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Deep Learning's Impact on MRI Image Analysis: A Comprehensive Survey

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Abstract
Modern deep learning technology is without a doubt catalyzing a transformative revolution across various critical domains, including image analysis, natural language processing, and expert systems. It stands as an indispensable technique with a profound potential for shaping future applications. Recently, Magnetic Resonance Imaging (MRI) has garnered substantial attention due to its non-invasive attributes and its remarkable ability to provide intricate soft tissue contrasts within the body. Leveraging the significant advancements in deep learning, researchers have proposed ingenious approaches to augment the processing and analysis of MRI images. This article endeavors to present a comprehensive overview of how deep learning is being effectively employed for MRI image processing and analysis. The narrative commences with a succinct introduction to the fundamental concept of deep learning, followed by an elucidation of the diverse imaging modalities employed within the realm of MRI. Subsequently, the article delves into a comprehensive exploration of prevalent deep learning architectures. Building upon this foundation, the article navigates through a diverse array of applications made possible by harnessing deep learning within the domain of MRI. This encompassing exploration includes an emphasis on fundamental deep learning techniques, the transfer of knowledge between varying domains, classification paradigms, as well as the intricate domain of image segmentation. However, the article's exploration does not conclude here; it extends to deliberating on the strengths and limitations inherent in widely adopted tools. Additionally, it introduces specific deep learning tools that have been meticulously tailored to cater to the unique demands of MRI applications. In the final stretch, the article provides an impartial assessment of the role and impact of deep learning within the context of MRI. It also offers insightful projections into the landscape of future advancements and emerging trends. With a discerning eye on the trajectory ahead, the article articulates the immense potential for deep learning to significantly advance MRI image analysis, solidifying its pivotal role as a leading-edge technology shaping the landscape of medical imaging. In summation, the fusion of deep learning techniques with MRI analysis is poised to bring forth transformative advancements. The amalgamation of these disciplines stands to propel the boundaries of MRI image analysis, redefining the horizons of medical imaging while fortifying deep learning's status as a cornerstone technology driving this evolution.
Key terms: magnetic resonance imaging, deep learning, segmentation, classification, transfer learning.

1. Introduction

Artificial intelligence (AI) is a rapidly evolving field that has expanded since its inception in the 1950s. It encompasses practical applications and areas of active research. The objective of AI is to simulate human intelligence and develop intelligent machines that possess human-like consciousness, behavior, and thinking. The ultimate goal is to create sophisticated robots that mimic human brain functions. AI has made significant contributions to various domains, including image analysis, natural language processing, robotics, and expert systems. Machine learning lies at the core of AI and serves as a fundamental approach to designing intelligent computers. It draws from disciplines such as probability theory, statistics, approximation theory, convex analysis, and algorithm complexity theory. Machine learning primarily utilizes induction and synthesis to enable computers to acquire new knowledge, simulating human learning behavior. This acquired knowledge is then organized and used to continually enhance computer performance. Machine learning finds extensive applications in fields such as computer-aided disease diagnosis, bioinformatics and computer vision. Its applications span the entire breadth of AI. In summary, AI is a dynamic field dedicated to replicating human intelligence, with machine learning serving as a crucial component in designing intelligent computer systems. Together, they have revolutionized numerous industries and continue to drive advancements in AI research and applications. Deep learning, which has emerged with advancements in artificial neural networks, is not only an enhancement to these networks but also a distinct field in machine learning research [1-2]. Successful applications of deep learning have brought machine learning closer to achieving artificial intelligence. The concept of artificial neural networks is inspired by our understanding of the human brain, which consists of interconnected neurons. However, there are notable differences between artificial neural networks and the human brain. While each neuron in the human brain is connected to other neurons through specific physical pathways, neural networks are composed of discrete layers, connections, and data propagation directions. Deep learning surpasses traditional artificial neural networks by incorporating multiple hidden layers. This architecture allows for the combination of low-level features to form more abstract high-level representations for different classes. By leveraging these deep architectures, deep learning models can learn hierarchical representations of data, capturing complex patterns and relationships. Similar to the goal of artificial intelligence, deep learning seeks to build and simulate the human brain to analyze the learning process of neural networks. It attempts to mimic the learning mechanisms of the human brain when it encounters unfamiliar concepts. Through this simulation, deep learning aims to enhance our understanding of how neural networks learn and improve their ability to handle complex tasks. Deep learning has revolutionized the field of machine learning by enabling the automatic extraction of features from datasets tailored to specific applications. Unlike traditional feature extraction methods, which rely on prior knowledge and human intervention, deep learning can discover new and previously unknown features that are highly relevant to a given task. This ability to learn intricate representations from raw data has propelled deep learning closer to the realm of artificial intelligence. One key distinction between artificial neural networks and the human brain lies in their architecture. While the human brain consists of interconnected neurons with specific physical pathways, neural networks are composed of discrete layers, connections, and directional data propagation [3]. Deep learning, with its multiple hidden layers, enables the formation of abstract high-level feature representations by combining lower-level features. This hierarchical feature extraction approach allows for the learning of complex patterns and representations, enhancing the model's capability to understand and categorize different classes of data. Deep learning also shares a common goal with artificial intelligence: understanding and simulating the learning process of the human brain. By analyzing the learning mechanisms employed by neural networks, which mimic the brain's learning processes when faced with unfamiliar concepts, deep learning seeks to unlock the mysteries of intelligence and push the boundaries of machine learning further. In the domain of medical image processing and analysis, two critical factors significantly impact the results: image acquisition and image interpretation Image quality plays a vital role in the success of image processing and analysis. Magnetic Resonance Imaging (MRI) has gained considerable attention due to its non-invasiveness, excellent soft tissue contrast, and the absence of ionizing radiation exposure. MRI provides valuable insights into tissue structures, including shape, size, and localization, making it a valuable tool in clinical routines and computer-aided diagnosis. Structural imaging techniques, such as T1-weighted MRI, T2-weighted MRI, and Diffusion Tensor Imaging, along with functional imaging techniques like resting-state functional MRI and task-based functional MRI, contribute to a comprehensive understanding of the human body and aid in accurate diagnosis. In summary, deep learning's ability to automatically extract features, combined with advancements in image acquisition techniques such as MRI, has paved the way for significant advancements in various fields, including medicine and artificial intelligence [4].

