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Segmentation and Classification of Medical Images Using Artificial Intelligence: A Review

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Abstract. *In the realm of medical imaging, segmenting and classifying medical images is essential for helping medical professionals diagnose and treat a variety of medical disorders. This review discusses artificial intelligence (AI) techniques. AI systems have shown impressive accuracy and efficiency in identifying and quantifying elements in medical images, such as MRI, CT, and X-rays, by utilizing deep learning techniques, in particular convolutional neural network (CNNs). We describe CNN design and training for medical image segmentation and classification, emphasizing the usefulness of CNNs in identifying and defining diseased regions and anatomical features. Even with obstacles like data privacy, requiring sizable annotated datasets, and requiring model interpretability, further research and development in AL-driven medical images analysis has promise for improving clinical decision-making and diagnostic accuracy. Future research in this area should concentrate on improving the generalizability and resilience of AI models by using methods like data augmentation, transfer learning, and the creation of more complex network topologies. Furthering the area also requires guaranteeing ethical concerns, enhancing data-sharing mechanisms, and encouraging cooperation between medical practitioners and AI researchers.*

Keywords: *Medical Image, AI, Classification, Segmentation, Deep Learning, Machine Learning.*

1. INTRODUCTION

Medical imaging analysis is a critical component of modern medicine, helping with disease diagnosis, treatment planning, and ongoing patient monitoring. The use of imaging tools, including as computed tomography (CT) scans, ultrasound, magnetic resonance imaging (MRI), and X-rays, to reveal anatomical features, abnormalities, and physiological processes, has long been considered a critical component of clinical medicine. This was true for the most part [1-3]. Nonetheless, there is an increasing need for automated and precise image processing systems due to the volume and complexity of medical imaging data.in response to this desire, a significant advance other than diagnostic precision and therapeutic efficacy was the fusion of artificial intelligence with medical image analysis [4],[5]. In the past, medical image analysis has mainly depended on human interpretation of images and annotations. Even while this process has produced priceless knowledge, labor costs are high, it takes a long time, and mistakes might happen. Because robots can now extract, analyze, and comprehend complicated data from medical imaging, artificial intelligence-especially deep learning-has drastically changed the medical imaging industry. Artificial intelligence methods used in medical imaging, like recurrent neural networks (RNNs) and convolutional neural networks (CNNs), have demonstrated exceptional efficacy in image segmentation, anomaly identification, and pattern recognition [6-8]. This paper provides in-depth coverage of a broad range of AI-based medical image analysis issues. The first part of the talk provides a comprehensive historical review of the evolution of medical image analysis, covering its beginnings, expansion and the role that AI has played in this particular field. After that, a variety of medical images that are frequently utilized in clinical settings were looked at, and the nuances related to these images were carefully considered and studied. In addition, we wanted to emphasize how important it is to use top-notch datasets and pre-treatment methods specifically designed for medical image analysis. Our research focuses on the application of AI methods to divide and classify medical images. Assigning a distinct label or diagnosis to a complete image is the process of classification. On the contrary, segmentation is the process of identifying and dividing certain deformed areas or structures in an image. These tasks are crucial from a therapeutic perspective because they play a role in diagnosing disease, evaluating disease progression, and evaluating the effectiveness of treatment [9-11]. The aim of this review paper is to provide a comprehensive and up-to-date assessment of medical image classification and segmentation techniques, focusing on AI methodologies. In medical image processing, AI is helpful because it can automate tasks that would otherwise require highly skilled radiologists and physicians. Ultimately, improved patient outcomes result from this automation's increased efficiency and precision. The following portions of this work are arranged as follows: In the second section, the field of medical image types and datasets is reviewed historically, and the conventional methods used in the field are thoroughly explained. The third section of this paper deals with artificial intelligence techniques in the field of medical images, including machine learning and deep learning such as CNN, GAN, and RNN. Comprehensive tutorials on segmentation and classification techniques in medical images are provided in Sections 4 and 5, respectively. Sections 6 and 7 focus on the applications used as well as performance metrics and evaluation of medical image analysis. Section 9 discusses the challenges encountered and future directions.

2. MEDICAL IMAGE TYPE AND DATASETS

Medical imaging comes in a variety of forms, such as CT, MRI, X-ray, ultrasound, PET, and digital pathology. Each of these methods has benefits and drawbacks, and based on the patient's and the healthcare provider's particular needs, they can be applied to different imaging studies.

2.1 Types of medical images

Medical imaging encompasses a wide array of modalities, each tailored to capture specific aspects of the human anatomy and pathology. Table (1) provides an overview of some common types of medical images [12], [13]. The classification of important medical imaging modalities is illustrated in Figure (1).

Table 1: Medical Image Type

Medical Image Type	Description
X-rays	2D images commonly used for visualizing skeletal structures and detecting abnormalities such as fractures and lung conditions.
Magnetic Resonance Imaging (MRI)	Produces high-resolution, high-contrast 3D pictures of soft tissues, organs, and the brain using radio waves and magnetic fields. Ideal for musculoskeletal and neurological disease diagnosis.
Computed Tomography (CT) scans	Uses a variety of X-ray angles to produce cross-sectional 3D pictures.

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	Used for guiding surgical procedures, detecting malignancies, and seeing into organs.
Ultrasound	This method, which makes use of ultrasonic waves, is frequently used in obstetrics since it provides instantaneous 2D or 3D imaging, cardiology, and assessing soft tissue injuries.
Positron Emission Tomography (PET)	Combines molecular imaging with CT to visualize metabolic processes and tissue functionality, often used in oncology and neurology.
Digital Pathology	Involves scanning and digitizing tissue samples for pathological analysis, enabling remote diagnosis and research.

