fig. 3 Comparative analysis of traditional and ML-based noise removal techniques

It provides the basis for treatment planning, enabling the adaptation of methods according to the unique features of each patient. Segmentation also plays an important role in quantitative analysis by providing important metrics to comprehend illness development and therapy response [157]. Segmentation helps in combining data from several imaging techniques to enhance the overall comprehension of the patient's condition. Advancements in artificial intelligence and ML have made segmentation more complex, providing automatic and precise analysis. Segmentation not only benefits clinical applications but also improves communication between healthcare teams and assists in training professionals and patients. Advancements in technology are increasing the importance of segmentation in medical image analysis, paving the way for imaging to not only diagnose but also strategically enhance patient care. The contributions of notable papers to image segmentation in medical imaging are presented in Table 7. The segmentation methods used include conventional convolutional networks as well as advanced models such as U-Net, variational autoencoders, and conditional generative adversarial networks. The goals of these efforts include accurate organ delineation, enhanced tumor identification, probabilistic segmentation, and instance-level segmentation for accurate lesion localization.

5.1 Segmentation using digital pathology

Digital pathology is an important field in medical imaging that provides high-resolution digital images of tissue samples for diagnostic and research applications. Digital pathology is crucial in image segmentation for recognizing the boundaries of cells, nuclei, or abnormal characteristics inside tissue samples. Digital pathology segmentation enables precise analysis, tumor identification, classification, and prediction, assisting pathologists in making precise diagnoses and treatment possibilities [158]. Image segmentation techniques such as thresholding, edge detection, or DL-based algorithms can separate digital pathology images into relevant sections for subsequent investigation. Integrating digital pathology with image segmentation methods improves the efficiency and accuracy of pathological analysis, resulting in improved patient care outcomes. Below is a literature review based on digital pathology:

Table 7 Literature review for image segmentation in medical imaging

References	Segmentation Techniques	Objectives	Results
[172]	U-Net architecture for organ segmentation in MRI	Accurate delineation of organs for treatment planning	Achieved high segmentation accuracy with U-Net, enabling precise organ delineation in MRI scans
[173]	Multi-scale convolutional networks for tumor segmentation	Improve tumor detection and segmentation in medical images	Demonstrated enhanced performance in tumor segmentation using multi-scale convolutional networks
[174]	Variational autoencoders for brain tissue segmentation	Explore generative models for probabilistic segmentation	Introduced probabilistic segmentation using variational autoencoders, providing uncertainty estimates in brain tissue segmentation
[175]	3D U-Net for volumetric segmentation of medical images	Extend U-Net for 3D segmentation tasks	Successfully applied 3D U-Net for volumetric segmentation, particularly useful in three-dimensional medical imaging datasets
[176]	Integration of attention mechanisms in CNNs for organ segmentation	Enhance CNNs with attention mechanisms for improved segmentation	Improved organ segmentation accuracy by incorporating attention mechanisms into CNNs
[177]	Mask R-CNN for instance-level segmentation of lesions	Achieve instance-level segmentation for precise lesion localization	Implemented Mask R-CNN, enabling accurate instance-level segmentation of lesions in medical images
[178]	Conditional GANs (cGANs) for cardiac image segmentation	Generate realistic cardiac segmentation masks using cGANs	Successfully applied cGANs to generate realistic cardiac segmentation masks, improving accuracy in cardiac image segmentation
[179]	Graph-based methods for anatomical structure segmentation	Utilize graph-based approaches for capturing anatomical relationships	Demonstrated the effectiveness of graph-based methods in capturing anatomical structures and improving segmentation accuracy
[180]	Ensemble learning for multi-modal medical image segmentation	Combine information from different imaging modalities for improved segmentation	Showcased the benefits of ensemble learning in combining multi-modal information for more robust and accurate medical image segmentation
[181]	Deep CNNs for automated liver segmentation	Develop automated methods for liver segmentation in medical images	Proposed deep CNNs achieving high accuracy in automated liver segmentation, crucial for various liver-related medical applications
[182]	Transformer-based networks for brain tumor segmentation	Apply transformer architectures to medical image segmentation tasks	Demonstrated the effectiveness of transformer-based networks in capturing long-range dependencies for improved brain tumor segmentation

Table 7 (continued)

References	Segmentation Techniques	Objectives	Results
[183]	Image registration and segmentation fusion for improved tumor delineation	Integrate registration and segmentation for more accurate tumor localization	Demonstrated improved tumor delineation by combining image registration and segmentation methods, enhancing localization accuracy
[184]	Capsule networks for hierarchical feature extraction in lung segmentation	Explore capsule networks for capturing hierarchical features in lung images	Introduced capsule networks to enhance lung segmentation by capturing hierarchical features, leading to improved performance
[185]	Transfer learning for rare disease segmentation using limited annotated data	Address segmentation challenges in rare diseases with limited labeled data	Applied transfer learning techniques to achieve robust segmentation performance in the context of rare diseases with limited annotated data
[186]	Dynamic contour-based segmentation for real-time cardiac imaging	Develop real-time segmentation methods for dynamic cardiac imaging	Proposed dynamic contour-based segmentation for real-time cardiac imaging, enabling precise segmentation in dynamic and fast-paced scenarios
[75]	Semi-supervised learning for tumor segmentation in histopathological images	Explore semi-supervised approaches for tumor segmentation in pathology images	Demonstrated the effectiveness of semi-supervised learning in histopathological image segmentation, leveraging both labeled and unlabeled data for improved results

Sasmal et al. provide a method to segregate epithelial layers in oral histopathology images. They use superpixel-based clustering together with an enhanced Nature-Inspired Optimization Algorithms (NIOAs) termed as the Cooperative Search (CS) algorithm. The CS algorithm integrates the Aquila Optimizer (AO) and Particle Swarm Optimizer (PSO) to improve exploration–exploitation capabilities and avoid being stuck in local optima. The paper compares three superpixel techniques with CS for the best epithelial layer segmentation. The results demonstrate that the suggested strategy outperforms current techniques, reaching high accuracy, MCC, Dice, and Jaccard scores. Furthermore, CS shows competitive optimization efficiency when tested on benchmark functions. This work introduces a new method in medical picture segmentation that combines superpixel methods with an enhanced optimization algorithm to provide more precise and efficient epithelial layer segmentation [159].