2. Magnetic Resonance Imaging

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Among various medical imaging modalities, three are frequently utilized such X-ray, computed tomography (CT), and magnetic resonance imaging (MRI). Notably, MRI stands out distinctly from the other two modalities. CT and MRI share similarities as both reveal internal structures. However, while MRI relies on powerful magnets and radio waves, CT employs advanced X-ray technology to create 360-degree images of targeted internal areas and organs. During a CT scan, the subject lies on a movable table, while the machine rotates to capture cross-sectional images. In contrast, X-rays use electromagnetic waves with wavelengths of approximately 0.01 to 10 nanometers. Pre-tibial edema (PTE) indicates abnormal fluid levels in the body. All three imaging modalities—X-ray, CT, and MRI—are integral to medical image processing. In this domain, MRI often outperforms X-rays and CT scans. Medical imaging primarily aims to visualize internal organs, aiding disease diagnosis. A foundational understanding of human body chemistry is essential before image capture. Atoms constitute the human body's fundamental elements. Comprising an electron, nucleus, and proton, atoms feature electrons orbiting nuclei. Modalities create a well-aligned boundary around the nuclei within the body. The variable magnetic field within the body, leading to atom resonance, is known as nuclear magnetic resonance (NMR). Nuclei generate robust magnetic fields, which the scanner detects to produce images. MRI utilizes the same physical principle as NMR. The human body primarily comprises water ($H2O$), composed of two hydrogen atoms ($H2$) and one oxygen atom. Hydrogen nuclei (protons) align with magnetic fields ranging from 0.2 to 3 teslas. The scanner generates a potent magnetic field, inducing varied magnetic fields. As protons are atomic constituents, they absorb diverse energies from the scanner's variable field. Upon field deactivation, they shift their spins and gradually revert to their original spin state, termed precession. This spin return emits radio frequencies, captured by the scanner's receiver to form an image[5]. Different body parts' protons return to their original spins at distinct rates, enabling the scanner to distinguish between tissues. The scanner settings adjust contrast, enhancing tissue differentiation. Detection of brain tumors is facilitated through magnetic resonance imaging (MRI). An abnormal mass or aggregation of cells in a specific body area is termed a tumor. When this occurs in the brain, it is referred to as a brain tumor. Tumors can be either benign (noncancerous) or malignant (cancerous). Both types have the potential to grow within the brain, exerting pressure and posing a life-threatening condition. Brain tumors are classified into primary and secondary categories. Those originating within the brain are called primary benign tumors. When they spread to other parts like the lungs and chest, they become secondary tumors, leading to metastasis and further tumor spread. Risk factors for brain tumors include age, race, family history, and genetics. Symptoms may encompass vomiting, headaches, confusion, and weakness. Typically, physicians initiate examinations by assessing brain health through MRI. If a tumor is detected, further examinations are conducted to determine its nature as benign or malignant [6]. MRI measures the size of brain tumors after detailed brain imaging is performed. Prior to imaging, a tracer is injected into the patient's vein, serving as a marker. This tracer highlights the region of interest (ROI), followed by detailed MRI to detect the tumor. T1 and T2 relaxation times are significant factors for tissue differentiation. The time constant for the z-axis is termed the T1 parameter, while the time constant for the x y-axis is referred to as the T2 parameter. T1 is greater than T2 in biological contexts. The difference in T1 relaxation times produces a T1-weighted image, while the difference in T2 relaxation times yields a T2 image. To ascertain the protons in each tissue, the total protons per unit volume are measured, resulting in a proton density (PD) image. Figure 1 displays examples of diverse tumor types across various planes. The tumors are delineated with red outlines.