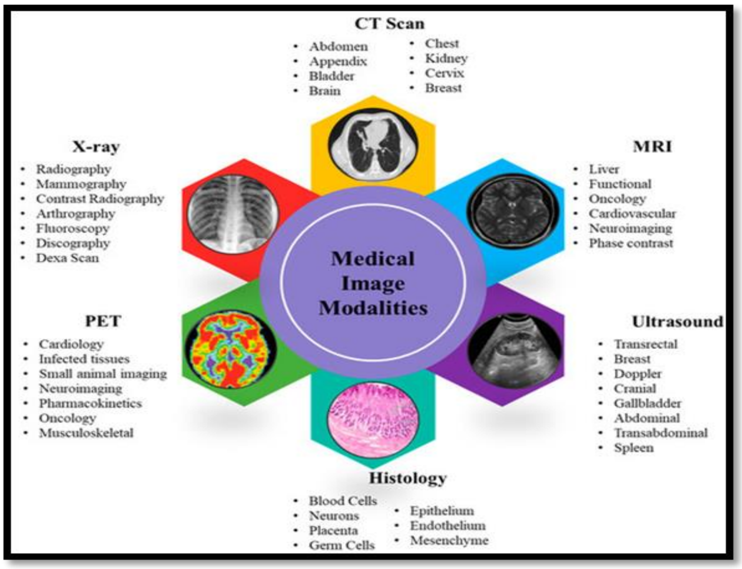

Figure 1: Classification of Important Medical Imaging Modalities [14].

2.2 Commonly used medical image datasets

Several publicly available datasets have been curated to facilitate research and benchmarking in medical image analysis. These datasets cover a range of medical conditions and imaging modalities and provide a standardized platform for algorithm development and evaluation. Below, we highlight some commonly used medical-image datasets [15-22].

- Medical Image Computing and Computer-Assisted Intervention (MICCAI) Datasets: MICCAI offers a collection of datasets for various tasks including brain MRI, cardiac imaging, and histopathology.
- Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI): This dataset includes chest CT scans and is widely used for lung nodule detection and classification tasks.
- The Cancer Imaging Archive (TCIA): The TCIA provides access to a vast repository of cancer-related imaging data encompassing multiple modalities and cancer types.
- Alzheimer's Disease Neuroimaging Initiative (ADNI): ADNI offers MRI and PET scans for the study of Alzheimer's disease, aiding diagnosis and progression monitoring.
- ImageNet: Although not specific to medical imaging, ImageNet's large-scale image dataset has been adapted for transfer learning in medical image analysis.

2.3 Data preprocessing techniques

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Effective data pretreatment is critical for ensuring that medical image data is of sufficient quality and suitability for AI analysis. Here are some common preprocessing approaches [23-30].

- To reduce variation between images, normalize pixel intensity values to a single scale.
- Filters and denoising algorithms eliminate artefacts and improve image clarity.
- Image registration involves aligning images from many modalities or time points to maintain consistency in longitudinal investigations.
- Augmentation: Increasing dataset size through transformations like rotation, flipping, and scaling to improve model robustness.
- Identify and annotate areas of interest (ROI) in images for better supervised learning.
- Correcting imaging artefacts and biases induced during data capture.

These preparation techniques are crucial for improving the performance and dependability of AI models trained on medical image data, ensuring that they are prepared to face the challenges of real-world clinical data. As mentioned in this study, incorporating these different image types, as well as leveraging relevant datasets and preprocessing approaches, are critical steps towards furthering AI applications in medical image classification and segmentation.

3. ARTIFICIAL INTELLIGENCE TECHNIQUES

Medical image analysis has recently profited substantially from the use of machine learning (ML) and deep learning (DL) techniques, which enable automatic feature extraction and pattern discovery (see Figure 2).The application of these approaches has proven critical to improving the precision and effectiveness of medical image categorization and partitioning. Machine learning includes a wide range of approaches such as decision trees, support vector machines, and random forests. Nonetheless, deep learning, a subset of machine learning, has received a lot of interest in recent years due to its ability to automatically acquire hierarchical features from data. Deep learning architectures, which are defined by the utilisation of linked neurons grouped in several layers, have demonstrated outstanding abilities in effectively processing complex and high-dimensional medical imaging data [31], [32].

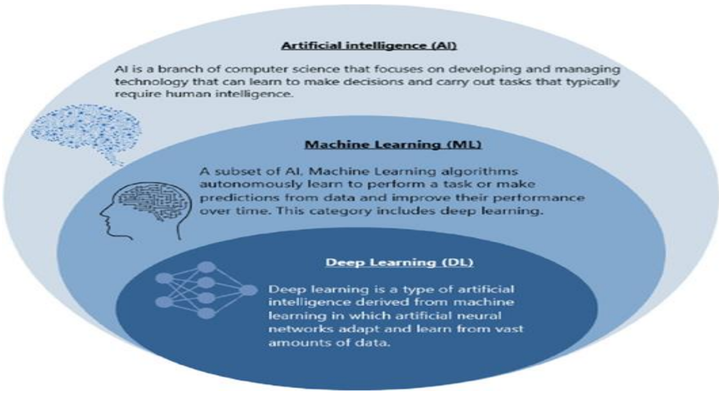

Figure 2: Artificial Intelligence Categories [33].