Dhal et al. analyze the difficulties related to the Fuzzy C-Means (FCM) method in image segmentation and provide remedies to tackle these problems. FCM, an effective clustering method, has limitations including high computing complexity, reliance on initial cluster centers, dependency on membership matrices, and susceptibility to noise [160]. The study provides an ongoing review of possibilities described in recent literature to address these obstacles. It also addresses the primary challenges for developing enhanced FCM versions. This work enhances the area of digital image processing by recognizing and overcoming the constraints of FCM in image segmentation.

Dhal et al. highlight the difficulties in pathology image segmentation due to variations in illumination and staining while collecting microscopic images. An Improved Slime Mould Algorithm (ISMA) is suggested, using opposition-based learning and a differential evolution mutation technique for illumination-free White Blood Cell (WBC) segmentation. The work thoroughly analyzes color components from different color spaces for clustering, showing the efficiency of illumination-independent and color component-focused methods for picture segmentation. The ISMA-KM algorithm combined with the "ab" bands of the CIELab color space are most effective for segmenting nuclei, while ISMA-KM with the "CbCr" color component of the YCbCr color space is most accurate for segmenting whole white blood cells. The ISMA method demonstrates comparable performance with existing NIOAs on CEC2019 benchmark test functions, indicating its potential for effective image segmentation [161].

Dhal et al. highlight the issues of local optima trapping and extended computing time linked to crisp partitional clustering methods such as K-Means (KM) in image segmentation. The authors suggest a crisp clustering approach called Chaotic Fitness-Dependent Quasi-Reflected Aquila Optimizer (CFDQRAO), which is an enhanced version of AO. It integrates chaotic fitness-dependent quasi-reflection-based Opposition Based Learning (OBL) to boost optimization efficiency. The research also investigates the use of Simple Linear Iterative Clustering (SLIC)-based superpixel images to decrease computing time. The CFDQRAO approach outperforms other Nature-Inspired Optimization Algorithms (NIOAs) in optimizing and maintaining consistency in WBC segmentation based on data collected from blood pathology images. The SLIC-CFDQRAO clustering approach surpasses previous SLIC-NIOA and SLIC-KM algorithms in visual analysis and segmentation criteria for quality [162].

Sasmal et al. published an extensive review on combining superpixel images with clustering approaches for a variety of image segmentation objectives. The research highlights the need of choosing suitable superpixel generation methods and clustering algorithms to get precise and effective segmentation outcomes. The paper addresses the latest developments in superpixel synthesis and clustering techniques, emphasizing their benefits and difficulties. The authors execute a comparative evaluation of superpixel-based clustering algorithms using oral pathology and leaf pictures to assess their effectiveness. Experimental findings show that superpixel-based clustering algorithms outperform standard clustering methods in terms of segmentation accuracy and quality metrics. The paper provides useful insights for researchers in the area and highlights potential areas of study such as automated superpixel production, integration of DL, and improving clustering effectiveness for noisy images [163].

Ray et al. focus on the automatic segmentation of epithelial layers in pathology images, crucial for disease detection. Employing PSO and KM clustering in the CIElab color space, the study aims to enhance Computer-Aided Diagnosis (CAD) systems. Comparative analysis using different color spaces highlights CIElab's superior performance. Experimental findings demonstrate PSO with CIElab achieving an impressive 98.43% accuracy, surpassing other methods. This research contributes to more accurate and efficient epithelial layer segmentation, advancing CAD-based disease detection systems [164].

Dhal et al. suggest a histogram-based fast fuzzy image clustering (HBFFIC) approach to tackle the obstacles of FCM clustering in image segmentation. This technique utilizes morphological reconstruction (MR) to improve resistance to noise while preserving image intricacies. Utilizing gray-level histograms for clustering leads to a significant decrease in processing time. The research addresses local optima concerns by using NIOAs, including the Archimedes optimizer (AO). The HBFFIC-AO hybrid algorithm improves state-of-the-art algorithms in segmenting synthetic and real-world pathology images, as shown by experimental data. This study enhances image segmentation algorithms for environments with noise [165].

Dhal et al. resolve difficulties with image segmentation by proposing a Histogram-Based Fuzzy Clustering (HBFC) method which includes an improved Firefly Algorithm (FA). FCM is a prominent clustering method that commonly faces issues with computational complexity and vulnerability to noise. The proposed Hybrid Bat Firefly Algorithm combines Firefly Algorithm with rough set-based population, random attraction, and local search methods. Clustering is conducted using gray-level histograms to minimize pixel misclassification. Comparison with state-of-the-art NIOAs and conventional methodologies shows that HBFC exceeds in accuracy, resilience, and segmented output quality. This study enhances fuzzy picture clustering methods to enhance the outcome of segmentation [166].