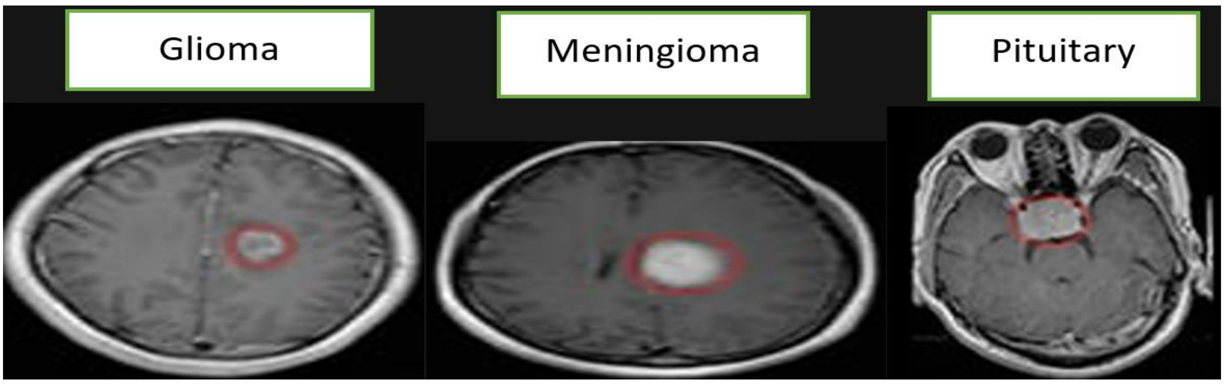

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Figure 1. Illustrates normalized magnetic resonance imaging (MRI) images displaying various tumor types in distinct planes. The tumors are highlighted with red outlines. Each tumor type is exemplified within its corresponding plane for clarity.