3.1 Machine learning

"Machine learning" is a subfield of artificial intelligence that focuses on creating devices that can learn from and improve upon the data they process. Machine learning can be applied to anything that can be digitally stored as data. Through the identification of patterns within this data, the algorithms acquire knowledge and enhance their efficacy in executing a particular task. Machine learning can be classified into four primary categories: supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning [34].

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3.2 Deep learning

Diagnostic, therapeutic, and health monitoring parts of healthcare all heavily depend on medical image analysis. It entails analyzing and interpreting images from several modalities to learn more about the human body and support medical decision-making. Medical image analysis has undergone a revolution thanks to the combination of deep neural networks and computer vision techniques, which have improved treatment outcomes, allowed for earlier and more accurate diagnosis, and eventually progressed in the field of healthcare [35]. The most often used medical imaging procedures include ultrasound, CT scans, X-rays, PET, and MRI. These imaging modalities provide essential functional and anatomical information about different bodily organs, making them important for the detection, segmentation, classification, or diagnosis of defects. The main purpose of medical image analysis is to assist doctors and radiologists in accurately diagnosing patients and predicting their prognoses. In medical image analysis, deep learning is utilized for many tasks, the most crucial being segmentation, detection, and classification or diagnosis. [36-38]. Different algorithms are used in the learning process by DL models.

3.2.1 Convolutional neural networks (CNNs)

In deep learning, convolutional neural networks (CNNs) have quickly become the de facto industry standard for image processing. Convolutional Neural Networks are perfect for processing medical imaging because they were created with handling spatial data in mind. Filters are employed in convolutional layers to extract characteristics at various spatial levels. To assist in determining the classification or segmentation, these features were then hierarchically integrated through layers that were completely linked. As demonstrated in Figure 3, convolutional neural networks have demonstrated remarkable efficacy in various medical image analysis tasks such as tumour detection in radiological images, organ fragmentation in magnetic resonance imaging (MRI), and diabetic retinopathy categorization in fundus images. The accuracy and dependability of these processes were greatly increased by the capacity to separately extract pertinent data from huge datasets. Its applications include tumor detection, organ segmentation, and anomaly detection [39], [40].

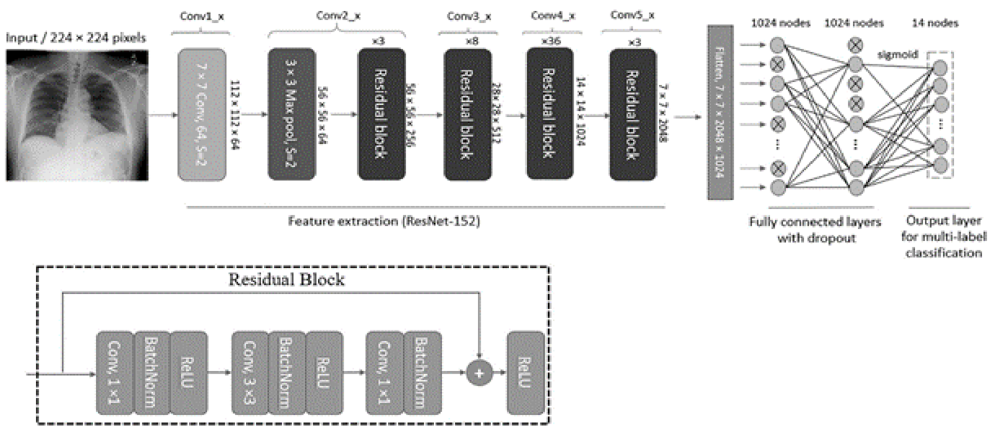

Figure 3: CNN-based medical image analysis [41].

Convolutional neural networks (CNNs) are more commonly used than recurrent neural networks (RNNs) to analyze medical images. However, they are used in applications such as cardiac signal analysis and video-based medical imaging that require sequential or time-series data. Repetitive neural networks (RNNs) are ideal for tasks that require a high degree of temporal correlations due to their frequent connections, which enable information to be retained continuously [42].

3.2.2 Generative adversarial networks (GANs)

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Generative adversarial networks, or GANs, are a strong type of neural networks that are frequently employed in unsupervised learning. Their ability to analyze, capture, and replicate natural changes observed in a particular dataset stems from their competitive interaction between two neural network models (see Figure 4). The discriminator and the generator are two essential elements found in the GAN environment. The generator is in charge of creating fake data samples, like higher image quality, in order to trick the discriminator. On the other hand, the discriminator seeks to identify and distinguish between synthetic and real samples. Both the generator and the discriminator function like neural networks and compete with one another throughout the training phase. Every iteration of the process-which is carried out multiple times-allows the generator and discriminator to perform better in their respective roles [43, 44]. One purpose for it is to improve image from CT and MRI scans.

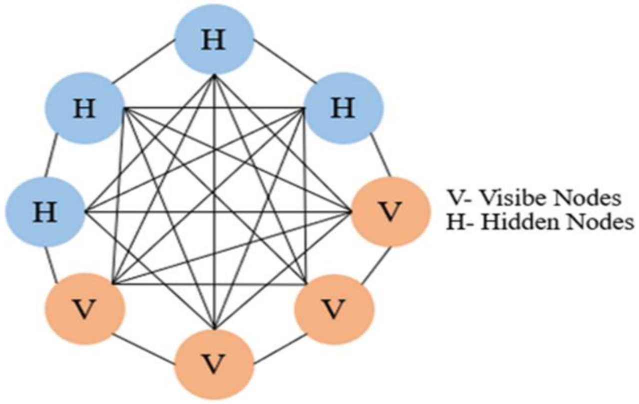

Figure 4: GANs Architecture [45].