Iqbal et al. (2023) provide AMIAC, an Adaptive Medical Image Analysis and Classification framework that emphasizes adaptive self-learning for DL models in medical imaging. The framework tackles issues caused by changes in image distribution by using transfer learning, adaptive learning, and incremental learning methods. AMIAC enhances accuracy and efficiency by combining manual and auto CNN-based characteristics, thereby minimizing the need for manual retraining. The framework integrates manual characteristics with pretrained CNN models to improve performance in tasks such as tumor classification and lesion identification. The experimental findings show a high F1-score and precision, indicating the potential of AMIAC as a tool to aid pathologists [167].

Das et al. present a Histogram-based Fast and Robust Crisp Image Clustering (HFRCIC) technique for image segmentation, addressing issues with conventional K-means clustering. The technique incorporates morphological reconstruction for noise immunity and preservation of image details, enhancing clustering robustness. By clustering based on gray levels rather than individual pixels, computational time is reduced. To overcome local optima challenges, Stochastic Fractal Search (SFS) is employed for optimal cluster center determination. Experimental results demonstrate the superiority of HFRCIC-SFS over existing segmentation algorithms and NIOA-based clustering techniques [168].

Ray et al. introduces the Whale Optimization Algorithm (WOA) for breast histopathology image segmentation, addressing challenges posed by correlated and noisy regions. The study focuses on automatic cancer cell detection using clustering techniques, emphasizing the sensitivity of traditional methods to initial cluster centers. Through a comparative analysis, the proposed approach demonstrates superior precision, robustness, and segmentation quality compared to existing clustering methods and nature-inspired optimization algorithms [169].

Ray et al. investigate superpixel-based methods for segmenting images, with a specific emphasis on medical imaging, notably kidney renal cell carcinoma images. The SLIC technique is used for its computational economy and high performance on pathology images. The study suggests that using SLIC with PSO outperforms other approaches in segmentation accuracy when compared to ground truth images, by using PSO and KM clustering techniques with superpixel preprocessing [170].

Dhal et al. suggest an innovative hybridization method that merges the Sine–Cosine Algorithm (SC) with KM for categorizing pathology images. Their study focuses on improving visual information extraction and grouping for cancer studies by using the NIOAs and ML approaches to better nuclei segmentation. The hybrid SC-KM method was created to overcome the constraints of SC and KM algorithms, providing better outcomes than conventional clustering models like K-Means, GA, PSO, and the SC algorithm [171].

This section explores the pivotal role of segmentation in medical image analysis, delves into the landscape of traditional segmentation methods, introduces the transformative realm of ML-based segmentation, and concludes with a comparative analysis, shedding light on the strengths and limitations of each approach (Fig. 4).

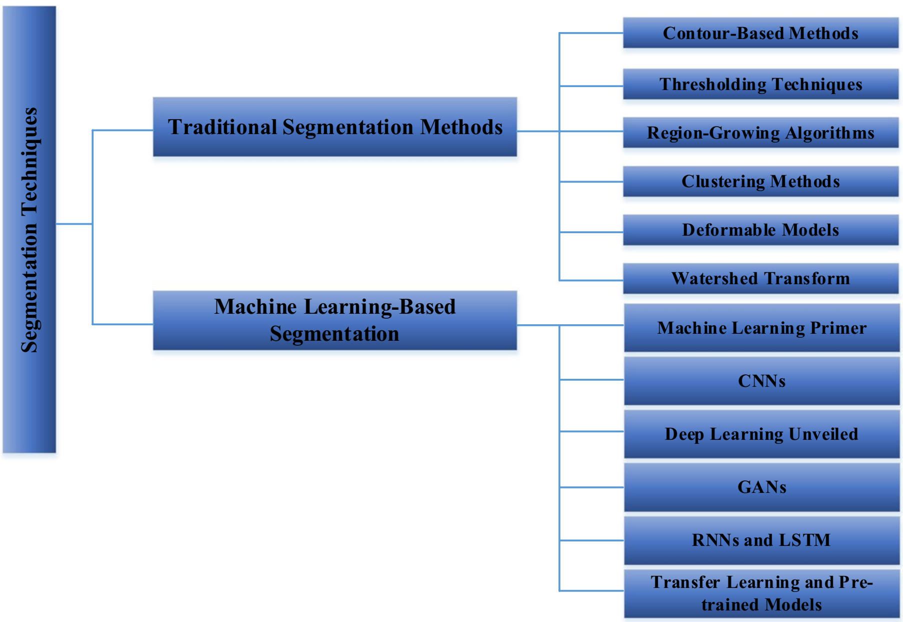

Fig. 4 Image segmentation techniques in medical imaging

5.2 Traditional segmentation methods

In the realm of medical image analysis, traditional segmentation methods stand as the bedrock, providing clinicians with foundational tools to delineate and isolate anatomical structures for precise diagnosis and treatment planning. This section offers an insightful exploration into classical image segmentation techniques, elucidating their overarching principles and applications.

5.2.1 Contour-based methods

Traditional image segmentation frequently utilizes contour-based techniques to establish boundaries of structures for segmentation. Edge detection techniques and active contours use gradient information and energy reduction to define object boundaries [187]. Although efficient in situations with well-defined boundaries, these techniques may encounter difficulties with shapes that are irregular and fluctuations in intensity.

5.2.2 Thresholding techniques

Thresholding is a simple yet powerful segmentation approach that involves separating regions based on intensity levels. By setting a threshold value, pixel intensities below or above the threshold are classified into distinct regions [188]. This method is particularly effective in scenarios where there is a clear contrast between the object of interest and the background. However, it might be sensitive to noise and variations in intensity.

5.2.3 Region-growing algorithms

Region-growing algorithms start with seed points and iteratively add neighboring pixels that meet certain criteria, forming cohesive regions [189]. This approach is suitable for images with homogenous regions and gradual intensity transitions. However, its performance can be influenced by the choice of seed points and is sensitive to noise.