3. Deep Learning

Deep learning has a significant role in MRI classification and detection, revolutionizing medical imaging. It enables automatic analysis and interpretation of MRI images, leading to accurate classification and detection of abnormalities. Deep learning's key roles in MRI include feature extraction (Deep learning models, particularly convolutional neural networks (CNNs), excel at automatically extracting relevant features from MRI images. CNNs can capture intricate spatial patterns, edges, and textures within the images, enabling effective feature extraction. This eliminates the need for manual feature engineering, making the process more efficient and accurate), classification of abnormalities (Deep learning models can accurately classify MRI images into different categories based on the presence or absence of specific abnormalities. For instance, they can distinguish between normal and abnormal brain scans, identify the type and stage of tumors, detect lesions or multiple sclerosis (MS) plaques, and classify various brain pathologies [8-9]. Deep learning models leverage their ability to learn complex representations from large datasets, enabling precise and reliable classification), object detection and segmentation (Deep learning techniques, such as region-based convolutional neural networks (R-CNN) and U-Net architectures, are commonly used for object detection and segmentation in MRI images. These models excel at identifying and localizing specific structures or abnormalities within the image, such as tumors, cysts, or blood vessels. This enables precise delineation of regions of interest and facilitates subsequent analysis and treatment planning.), improving diagnostic accuracy (Deep learning algorithms assist radiologists and clinicians in making accurate diagnoses by providing additional information and detecting subtle abnormalities that may be challenging to identify visually. By leveraging large-scale labeled datasets, deep learning models learn from a wealth of knowledge and contribute to more reliable and consistent diagnoses.), speeding up analysis (Deep learning models automate and expedite the analysis of MRI images, reducing the time and effort required for manual interpretation. This enables faster diagnosis and treatment planning, allowing healthcare professionals to focus on more critical tasks.), and transfer learning and generalization (Deep learning models trained on large-scale datasets can extract generalized features, making them adaptable to new datasets and domains. Pre-trained models, such as those trained on natural image datasets like ImageNet, can be fine-tuned for MRI analysis, leveraging their learned representations and enhancing performance even with limited labeled medical image data.). Overall, deep learning enhances MRI analysis, improves diagnostic accuracy, and expedites the interpretation process [10-11].

3.1. Deep Learning Architectures for MRI Brain Classification

Medical image analysis has significantly benefited from the advancements in deep learning architectures, particularly in the context of MRI brain classification. Magnetic Resonance Imaging (MRI) scans provide detailed insights into brain structures and abnormalities, making them crucial for diagnosing various neurological conditions. Deep learning, with its ability to automatically extract intricate patterns from raw data, has emerged as a powerful tool for accurately classifying different brain conditions using MRI images. This abstract reviews prominent deep learning architectures employed for MRI brain classification tasks. Convolutional Neural Networks (CNNs) have proven foundational, extracting relevant features from 2D slices or 3D volumes of brain scans. Variations such as VGG, ResNets, and Inception networks have demonstrated proficiency in capturing intricate spatial features, enabling improved diagnostic accuracy. Moreover, the extension to 3D CNNs acknowledges the inherent 3D nature of MRI scans, further enhancing the model's ability to capture contextual information [12-13-14].

3.2. Deep Learning Tools

There are several popular deep learning tools and frameworks available that facilitate the development and implementation of deep learning models. These tools provide a wide range of functionalities, including model creation, training, evaluation, and deployment. Here are some commonly used deep learning tools as show in table 1.

Table 1. The tools of deep learning

Tools	Strengths	Weaknesses

ISSN NO: 2770-4491
Date of Publication:30-10-2023

Tensor Flow	Tensor Flow is widely adopted and has a large community, making it easy to find support and resources. It offers a comprehensive set of tools and libraries, including Keras, for building and training deep learning models. Tensor Flow supports distributed computing and deployment on various platforms.	Tensor Flow's API can be complex, and the learning curve may be steep for beginners. It can be resource-intensive and requires careful optimization for efficient performance
PyTorch	PyTorch has gained popularity due to its dynamic computational graph, allowing for more flexibility in model creation and experimentation. It has a python and intuitive interface, making it user-friendly. PyTorch offers strong support for research projects and encourages experimentation.	PyTorch may not be as optimized for large-scale distributed training compared to Tensor Flow. Its ecosystem, while growing, may not be as extensive as Tensor Flow's.
Keras	Keras is a high-level API that runs on top of Tensor Flow, Thea no, or CNTK. It provides a user-friendly interface for defining and training neural networks, enabling rapid prototyping. Keras has a large collection of pre-trained models and supports both convolutional and recurrent neural networks.	Keras may be less flexible compared to lower-level frameworks like Tensor Flow and PyTorch. It may not provide as much control over model customization and experimentation.
Caffe	Caffe is known for its efficiency and speed, making it suitable for large-scale deep learning projects. It has a clear and expressive architecture definition language, making it easy to specify network architectures. Caffe's pre-trained models and model zoo are widely used and accessible.	Caffe's ecosystem may not be as extensive as other frameworks, limiting the availability of certain features or community support. Its flexibility for custom model architectures may be more limited compared to frameworks like Tensor Flow or PyTorch.
MXNet	MXNet is known for its efficiency and scalability, making it suitable for both research and production use. It	The community and available resources for MXNet may be relatively smaller ompared to Tensor Flow or PyTorch. It