3.2.3 Recurrent Neural Networks (RNNs)

Recurrent neural networks (RNNs) are an essential tool for medical image analysis utilizing deep learning algorithms because they can collect contextual information and temporal connections. When it comes to jobs involving sequential or time-series data, such assessing dynamic imaging modalities or medical image sequences, RNNs excel. They can follow tumor growth, identify patterns, and forecast the course of disease by modeling long-time dependencies and utilizing data from earlier time steps. The ability to capture complicated temprol dynamics is further enhanced by RNN variations like LSTM and GRU, which makes them essential for extracting valuable information from medical image sequences. [46] in figure 5, a recurrent neural network is shown.

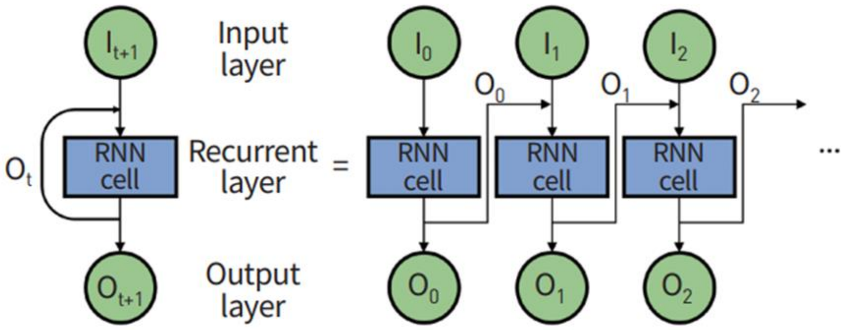

Figure 5: RNNs Architecture [47].

Transformative learning, or the capacity of trained models to adjust to novel situations, has had a significant impact on medical image processing. Using pre-trained models from large-scale image datasets, like ImageNet, is a common way to start developing networks for medical imaging. This approach can handle smaller medical datasets and has numerous advantages, including shorter training. Transfer of learning, the effective application of learned models to a wide range of tasks, possesses the capacity to substantially advance the field of medical science. Utilizing pre-trained convolutional neural network models, lung nodule recognition on computed tomography (CT) images, skin diseases, and ocular diseases have all been addressed. By exposing a model to a wide range of non-medical images for training, pre-trained weights improve the model's ability to generalize to medical images.

4. MEDICAL IMAGE SEGMENTATION

In order to properly locate and identify ROLs in images, medical image segmentation is a crucial step. An extensive analysis of several widely used segmentation methods in the domain of AI-driven medical image segmentation is shown in Table 2 [48], [49].

Table 2: Types of Medical Image Segmentation Techniques

Segmentation Technique	Description
Semantic Segmentation [50]	Categorizes every visible pixel and assigns a pixel label to any structures or aberrations. It is widely used in organ and tumor segmentation.
Instance Segmentation [50]	Improves semantic segmentation by distinguishing across elements from the same class. This is useful for identifying individual instances of a structure.
Region-based Segmentation [51]	Uses the image's intensity, texture, and other properties to segment It is into meaningful pieces. Histology and magnetic resonance imaging (MRI) of the brain both make frequent use of it for tissue Classification and tumor detection.
Contour-based Segmentation [51]	Targets the process of identifying and removing image objects by their edges or outlines. This is essential for precise organ or lesion delineation, particularly for radiotherapy planning.
Deep Learning-based Segmentation [52]	Pixels are segmented using deep neural networks, including CNNs or U-nets for complex learned representations. For certain medical imaging applications, the models have demonstrated exceptional performance when compared to current benchmarks.

This table presents a comprehensive comparison of the medical image segmentation techniques that have been addressed [15].

Table 3: Comparison of Segmentation Techniques

Segmentation Technique	Use Cases	Advantages	Challenges
Semantic Segmentation	Organ and tumor segmentation, tissue labeling	Pixel-wise precision, broad applicability	Complexity in handling fine details, computationally intensive
Instance Segmentation	Multiple lesion or object detection	Individual instance separation, enhanced diagnostics	Increased complexity in annotation, higher computational requirements

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Region-based Segmentation	Tissue classification, lesion detection	Robust to intensity variations, interpretable results	Heavily dependent on feature selection, may require domain expertise
Contour-based Segmentation	Organ contour delineation for radiotherapy	Precise boundary extraction, essential for treatment planning	Sensitive to noise, manual annotation often needed
Deep Learning-based Segmentation	Various applications across medical imaging	End-to-end learning, state-of-the-art performance	Data-hungry, model interpretability

Segmentation techniques are essential in the field of medica imaging because they enable the vital duty of finding and assessing structures or anomalies. Each method has special advantages and is necessary for artificial intelligence-based medical image interpretation. It is up to researchers and practitioners to decide which technique work best for their goals and datasets.

5. MEDICAL IMAGE CLASSIFICATION

Medical image classification entails automatically identifying and classifying medical image using DL and ML techniques. Improving treatment planning, facilitating diagnosis, and boosting patient outcomes all depend on this procedure. This is a thorough synopsis of the main points.

5.1 AI-based classification of medical images

The classification of medical images is critical within the healthcare industry due to its multifaceted applications, which encompass disease diagnosis and treatment strategizing. The implementation of AI technology has substantially improved the accuracy, efficiency, and uniformity of medical image processing. Investigates in depth the many AI methods being used to classify medical images. Both conventional machine learning methods and state-of-the-art deep learning models are included in this range of methodologies. The following essential elements were examined in this study: [12], [53].