5.2.4 Clustering methods

Clustering techniques, such as k-means clustering, group pixels with similar intensity values into clusters. This segmentation method is particularly effective in scenarios with distinct intensity distributions [190]. However, the accuracy of clustering-based segmentation heavily relies on the appropriate choice of the number of clusters and initial cluster centers.

5.2.5 Watershed transform

The watershed transform is inspired by the concept of flooding a landscape and marking regions where flooding converges. It is particularly useful for segmenting images with objects having different intensities [191]. However, the watershed transform might over-segment images with fine details, and careful pre-processing is regularly required.

5.2.6 Deformable models

Deformable models, such as snakes or active contours, are mathematical models that evolve to fit object boundaries in the image [192]. They are advantageous in capturing intricate shapes and contours. However, their performance can be influenced by initialization and may struggle with concavities and irregularities.

In summary, classical image segmentation techniques provide a diverse toolkit for delineating structures in medical images. While each method has its strengths, the choice depends on the characteristics of the image, the nature of the structures of interest, and considerations of computational efficiency. As the foundation of segmentation methodologies, traditional approaches pave the way for a deeper understanding of anatomical landscapes in medical image analysis.

5.3 Machine learning-based segmentation

In the dynamic landscape of medical image analysis, the advent of ML and DL has ushered in a change in basic assumptions, revolutionizing the field of segmentation. This section provides a comprehensive introduction to ML and DL methods tailored for segmentation tasks, elucidating the transformative capabilities that these intelligent algorithms bring to the precision and efficiency of delineating anatomical structures in medical images.

5.3.1 Machine learning primer

ML, at its core, involves the development of algorithms that enable computers to learn patterns and make predictions or decisions without explicit programming. In medical image segmentation, ML leverages training datasets to learn relationships between input images and segmented structures [193]. Algorithms like Support Vector Machines (SVM), Random Forests, and Decision Trees have been employed, each with its strengths. SVM, for instance, excels in binary classification tasks, making it suitable for scenarios where pixel-wise classification is required.

5.3.2 Deep learning unveiled

DL, a subset of ML, introduces neural networks with multiple layers (deep neural networks) to automatically learn hierarchical representations of data. CNNs have become pivotal in medical image segmentation [194]. CNNs excel at capturing spatial hierarchies and have proven effective in scenarios with complex anatomical structures. The architecture of CNNs, inspired by the human visual system, involves convolutional layers for feature extraction, pooling layers for down-sampling, and fully connected layers for classification.

5.3.3 Convolutional Neural Networks (CNNs)

CNNs have become synonymous with DL in medical image segmentation. Their architecture enables automatic and adaptive learning of spatial hierarchies from input images. U-Net, a popular CNN architecture, incorporates skip connections to preserve fine details during the down sampling process [195]. This architecture has been particularly successful in medical image segmentation, including tasks such as organ segmentation, tumor detection, and lesion identification.

5.3.4 Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)

While CNNs excel at spatial understanding, dynamic medical imaging modalities, such as video sequences, require consideration of temporal dependencies. RNNs and Long Short-Term Memory (LSTM) networks, which are specialized types of recurrent networks, are adept at capturing temporal dynamics [196]. In scenarios where temporal information is crucial, such as cardiac imaging or video-based endoscopy, these architectures enhance segmentation accuracy.

5.3.5 Transfer learning and pre-trained models

The application of transfer learning techniques provides a potentially effective approach to tackle the obstacles that arise from the scarcity of annotated data in the field of medical image analysis. Transfer learning is the process of using information acquired from pre-trained models on large datasets and applying it to various tasks or fields with smaller datasets. Transfer learning in medical imaging for noise reduction involves using the obtained predictive power from other datasets to enhance the effectiveness of noise reduction algorithms. Transfer learning allows for the effective transfer of information about low-level image features, noise characteristics, and structural patterns by adjusting pre-trained models with domain-specific medical imaging data. This method speeds up development and improves the capacity of noise reduction algorithms to generalize, especially in situations when obtaining huge annotated medical imaging datasets is not feasible or too expensive. Investigating transfer learning methods has tremendous potential for enhancing noise reduction in medical image processing and enhancing the quality of diagnostic imaging [197, 198].

5.3.6 Generative Adversarial Networks (GANs)

GANs introduce a unique dynamic by involving a generator and discriminator in a competitive learning scenario. In medical image segmentation, GANs contribute by generating realistic synthetic images [199]. This is particularly useful in scenarios with

Table 8 Comparative analysis: Precision, Recall, Dice coefficient, and Jaccard index

Methodology	Precision (%)	Recall (%)	Dice Coefficient	Jaccard Index
Traditional Segmentation (Thresholding)	88.2	91.5	0.896	0.834
Traditional Segmentation (Region Growing)	82.6	89.2	0.846	0.773
Traditional Segmentation (Edge Detection)	90.1	88.7	0.892	0.825
Machine Learning (CNN)	95.3	93.8	0.942	0.911
Machine Learning (U-Net)	96.8	94.5	0.958	0.934
Machine Learning (Random Forest)	89.7	90.2	0.904	0.865