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Date of Publication:30-10-2023

	supports multiple programming anguages, offers a symbolic and imperative programming interface, and provides strong GPU acceleration capabilities.	may have a steeper learning curve due to its unique programming model.
Theano	Theano enables efficient mathematical computations and automatic differentiation, making it suitable for building and training deep learning models. It provides a lot of flexibility and control over model creation and optimization.	Theano is no longer actively developed and maintained, and its ecosystem may not be as up-to-date as other frameworks. It may have a steeper learning curve and less community support compared to other tools.
Microsoft Cognitive Toolkit (CNTK)	CNTK provides a highly optimized and scalable framework for building deep neural networks. It offers strong support for distributed training, efficient deployment, and integration with Microsoft Azure services.	CNTK's ecosystem and community support may not be as extensive as other frameworks like TensorFlow or PyTorch. It may have a steeper learning curve and fewer available resources.

These tools provide a range of functionalities and support various programming languages, making it easier for researchers and developers to build, train, and deploy deep learning models in different domains. The choice of tool depends on factors such as project requirements, familiarity with the framework, and available resources [15-16-17].

4.Image segmentation

Segmentation plays a crucial role in the classification of MRI images for the brain. Overall, segmentation plays a vital role in the classification of MRI images for the brain by extracting relevant regions, enabling feature extraction, improving classification accuracy, and facilitating integration with deep learning models. Detecting brain tumors accurately and quickly from MRI images is a challenging task. Medical image processing has advanced significantly, particularly in brain tumor segmentation, which has shown promise in clinical settings. However, there are challenges in bridging the gap between computer vision frameworks and real-world medical applications. Locating tumors accurately is a key goal, and segmentation techniques based on distinguishing characteristics, such as intensity or shape, have been employed. While automated methods have shown promising results, they are not widely accepted in routine clinical practice due to factors like the lack of standardized procedures and the need for transparent and interpretable decision-making [18-19-20]as show in figure 2 show Process of medical image segmentation. The Segmentation contributes to the classification process [21-22]:

- Region of Interest Extraction: Segmentation helps in extracting the specific regions of interest (ROIs) from the MRI images. These ROIs can include various brain structures such as gray matter, white matter, lesions, tumors, or specific anatomical regions. By segmenting these regions accurately, the subsequent classification algorithm focuses only on the relevant areas, reducing noise and improving classification performance.
- Feature Extraction: Segmentation provides delineation of different tissue types and structures within the brain. Once the regions of interest are segmented, specific features can be extracted from each segmented region. These features can include shape, texture, intensity, or statistical properties, which capture important characteristics for classification. By segmenting the brain into distinct regions, the classifier can extract relevant features from each region and consider their contributions separately.

- Improved Classification Accuracy: By segmenting the MRI images, the classification algorithm can focus on specific regions or structures that are known to be indicative of certain pathologies or conditions. For example, segmenting tumors or lesions allows the classifier to concentrate on these areas for accurate classification. Segmentation helps in reducing the influence of irrelevant or confounding factors, leading to improved classification accuracy.
- Integration with Deep Learning Models: Segmentation can be used as a pre-processing step in conjunction with deep learning models. By segmenting the brain into different regions, these regions can be fed as input to the deep learning model, allowing it to learn and classify based on the segmented features. This integration of segmentation and deep learning provides a powerful approach for brain image classification tasks.