- Feature Extraction: In this section several feature extraction techniques encompassing both manually designed features and learned representation, emphasizing their significance in medical image categorization.
- Traditional Machine Learning methods: Traditional machine learning techniques such as preprocessing, feature extraction, feature selection, dimension reduction, and classification are thoroughly analyzed here. In the medical image classification challenges.
- In-depth Analysis of Deep Learning Architectures: A comprehensive look into deep learning models, with a focus on CNNs and the many variations on them. This research, looked into Convolutional Neural Networks (CNNs) ability to independently learn hierarchical characteristics from medical images. With this skill, you can easily pull out generalizations and spot repeating structures.

5.2 Examples of classification tasks

We give a collection of case studies and examples of successfully completed classification assignments across a range of medical imaging modalities to demonstrate the practical uses of artificial intelligence in the field of medical image classification. The above real-world examples show how adaptable and effective artificial intelligence techniques may be in healing environments. Several cases might be given [12], [54-58] including:

- Breast Cancer Diagnosis: Emphasize how AI models can consistently classify mammograms and discriminate between malignant breast tumours.
- Chest radiographs: This study demonstrates how deep learning techniques can be used to distinguish between radiographs of healthy lungs and those of pneumonia.
- Skin lesion classification: This work investigates the use of artificial intelligence for the categorization of skin lesions obtained from skin images, to assist in the early identification of skin cancer.
- Alzheimer's disease detection: This study demonstrates how brain MRI data can be analyzed using AI in find structural abnormalities associated with Alzheimer's disease.
- The objective of this study was to utilize artificial intelligence techniques to evaluate the severity of diabetic retinopathy in retinal images taken. The proposed AI techniques will provide a prompt and efficient solution for this issue.

6. APPLICATION OF MEDICAL IMAGE ANALYSIS

Numerous uses of deep learning techniques have been demonstrated in the field of medical image processing. Convolutional neural networks (CNNs), one of the most popular deep learning methods, have been utilized extensively for image restoration, object recognition, segmentation, and disease classification [59]. These algorithms are useful in the identification and diagnosis of many disorders in medical image analysis, including tumors, lesions, anatomical anomalies, and pathological alterations. They can also be applied to assess the prognosis, treatment response, and progress of the illness. Deep learning systems can automatically add important annotations to medical images, making interpretation accurate and efficient [60]. Using this technology could enhance clinical decision-making in healthcare settings, optimize resource allocation, and improve patient outcomes. Deep learning algorithms can also be applied to multimodal fusion, image registration, and data augmentation, enabling an extensive and comprehensive analysis of medical images obtained with a range of modalities. Deep learning algorithmic advances are driving substantial advancements in medical image analysis. This offers fresh prospects for personalized treatment regimens, precision medicine, and enhanced healthcare solutions [61].

7. PERFORMANCE METRICS AND EVALUATION TO MEDICAL IMAGE ANALYSIS

A thorough investigation is required to validate the quality and reliability of the AI model utilized for medical image processing. One method for identifying distinguishing traits and reducing error rates is to use expert metrics and methods designed for medical imaging evaluation.

The challenges of using assessment methods and scales to evaluate medical images are highlighted in this section’s study.

- The dice coefficient analyzes the degree of agreement between observed and spatially intended region; it is sometimes called the Sorensen-Dece indicator. Discovering where a cipher task stands at any given time is essential.
- The specificity and sensitivity of the model show that it can find favorable situations. When doing disease detection tasks based on binary classification, it is essential to use these features.
- Statisticians use PPV and NPV to evaluate predictions. Predictive accuracy value (PPV): This metric indicates how frequently accurate predictions are associated with positive outcomes. These measurements improve visual clarity by highlighting forecast accuracy.
- AUC-ROC statistics can measure a model's efficacy in class identification. This is accomplished by balancing quality and sensitivity across a range of limit values.

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- Hash tasks use a statistical measure called the Hausdorff distance to determine the maximum deviation between the projected component limits and the real world state. This establishes the level of hash accuracy.
- The Jacquard Index, sometimes referred to as the Cross Union Intersection (IoU) scale, is one of the tools used to determine the extent of overlap between areas of predicted and terrestrial truth. It assesses the degree of pixel overlap and produces a numerical representation of the segmentation resolution.

Model generalization and performance were evaluated using a variety of assessment techniques, including model validation and cross-verification. The size of the dataset and the difficulty of the task at hand determine the best strategy. When working with smaller datasets, cross-validation—which includes K-fold cross-checking—is particularly useful because it provides a more reliable assessment of model performance. For larger datasets, wait validation is advisable because it successfully maintains the independence of the test set.

Furthermore, a number of methods, including boot, cross check of leave, and stratified sampling, were used to successfully address the particular challenges that arose in the field of medical image analysis. Using a variety of techniques is important because it maintains a balance between model testing and training. The choice of acceptable approach should be guided by considerations of overprocessing, data distribution and mainstreaming capacity.

8. LITERATURE REVIEW

Notwithstanding their valuable contributions, conventional approaches have demonstrated several limitations in effectively managing the diverse and intricate nature of medical images. Frequently, individuals experience difficulties when faced with the presence of disruptive data, nuanced anatomical modifications, or convergence of many structures. With the continuous advancement of medical imaging technology, the associated limits have become increasingly evident. Consequently, there is a need to transition towards data-driven and machine-learning-based techniques [62], [63].