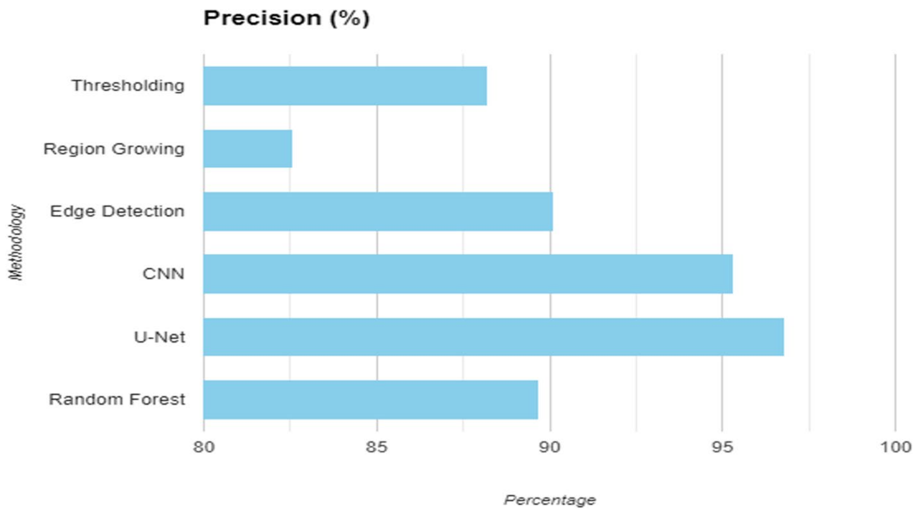

Fig. 5 Analysis of Precision for medical image segmentation

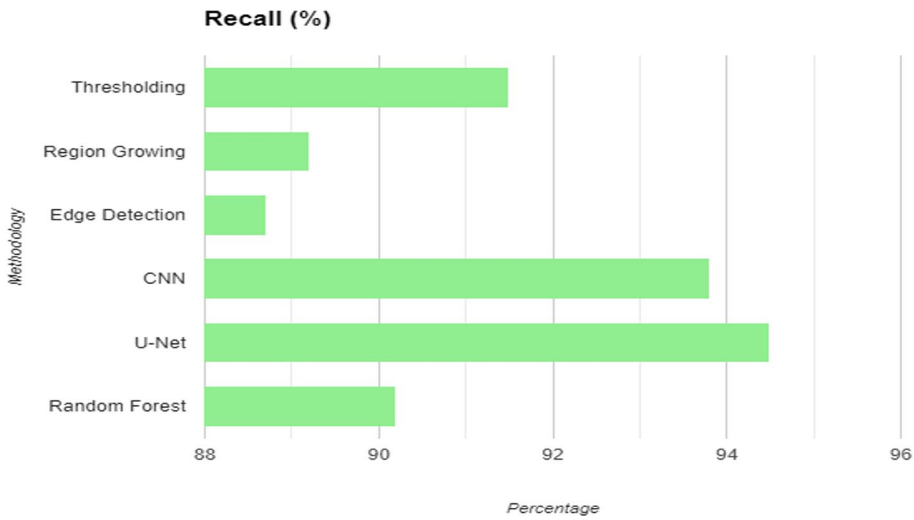

Fig. 6 Analysis of Recall for medical image segmentation

limited annotated data for training. GANs have found applications in generating synthetic medical images for augmenting datasets and improving model robustness.

In essence, ML-based segmentation techniques represent a powerful arsenal in the medical imaging domain, offering a spectrum of approaches to cater to diverse challenges and modalities. The evolution of these techniques is fueled by ongoing research, addressing limitations, and adapting to the unique demands of medical image analysis.