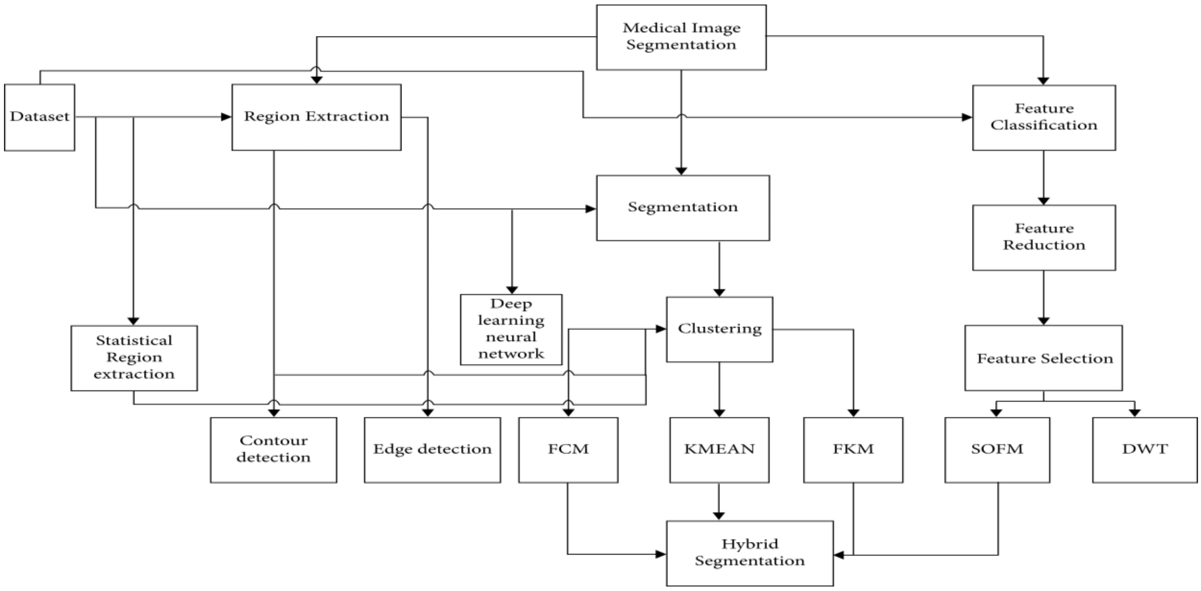

Figure 2. Process of medical image segmentation [18].

5. Classification

Detecting and segmenting brain tumors in medical image processing is a challenging and time-consuming task. Magnetic Resonance Imaging (MRI) is a non-invasive medical technique used by radiologists to visualize internal structures of the human body without the need for surgery. MRI provides valuable information about soft tissues, aiding in the diagnosis of brain tumors. Accurate segmentation of MRI images is crucial for computer-aided clinical tools to assist in brain tumor diagnosis. Once the brain MR images are appropriately segmented, tumors are classified as malignant or benign. However, this classification task is challenging due to the complex and varied characteristics of tumor tissues, such as shape, size, gray-level intensities, and location. In light of these challenges, this research focuses on highlighting the strengths and limitations of previously proposed classification techniques discussed in the current literature. Additionally, the paper provides a critical evaluation of the surveyed literature, unveiling new aspects of research in this field. In [23], the author managed to enhance classification performance compared to a shallower network. The paper presents a novel fully connected convolutional neural network (CNN) consisting of nine layers, which represents a deeper architecture in contrast to shallower convolutional networks. Residual learning was employed to improve learning efficiency. The proposed technique introduces multi-scale filters to capture spatio-spectral interactions, achieved through a set of three convolutional filters. In [24], the author addresses the challenge of limited availability of datasets and enhances classification accuracy by introducing a cross-domain CNN technique. This technique is designed for hyper-spectral image classification across multiple categories. The proposed approach demonstrates improved performance across various datasets compared to its performance on a single dataset. In [25], a novel deep CNN methodology is introduced for the purpose of scene classification. Two distinct approaches for CNN feature extraction are employed the Utilizing a pre-trained CNN as a universal feature extractor, Employing a pre-trained CNN model specifically for our classification dataset. To accomplish scene classification, a new Support Vector Machine (SVM) classifier is utilized. The methodology is evaluated on publicly available datasets, and the results highlight the efficacy of

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Date of Publication:30-10-2023