8.1 Recent studies and progress in artificial intelligence-based methodologies

Recently, the incorporation of artificial intelligence (AI), particularly deep learning, has sparked significant transformations in the field of medical image analysis. When it comes to autonomously obtaining hierarchical properties from images, deep neural networks, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown exceptional ability. Many applications, including those involving image classification and object recognition, have benefited greatly from the use of Convolutional Neural Networks (CNNs).The utilization of transfer learning, a technique that involves adapting pre-trained models for specific medical image-processing tasks, has significantly expedited advancements in this field [64], [65].

The use of artificial intelligence (AI) extends beyond categorization and includes the complex domain of medical image segmentation. Semantic and instance segmentation methods have been developed to identify anatomical features and anomalies accurately. These technological improvements have created novel opportunities for quantitative analysis, facilitating precise measurements, illness identification, and therapeutic strategies [66], [67].

Tustison et al. [68] emphasizes the importance of diverse feature sets derived from different modalities' intensities, shapes, and irregularities. Via random forest derived probabilities, these features facilitate whole-brain and tumor segmentation. Noteworthy is the boost in discriminative powers provided by asymmetry-related attributes. At the MICCAI 2013 Multimodal Brain Tumor Segmentation challenge, there were notable gains made in tumor component segmentation accuracy thanks to an advanced algorithmic framework.

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Through the work of Kamnitsas et al. [69] a deep learning solution emerges for brain lesion segmentation. Utilized are two channels for efficient process of multi-channel MRI data by their novel three-dimensional CNN architecture. By leveraging a specialized dense training program and a 3D Conditional Random Field during post-processing, we work to minimize false positives caused by class imbalance. Clinical applications require computational efficiency for lesion segmentation, an area where our approach excels. Sehgal et al. [70] provides a five-step automated process for identifying brain tumors: The steps of acquiring images, preparing them, segmenting using fuzzy c-means, extracting tumors, and evaluating their efficacy, are all required. Tumor extraction using Area and Circularity is validated against human-segmented Ground Truth for accuracy. The Dice coefficient, with an average value of 0.729, is useful for conducting credible assessments.

Nabizadeh and Kubat [71] proposed a completely computerized method that pinpoints tumor pieces and distinguishes malignant growth regions in cerebrum MRI images has been created. Accuracy is high and computational simplicity is low in the proposed method for brain tumor tissue segmentation. Comparison of statistical aspects and Gabor wavelets across different classifiers adds to the body of knowledge regarding tumor segmentation applications, as seen in recent studies. An automated approach was presented by Amin et al. [72] for identifying cancerous versus non-cancerous brain MRI scans. Shape, texture, and intensity serve as basis for feature extraction during lesion segmentation, which makes up the whole process. With unrivaled precision and effectiveness, SVM classification excels at identifying brain tumors through its impressive accuracy, sensitivity, and specificity across diverse dataset samples.

Through transfer learning, Almalki et al. [73] derives deep insights from brain MRI scans. Building multiple solitary models and then training them yields valuable deeper features for training subsequent Support Vector Machine classifiers. With an accuracy rate of 98%, the proposed method shows great potential in helping medical experts identify brain tumors. With only few annotated images and countless untagged ones at their disposal, researchers like Ito et al. [74] suggest a semi-supervised learning framework for training DNNs. By leveraging image registration, attaching pseudo-labels to unlabeled images has been shown to result in superior and more stable segmentation outcomes compared to prior approaches, particularly when the same volume of atlases are used during training. Refining feature representations, SSLDEC relies on deeply embedded clustering algorithm initially proposed by Enguehard et al. [75] Adapting to different deep neural network designs without much labeled information requires SSLDEC. Superiority was shown by it in image classification projects, besting existing semi-supervised techniques.

Proposing a semi-supervised approach for full brain segmentation with FLAIR images, Rieu et al. [76] made significant contributions. High reliability was found when comparing the results against labels produced by FreeSurfer segmentation of T1w MRI scans. With multiple MRI modalities, including T1w, this approach has extensive application potential in brain tissue segmentation. Through their work on BTSCNet, Chaki and Woźniak [77] sought to advance a fully automated technique that would sort brain tumors according to T1-weighted contrast CE-MR images analysis. Segmentation, ROI selection, feature extraction, and classification form part of BTSCNets structure. By tackling insufficient annotated sample availability head-on, our strategy yielded remarkable performance benchmarks that exceeded established approaches.

A deep-learning based semantic segmentation approach was proposed by Markkandeyan et al. [78] tailored towards brain tumor segmentation in MRI images. Utilizing CNNs, this approach scored impressively on the BRATS 2013 dataset thanks to hyperparameter optimization and effective GPU training. Through their collaboration, Arunachalam and Sethumathavan [79] refined a novel approach relying upon YOLOV5 for identifying brain tumors through MR imaging. With HPO, they optimized their model using HGSOA. Brain tumor classification through MRI requires more exactness, which their method shows. By Talo et al. [80] a radical new method called deep transfer learning has been developed to distinguish between healthy and diseased brain MRIs. Leveraging these techniques, they created a

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model based on the ResNet34 architecture. With an impressive 5-fold classification accuracy shown, there is potential for MR image screening support.

In their paper, Pratondo et al. [81] presents a combined framework for machine-learning based and actively controlled contours in image processing. With machine learning algorithm classification probability scores, they improved energy minimization during segmentation, leading to enhanced accuracy and resilience. With no need for post-processing, State Of art performance was demonstrated by Naceur et al. [82] Through three end-to-end Incremental DNN designs for automated brain tumour segmentation. Time was saved during diagnostic tasks thanks to these models.