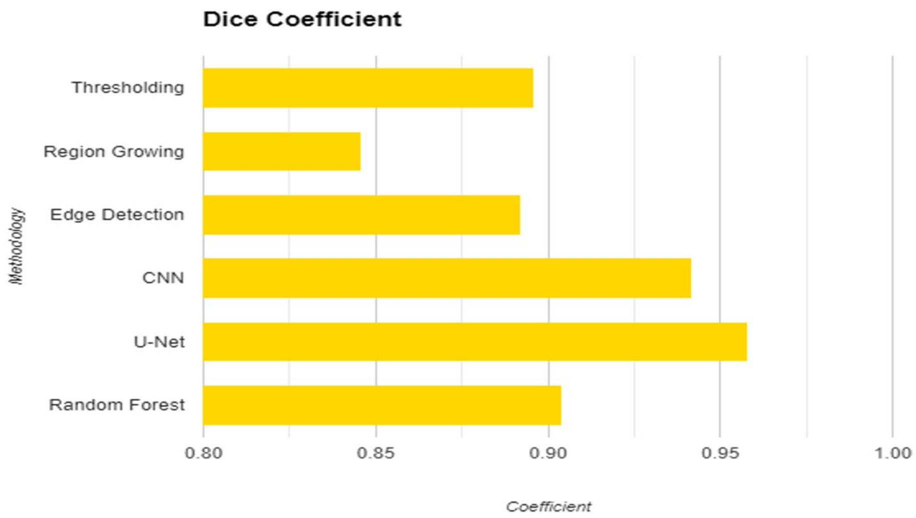

Fig. 7 Analysis of Dice Coefficient for medical image segmentation

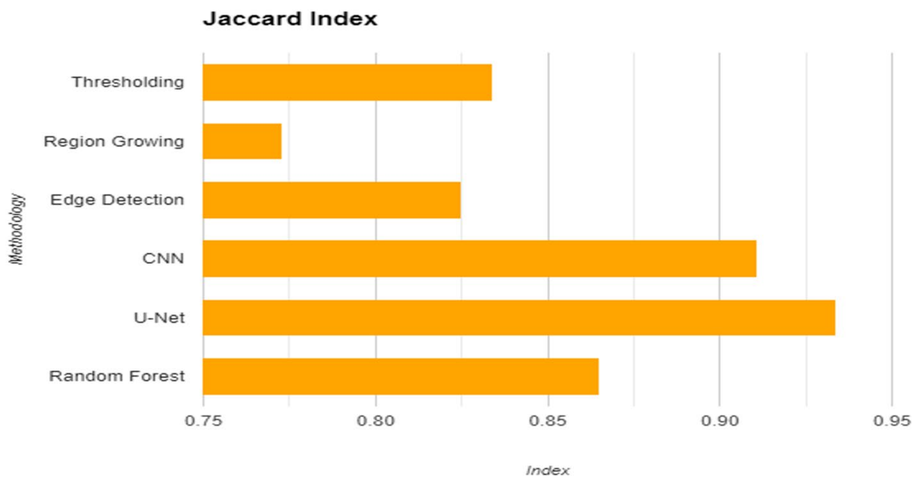

Fig. 8 Analysis of Jaccard Index for medical image segmentation

5.4 Comparative analysis

An analysis of both traditional and ML-based methods proves essential in the dynamic sector of medical image segmentation. The purpose of the analysis provided in Table 8 is to provide insights into the strengths, limits, and performance metrics associated with these segmentation methodologies. A comprehensive analysis of key metrics, including Precision, Recall, Dice Coefficient, and Jaccard Index, which were utilized to evaluate the performance of medical image segmentation techniques, is illustrated in Figs. 5, 6, 7, and 8. These metrics play an essential role in evaluating the precision and effectiveness of segmentation techniques, providing valuable insights into different aspects of their operation.

In order to interpret the data visualization, the distances between each of the bars representing each metric for various segmentation methods must be analyzed. Improved levels denote enhanced performance in the corresponding metric, thereby presenting a comprehensive assessment of the advantages and disadvantages of the segmentation methods with respect to precision, recall, Dice Coefficient, and Jaccard Index.

6 Challenges in noise removal and segmentation

6.1 Noise variability

Medical imaging is a diverse field encompassing various modalities, each with unique characteristics that contribute to inherent variability in noise patterns. Effectively addressing this variability presents a substantial challenge in the development of noise removal techniques. Various imaging modalities, including X-ray, MRI, and CT, exhibit distinct noise sources and characteristics [200, 201]. For instance, X-ray images may be afflicted by quantum noise stemming from the statistical nature of X-ray photon interactions, while MRI images may be influenced by thermal noise due to fluctuations in temperature during image acquisition. Crafting noise removal algorithms that can dynamically adapt to the specific noise profile of each modality is essential for achieving optimal results.

The challenge of noise variability extends beyond the inherent characteristics of each imaging modality. Factors such as acquisition settings, patient conditions, and equipment variations further contribute to the complexity of noise patterns [202]. Quantum noise in X-ray imaging may vary based on exposure settings, while thermal noise in MRI could be influenced by the magnetic field strength.

To address noise variability comprehensively, researchers are exploring adaptive algorithms that can analyze and learn the specific noise characteristics inherent in different imaging scenarios. ML techniques, including DL models, are being employed to create noise removal algorithms capable of adapting to the nuances of each modality, providing a more tailored and effective approach to noise reduction [203]. Navigating the intricate landscape of noise variability is paramount for advancing the accuracy and reliability of medical image analysis across diverse imaging modalities. The Table 9 outlines the aspects of the challenges related to noise variability of imaging modalities,

Table 9 Noise variability in medical imaging

Imaging Modality	Quantum Noise	Electronic Noise	Radiation Interference	Temperature Variations
X-ray [204]	✓	✓	✖	✖
MRI [205]	✖	✖	✖	✓
CT [206]	✓	✖	✓	✖
Ultrasound [207]	✖	✓	✖	✖
Nuclear Medicine [208]	✖	✓	✖	✖
PET [209]	✖	✓	✖	✖
Mammography [210]	✓	✓	✖	✖
Fluoroscopy [211]	✓	✓	✖	✖

each with parameters indicating the presence or absence of Quantum Noise, Electronic Noise, Radiation Interference, and Temperature Variations.

6.2 Anatomical variations

The intricate variability in anatomical structures across patients introduces a significant level of complexity in the domain of medical image segmentation. Anatomical structures can exhibit diverse shapes, sizes, and textures, influenced by factors such as patient age, gender, and health conditions [212]. Successfully addressing anatomical variations is paramount for accurate and reliable image segmentation, a crucial step in medical image analysis.

Segmentation algorithms face the challenge of accommodating the inherent diversity in anatomical structures to precisely delineate regions of interest. For instance, when dealing with abdominal CT scans, the task of segmenting organs becomes particularly challenging due to the inherent variations in organ shapes and positions among different individuals [213]. The liver, for example, may exhibit considerable differences in size, shape, and location from one patient to another.

To overcome the obstacles posed by anatomical variations, researchers are exploring advanced segmentation approaches, frequently incorporating ML and DL techniques [214]. These methodologies aim to develop robust segmentation models that can adapt to the intricacies of anatomical diversity. ML models, particularly CNNs, have shown promise in learning complex patterns and variations, making them suitable for accurate segmentation tasks.

Despite advancements, tackling anatomical variations remains a persistent obstacle in the field. Collaborative efforts between medical professionals, image processing experts, and ML researchers are crucial for developing segmentation models that can accommodate the inherent complexity of anatomical structures across diverse patient populations [215]. The ultimate goal is to enhance the precision and reliability of medical image segmentation for improved diagnosis and treatment planning. Table 10 outlines the challenges associated with anatomy variations using various imaging techniques.