deep CNNs for scene classification. In [26], a model named the Wish art auto encoder (WAE) is introduced for the classification of polarimetry synthetic aperture radar (POLSAR) images. In order to enhance the classification results, the author integrates this classification model with the concept of clustering. This involves the utilization of the WAE and K-means techniques to construct a clustering-WAE network. To accomplish the classification task, the clustering-WAE network is connected with a softmax classifier. In [27], the absence of a dedicated superpixel design for image classification, particularly, is addressed. The author introduces a technique called "fuzzy superpixel" to mitigate the occurrence of mixed super pixels, which can negatively impact performance. Fuzzy super pixels are devised to reduce the prevalence of mixed super pixels. Notably, this approach does not assign all pixels exclusively to their corresponding super pixels. Additionally, a novel algorithm named fuzzy s (FS) is proposed for Pol-SAR image classification. To assess the effectiveness of FS, three Pol-SAR images are utilized. Several experiments are conducted to demonstrate the performance of the FS algorithm. In [28], for hyper-spectral image classification, the author presents an iterative Support Vector Machine (ISVM) technique, which is an iterative version of SVM. The process involves taking the original image and forming a hyper-spectral data cube through its principal components. An initial classification map is generated using SVM. Subsequently, a Gaussian filter is applied to capture the spatial information from the SVM classification map. In each subsequent iteration, the spatial information is combined with the currently processed hyper-spectral cube. ISVM's performance is compared to other techniques to assess its efficacy. Experimental results demonstrate that ISVM achieves high classification accuracy. In [29], a curriculum learning approach is proposed to enhance the quality of semi-supervised classification. This method involves gathering images from diverse features and assembling them into a curriculum learning sequence, which progresses from classifying simple to challenging unlabeled images. The study employs five semi-supervised classifiers for comparison against other techniques. The experimentation encompasses eight distinct datasets, revealing insights into the accuracy of semi-supervised image classification. Furthermore, the technique's applicability extends beyond its current context to various other semi-supervised classification problems. In [30], the authors introduce a spatially constrained Bag-of-Visual-Words (BOV) technique for image classification. This method utilizes two types of features. The BOV model represents images based on the statistical occurrence of visual words within each patch. The efficacy of this approach is compared against numerous other contemporary methods. In [31], the authors employ a patch-based methodology that captures both spectral and structural information to extract descriptors. This approach contributes to a scene classification system that aids in the identification of new and previously launched satellite missiles. In [32] proposes an algorithm centered around computer-aided detection (CADe) using images. This algorithm leverages Convolutional Neural Network (CNN) features specific to different regions, facilitating the observation of lung symptoms such as diffuse lung diseases and lung modules. In [33], the authors tackle the challenge posed by handcrafted features, which often overlook the interconnectedness between color information and intensity. They address this issue by employing a quaternion representation for color images. Through this approach, they effectively encode both intensity and color information in an image, amalgamating it as a variable for both manual representations and Convolutional Neural Networks (CNN). In [34], the authors introduce the Whole-Slide Image Color Standardize (WSICS) algorithm, utilizing both color and structural information to classify pixels into distinct components. This algorithm's performance is evaluated using two datasets, showcasing its ability to enhance accuracy in computer-based identification of histopathology data. In [35], the authors propose a method that employs multiple convolutional layers to capture gradient information across various structural combinations. This technique effectively handles the classification of large datasets from different sources. Notably, this method is distinct from conventional classification techniques and holds potential for intelligent medical treatment and clinical practices based on mobile terminals. In [36] is designed to enhance the performance of X-ray classification. Unlike existing methods that rely solely on predefined image features, this algorithm combines domain-transferred convolutional neural networks (DT-CNNs) with sparse spatial pyramid (SSP) features using a late fusion approach. This technique is applied to a public dataset of X-ray images and demonstrates superior performance compared to existing approaches. In [37], the author employs deep Residual Networks (ResNets) with varying depths and widths for spectral-spatial classification. Two publicly available datasets are employed for this classification. The author notes that as depth increases, the classification performance of deep learning models tends to decline. To counter this, two different models are used on different databases to enhance performance.

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Date of Publication:30-10-2023