Kabir et al. [83] advanced CNN architectures through genetic algorithms for accurate Glioma classification via MRI. An ensemble method that includes bagging shows promise when applied to brain tumor diagnosis at an early stage. To improve performance, Alduraibi et al. [84] leveraged the strength of combining pre-trained CNN-produced deep features with Particle Swarm Optimization (PSO) and ReliefF. Through this method, brain MRI image classification accuracy sees significant enhancement opening doors for real-time uses. By introducing BAT-IT2FCM clustering, Alagarsamy et al. [85] has created a technique that optimizes cluster placement through BAT algorithm integration for Interval Type-2 Fuzzy C-Means (IT2FCM) clustering in brain image segmentation. Existing segmentation approaches were exceeded by this method in terms of sensitivity and accuracy.

Kaur and Garg [86] proposed an approach that integrated Fisher and parameter-free BAT algorithms for glioma brain tumor categorization. This approach shows enhanced diagnostic accuracy when contrasted with standard metabolite ratios. Inbarani et al. [87] designed a hybrid supervised feature selection algorithm named TRSFFQR. Existing feature selection algorithms were surpassed by their approach in terms of critical feature identification for classification. Dixit and Nanda [88] proposed a model for brain tumor classification through PSO-segmented SVM classification. Separating brain regions was how their approach performed effectively. Optimizing base models and hyperparameters through the AdaBoost approach, Pandey et al. [89] tackled glioma classification. On the BraTS 2018 dataset, their model was trained and validated, achieving good results in identifying high-grade and low-grade glioma tumors.

Table 4: Comparison of different methods

Author	Dataset	Feature Selection	Method	Results
Tustison et al. [68]	MICCAI 2013 Multimodal Brain Tumor Segmentation challenge dataset	Multiple modality intensity, geometry, and asymmetry features	Random forest-derived probabilities, Markov random field	Dice overlap measures: 0.87 (complete), 0.78 (core), 0.74 (enhanced)
Kamnitsas et al. [69]	Multi-channel MRI patient data	NA	3D Convolutional Neural Network, Conditional Random Field	Results that place first on the 2015 BRATS and ISLES scales
Sehgal et al. [70]	NA	Area and Circularity criteria	Fuzzy C Means for segmentation	Dice coefficient: Average 0.729
Nabizadeh and Kubat [71]	NA	Single contrast mechanism	NA	Successful segmentation with high accuracy and low complexity
Amin et al. [72]	RIDER	Local Shape, texture, and intensity	Support Vector Machine (SVM)	97.1% accuracy, 0.98 AUC, 91.9% sensitivity, 98. 0% specificity

Almalki et al. [73]	Brain MRI datasets	Transfer learning	Convolutional Neural Network (CNN)	98% accuracy, 97.2% classification rate
Ito et al. [74]	Human brain images, marmoset brain images	Semi-supervised learning	Deep Neural Network (DNN),	Improved segmentation results in various applications
Enguehard et al. [75]	Benchmark image classification tasks, medical image segmentation	Deeply embedded clustering	Various deep neural network configurations	Outperformed several semi-supervised methods in classification tasks
Rieu et al. [76]	FLAIR MRI images	NA	Semi-supervised learning	High reliability in brain tissue segmentation
Chaki and Woźniak [77]	Public database	MR-GLCM	Brain Tumor Segmentation Network (BTSNet)	High correct classification rates (up to 98.1%)
Markkandeyan et al. [78]	BRATS 2013 dataset	Bias corrected filtering	CNN-based semantic segmentation, Improved multipath GoogLeNetCNN classifier	99.7% accuracy, 100% sensitivity, 99.717% specificity, 99.06% precision
Arunachalam and Sethumathavan [79]	MR images	Hyperparameter Optimization (HPO), Hybrid Grid Search Optimizer Algorithm (HGSOA)	YOLOV5, McCulloch's algorithm	Greater precision achieved by CNN
Talo et al. [80]	Brain MR images	Data augmentation, optimal learning rate finder, fine-tuning	ResNet34, CNN-based deep transfer learning	100% 5-fold classification accuracy on 613 MR images
Pratondo et al. [81]	NA	k-nearest neighbors, support vector machine (SVM)	Integration of machine learning and active contour model	Better accuracy and less sensitive to parameter tuning
Naceur et al. [82]	BRATS-2017 dataset	NA	Incremental Deep Convolutional Neural Networks, Ensemble Learning	Average 0.88 Dice score, 20.87 s for segmentation
Kabir et al. [83]	NA	Genetic algorithm (GA)	CNN-based deep learning, ensemble learning	The overall accuracy for identifying the three grades of glioma was 90.9%.
Alduraibi et al. [84]	Online dataset Relief	Particle Swarm Optimization (PSO)	Deep features from pre-trained CNNs, SVM model	Optimal concatenation of deep features has a success rate of 97.1%
Alagarsamy et al. [85]	MRI brain images	NA	BAT based Interval Type-2 Fuzzy C-Means (BAT-	values of 98.561.2% sensitivity and

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			IT2FCM) clustering	97.671.3% specificity
Kaur and Garg [86]	MRS data of 50 subjects	Fisher and Parameter-Free BAT (PFree BAT)	Fused metabolite ratio, K-nearest neighbor classifier	Sensitivity 96%, specificity 91%, accuracy 93.72%
Inbarani et al. [87]	MRI brain images	TRS (Tolerance Rough Set), Firefly Algorithm (FA)	Hybrid TRSFFQR	Effective feature selection with improvement over existing methods
Dixit and Nanda [88]	Brain MR images	Particle Swarm Optimization (PSO) based segmentation	SVM classifier	Classification of tumorous and non-tumorous brain from MR images
Pandey et al. [89]	BraTS 2018 dataset	AdaBoost, optimization of hyperparameters	Decision tree as base model, ensemble learning	Achieved reasonable accuracy in classifying high-grade vs. low-grade glioma

Despite considerable advancements in the utilization of AI for the interpretation of medical images, several gaps and obstacles continue to exist within the existing body of research. Concerns about the scarcity and quality of data persist, particularly in the area of uncommon diseases or specialized patient groups. Obtaining approval for the use of AI algorithms in therapeutic contexts and protecting patient privacy are only two of the many challenges that arise when ethical and organizational issues are integrated.