Table 10 Anatomical Variations across different imaging modalities

Challenge	X-ray	MRI	CT	Ultrasound	Nuclear Medicine	PET	Mammography	Fluoroscopy
Diverse organ shapes [216]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Variations in organ sizes [217]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Differences in organ textures [218]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patient age influence [219]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender-related variations [220]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

6.3 Lack of ground truth data

The reliance on annotated ground truth data for training ML models is fundamental to the development of accurate and robust noise removal and segmentation techniques. However, the limited availability of comprehensive and accurately annotated datasets regularly hinders this reliance. Acquiring ground truth data for medical images involves meticulous annotation by domain experts, a process that is not only time-consuming but also resource-intensive [221].

The annotation process requires skilled professionals who can accurately label images to serve as reference points for training ML models. Discrepancies in annotations may arise due to variations in interpretation among different experts, introducing ambiguity and potential challenges in model training. In addition, the lack of diverse and well-annotated datasets is a big problem that makes it hard to train ML models that work well in real-life situations [222].

Addressing the challenge of a lack of ground truth data requires collaborative efforts across disciplines. Medical professionals, image processing experts, and ML practitioners need to work together to create standardized and comprehensive datasets [223]. Initiatives such as data-sharing collaborations and the development of annotation guidelines can contribute to building datasets that accurately represent the complexities of medical images.

Advancements in addressing the lack of ground truth data are pivotal for unlocking the full potential of noise removal and segmentation methodologies in the realm of medical image analysis and diagnosis. Future progress relies on the commitment to overcoming these challenges through interdisciplinary collaboration and the development of robust, well-annotated datasets that reflect the diverse and nuanced nature of medical images [224]. Dataset availability, annotation process complexity, resource intensity, discrepancies in expert annotations, as well as potential ambiguity in the annotated data, are some of the factors that are emphasized in Table 11, which gives an organized overview of the issues that are associated with the absence of ground truth data.

7 Future research directions

Researchers are investigating the potential of advanced ML models, including DL architectures such as CNNs and RNNs, to enhance medical imaging. The present study aims to use advanced algorithms to improve noise reduction and segmentation in medical imaging, which leads to more accurate and comprehensive diagnostic assessments. A novel field of study is the combination of data from numerous imaging techniques, including X-ray, MRI, and CT, using multimodal data fusion. The aim of this effort is to improve the accuracy and comprehensiveness of evaluations by using the unique benefits of each modality. There is more emphasis on the need for interpretable AI models in healthcare. Researchers are investigating ways to improve the transparency and interpretability of AI models in medical imaging so that medical professionals can comprehend and depend on the assessments made by these sophisticated systems. Also, emphasizing the essential importance of immediate data in clinical decision-making, there is a focused endeavor to investigate methods and technology for attaining real-time segmentation in medical imaging. This improvement can provide rapid and precise information, greatly influencing clinical decision support procedures. These research issues aim to expand medical imaging by using advanced

Table 11 Lack of ground truth data challenges

Challenge	Mitigation Strategies	Collaboration Initiatives	Impact on Model Generalization	Data Sharing Guidelines
Limited availability of comprehensive datasets [225]	Encourage multi-institutional collaborations	Establish data-sharing platforms	High	Standardize annotation protocols
Time-consuming annotation process [226]	Invest in automated annotation tools	Foster interdisciplinary collaborations	Moderate	Develop annotation efficiency guidelines
Resource-intensive annotation process [227]	Optimize resource allocation for annotation	Support joint efforts between academia and industry	High	Define resource-efficient annotation norms
Discrepancies in expert annotations [228]	Implement inter-rater reliability assessments	Facilitate cross-disciplinary training programs	Moderate	Establish consensus-building frameworks
Ambiguity in annotated data [229]	Develop clear annotation guidelines	Promote ongoing communication among annotators	Moderate	Encourage continuous quality assessments

Table 12 Research issues and challenges in the field of medical imaging

Research Issue	Description
Ensuring the scalability of AI models in diverse settings	Evaluating the scalability of AI models to guarantee their efficiency and performance in various healthcare environments and organizations
Investigating the potential biases in AI predictions	Identifying and addressing any biases in AI predictions to guarantee fair and equal results for every group of patients
Studying the impact of AI on healthcare disparities	Evaluating the impact of using AI models in medical imaging on healthcare inequalities and aiming for equitable solutions
Addressing data privacy concerns in AI applications	Developing strong strategies to tackle data privacy issues related to the use of sensitive medical data in AI applications
Studying the ethical implications of AI-driven decision support	Exploring the ethical consequences of depending on AI-powered decision help in medical imaging and establishing ethical use protocols
Investigating the influence of AI on radiologist training	Investigating the potential effects of AI technology on the education and skill enhancement of radiologists and other healthcare practitioners
Developing frameworks for transparent AI decision-making	Providing transparent frameworks to help healthcare practitioners comprehend the decision-making process of AI models in medical imaging
Investigating the impact of AI on patient outcomes	Evaluating the effects of using AI in medical imaging on patient results, treatment effectiveness, and healthcare quality
Lack of annotated datasets for advanced models	Insufficient availability of annotated datasets suitable for training and verifying sophisticated ML models
Generalization challenges in diverse medical images	Issues for developing models that can effectively generalize over a wide range of medical images with various features
Limited interpretability of DL models	Issues in understanding the decisions made by DL models are impeding their use in medical applications
Integration challenges in multimodal data fusion	Issues in effectively combining data from several imaging techniques to obtain valuable information
Ethical considerations in AI applications	Exploring ethical, privacy, and bias issues connected with utilizing AI models in medical imaging
Ensuring model robustness in noisy environments	Improving the resilience of AI models in medical imaging in noisy environments and unpredictable circumstances
Cybersecurity concerns in AI applications	Maintaining patient data and privacy by addressing cybersecurity issues related to using AI models in healthcare
Investigating the impact of AI on healthcare workflows	Studying the impact of using AI models on present healthcare processes and identifying opportunities for improvement
Assessing long-term reliability of AI models	Evaluating the enduring dependability and steadfastness of AI models to guarantee sustained performance over prolonged durations
Exploring edge computing for real-time processing	Addressing the practicality of implementing AI models on edge devices for immediate processing in contexts with limited resources