Moreover, the main challenge that needs to be overcome is the intelligibility of AI models in medical contexts. Under such circumstances, medical specialists work to confirm the accuracy of the model and provide the necessary data for therapeutic interventions. Working together, experts in computer science, radiology, and related fields can make AI findings useful in healthcare settings. This paper examines the state of AI in medical image analysis in detail and takes into account the challenges this sector faces. Its objective is to attract attention to the existing barriers and limits, highlight the enormous promise that AI offers in this area, and advocate for further study and dialogue.

9. CHALLENGES ENCOUNTERED AND POTENTIAL FUTURE DIRECTIONS

9.1 Obstacels and limitations in medical image analysis driven by ai

AI driven medical image analysis holds great promise but also faces several obstacels and limitations. Here are some of the key challenges.

- Lack of data: In order for AI models to be trained, massive volumes of high-quality medical data are frequently difficult to come by.
- Diversity of data: Medical data comes from a range of sources and formats, making it difficult to handle and standardize (such as radiography, MRI scans, and ultrasound imaging).
- Protection of patient privacy: Ensuring the security of patient data and preventing unwanted access present significant challenges.

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- Diagnostic complexity: Due to the intricacy and requirement for advanced interpretation of medical conditions, models may encounter difficulties in making an accurate diagnosis in the absence of human aid.

- Compatibility with current systems: It will cost a lot of money and require considerable modifications to integrate AI solutions into current medical systems.

- Bias and errors: The accuracy of diagnoses may be impacted by bias or errors in AI models due to the data used for training.

- Regulation and accreditation: Strict requirements are necessary for regulatory approvals and model accreditation in order to guarantee the efficacy and safety of the technology.

- Constant updating: AI models must be updated frequently to be current and successful in the dynamic and ever-changing world of medicine.

It will take cooperation between researchers, medical professionals, engineers, and regulators to address these problems and ensure the development of safe and effective AI systems for medical imaging.

9.2 Future research prospects and areas of inquiry

Future research in artificial intelligence (AI)-based medical image segmentation and classification is probably going to concentrate on a few main areas:

1. Improved Accuracy and Robustness:
   - The creation of more complex algorithms that can manage the intricacy and unpredictability of medical imaging is known as advanced algorithms. This covers methods such as reinforcement learning, transfer learning, and deep learning.
   - Improving the capacity of models to adapt to diverse populations, imaging apparatuses, and environments is known as generalization.

2. Multimodal and Multitask Learning:
   - Integrating data from multiple sources, including clinical records, MRI, CT, and PET, allows for more thorough and precise diagnosis.
   - Many jobs: To expedite the diagnostic process, models that can execute many jobs at once, like segmentation, classification, and detection, should be designed.

3. Explainability and Interpretability:
   - Transparent Models: Creating techniques to improve the interpretability of AI models so that medical practitioners can comprehend and have faith in the choices AI systems make.
   - Developing tools to illustrate the decision-making process of models by emphasizing significant regions in medical imaging.

4. Scalability and Efficiency:
   - High-performance computing involves processing huge information rapidly and effectively by utilizing advances in hardware and software.
   - Cloud-based solutions: These solutions are accessible from any location and are expandable thanks to the use of cloud computing.

5. Personalized Medicine:
- Patient-specific models refer to the development of models that are customized for specific patients based on their individual characteristics and medical background.
- Personalized treatment plans are made possible by predictive analytics, which uses AI to anticipate the course of a disease and the results of treatment.

6. Collaborative Research:
- To enhance the training and validation of AI models, it is recommended that institutions share anonymized medical image datasets with each other.

7. Continual Learning:

Developing AI systems with adaptive capabilities allows them to continuously learn from fresh data and improve over time.

The ultimate goal of these fields is to improve patient outcomes, increase diagnostic accuracy, and seamlessly integrate artificial intelligence (AI) into clinical practice. They represent some of the major avenues for future study in medical image segmentation and classification.

10. CONCLUSION

The utilization of Artificial Intelligence in the classification and segmentation of medical images, mostly using machine learning and deep learning approaches, has resulted in a notable improvement in the accuracy, efficiency, and consistency of medical image analysis. The manner that many medical ailments are found, diagnosed, and treated has fundamentally changed as a result of these advancements, which have made it feasible to identify diseases, define tumors, and slice organs. Before AI in medical imaging can realize its full potential, a number of challenges still need to be solved, despite these positive developments. The issues include the need for large-scale, high-quality annotated datasets, the variability of imaging modalities, patient privacy and trust in AI models, and being compatible with current systems. Real-time processing, multi-modal learning, explainable AI, and improved accuracy and robustness are some of the avenues to overcome these challenges. As research and technology progress, these advancements should enhance the acceptability and efficacy of AI-driven tools in clinical practice. In conclusion, although artificial intelligence (AI) in medical image classification and segmentation is still in its early stages of development, medical diagnosis and treatment planning have already benefited greatly from its current applications. Future advancements will most likely produce even better results, reaffirming AI's position as a vital component of medical imaging.

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