Table 12 (continued)

Research Issue	Description
Evaluating the cost-effectiveness of AI adoption	Investigating the economic consequences and efficiency of using AI technology in medical imaging processes
Addressing regulatory compliance and patient consent	Ensuring adherence to regulations and gaining informed permission from patients for the use of AI in medical imaging
Establishing robust model validation procedures	Providing standardized and rigorous protocols for validating and assessing ML models in medical imaging
Bridging the gap between AI research and clinical practice	Facilitating in the implementation of AI research outcomes in healthcare environments
Investigating the impact of AI on diagnostic accuracy	Evaluating the impact of incorporating AI models on the diagnostic precision and decision-making skills of healthcare practitioners
Developing mechanisms for continuous model improvement	Providing methods to enhance models continuously by incorporating input, adapting to evolving medical practices, and integrating new data
Studying the psychological impact on healthcare professionals	Exploring the psychological effects of AI implementation on healthcare workers and resolving issues around employment responsibilities and obligations
Investigating the impact of AI on patient-doctor communication	Investigating the impact of AI integration in medical imaging on the interaction between healthcare providers and patients
Enhancing model interpretability for end-users	Developing methods to improve the interpretability of AI models, allowing medical professionals to have confidence in and comprehend the assessments generated by the model
Exploring unsupervised learning for limited annotated data	Exploring the use of unsupervised learning methods to make the most of scarce annotated data in medical imaging
Real-time processing constraints	Implementing algorithms that enable segmentation in real-time while considering advantage of computing limitations in clinical applications
Standardization of annotation protocols	Absence of specific requirements for annotating medical images causes variability in annotations and expected discrepancies
Lack of collaboration between academia and industry	Limited collaboration between academic researchers and industry specialists is impeding the transformation of research into practical solutions
Adapting models to evolving medical imaging tech	Ensuring that ML models are able to adapt to emerging technologies and improvements in medical imaging
Incorporating user feedback into model development	Providing solutions that integrate input from healthcare experts in order to enhance the usability and efficacy of AI models
Addressing bias and fairness in AI models	Addressing and reducing biases in AI models to guarantee equitable and impartial results, especially in varied patient demographics
Regulatory challenges in AI adoption	Addressing regulatory challenges while establishing criteria for using AI models in medical imaging

Table 12 (continued)

Research Issue	Description
Development of user-friendly AI interfaces	Provide interfaces that are intuitive and readily understandable for healthcare providers with less technological knowledge

ML, combining several modes of data, enhancing interpretability, and enabling real-time capabilities to enhance healthcare outcomes. The research challenges and issues in medical imaging are presented in Table 12. These concerns and problems encompass a variety of factors, such as advancements in technology, ethical implications, adherence to regulations, and the effective incorporation of artificial intelligence into healthcare procedures.

8 Conclusion

In summary, this paper has explored the intricate landscape of noise removal and segmentation techniques in medical imaging, delving into both traditional and advanced ML-based approaches. The investigation encompassed the significance of medical imaging in healthcare, highlighting its pivotal role in diagnosis and treatment. The research objectives centered on comparing the efficacy of traditional and ML-based methods for noise removal and segmentation. The paper meticulously navigated through various medical imaging modalities, elucidating their principles and applications. It provided insights into the challenges posed by noise variability, anatomical variations, and the scarcity of ground truth data in the medical imaging domain. The findings underscored the evolution from conventional noise reduction techniques to the promising realm of ML-based approaches. Comparative analyses shed light on the strengths and limitations of each methodology. The role of segmentation in medical image analysis was thoroughly discussed, emphasizing its importance in enhancing diagnostic precision. Challenges related to noise variability, anatomical variations, and the lack of ground truth data were dissected, recognizing the complexity of these hurdles. Looking forward, the paper proposed future research directions, advocating for the exploration of advanced ML models, multimodal data fusion, interpretable AI, and real-time segmentation. These directions aim to push the boundaries of medical imaging, promising more accurate, efficient, and real-time diagnostic capabilities. The implications for medical imaging are profound. The integration of advanced ML models holds the potential to revolutionize noise removal and segmentation techniques, paving the way for more accurate and timely diagnoses. The exploration of multimodal data fusion addresses the need for comprehensive diagnostic analyses, considering the unique strengths of different imaging modalities. The call for interpretable AI models responds to the crucial demand for transparency and trust in AI-driven decision-making, ensuring seamless integration into clinical workflows. Real-time segmentation emerges as a key component for prompt and effective clinical decision support. In closing, the significance of effective noise removal and segmentation in medical imaging cannot be overstated. These techniques are not mere technical processes but integral components that directly impact diagnostic accuracy, treatment planning, and patient outcomes. The continual evolution and integration of advanced methodologies, as outlined in this paper, underscore the dynamic nature of medical imaging research and its pivotal role in shaping the future of healthcare.

Author contributions In this study, R.R.K. and R.P. all contributed significantly to the research efforts. R.R.K. played a key role in the execution of the experiments, while R.P. contributed to various aspects of the research process. The collaborative efforts of R.R.K. and R.P. are evident in the combined writing and development of the paper.

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Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors have no conflict of interest to declare that are relevant to the content of this article.

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