Experimental results indicate that the proposed technique yields promising classification performance, effectively improving the accuracy of CNN-based classifications. In [38], the author assesses the performance of the proposed model by considering three crucial aspects: dataset characteristics, transfer learning, and deep CNN architecture. These factors collectively contribute to the evaluation of the model's effectiveness. In [39], the author's focus lies in reducing image feature redundancy and enhancing classification accuracy. To achieve this, they introduce the SPM-PCA algorithm, which integrates Spatial Pyramid Matching (SPM) and Principal Component Analysis (PCA) to improve image classification. This proposed model offers efficiency gains and superior classification performance while addressing conditional limitations. In [40], aiming to address the issue of low accuracy in military scene image recognition, the author presents a scene recognition approach based on Convolutional Neural Networks (CNN) and semantic information. The method involves CNN-based classification followed by refinement using semantic information. This approach is validated using a collected dataset of image scenes for military recognition. The results demonstrate that the proposed model surpasses the accuracy of traditional CNN methods. In [41], the author introduces a CNN-based model that classifies image features regionally to improve encoder efficiency. The resulting outputs are used downstream in systems for detecting the optimal coding unit in each block. The model is trained on a randomly selected 20k images dataset from the PASCAL dataset. Performance analysis involves comparing the output of this model with three other models. The theoretical outcomes showcase the effective reduction of encoder time through the proposed approach. In [42], a model named multi-CNNs is employed for the detection of abnormalities in chest X-ray images. This convolutional neural network-based model utilizes multiple CNNs to process input values, collectively referred to as multi-CNNs. The dataset is sourced from a Bin hospital. Additionally, the author proposes a fusion rule-based model called multi-CNN to integrate the outcomes of different models. The hypothetical results substantiate the feasibility of the proposed model for accurate diagnosis. The table 2 show others methods for classification MRI used in pre-researches and The process of classification as illustrated in Figure 3.

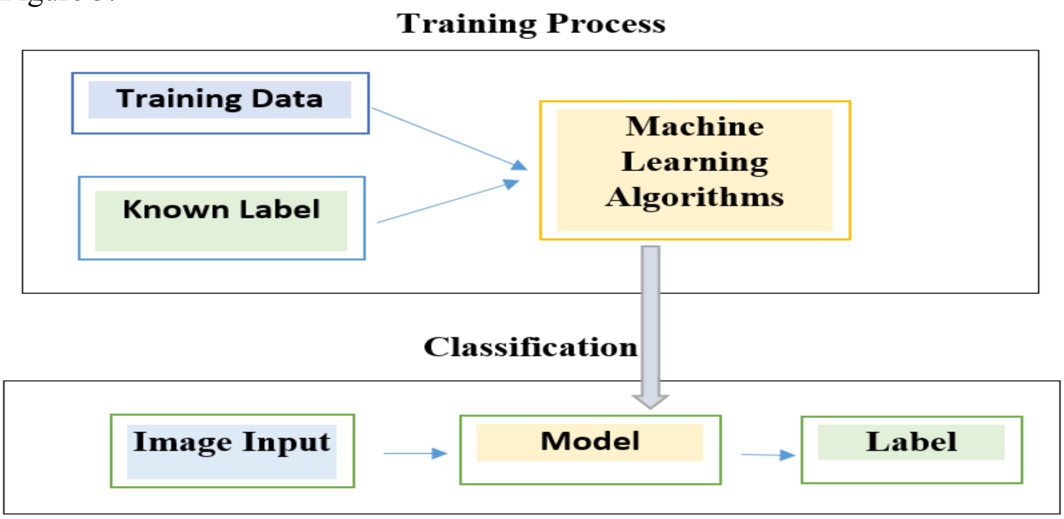

Figure 3. Classification and Training Process.

Table2. Comparison of Different Methods in another resources

No	Author	Year	Methods used	Limitation	Accuracy
43	N. Shafana, A. Senthilselvi	2023	Fuzzy Hybrid Filtration based Rician Noise Removal and Classification of MRI Images without Segmentation	Deep learning models, such as the Deep Wavelet Auto encoder (DWAE) classifier, are known for their complexity and lack of interpretability. Understanding the decision-making process of	it is more accurate in classifying MRI images for brain disease detection.

			using Deep Wavelet Auto based Encoder (DWAE) classifier	the model becomes difficult, which can be a limitation in medical applications where interpretability is crucial.	
44	Srigiri Krishnapriya, Yepuganti Karuna	2023	The research employed pre-trained deep convolutional neural networks to automatically classify brain MRI images.	using pre-trained deep convolutional neural networks for automated classification of brain MRI images is their potential lack of specificity to the unique characteristics of certain datasets or medical conditions.	it is more accurate in classifying MRI
45	FARUQ, OMAR; Islam, Md. Jahidul; Ahmed, Md. Sakib; Hossain, Md. Sajib	2023	The research introduces a classification technique for MRI brain scans, utilizing a probabilistic neural network.	is the lack of exploration into potential biases within the data set. If the dataset used for training is not well-balanced in terms of demographic factors or disease prevalence, the model's performance may be skewed, and its applicability to broader populations could be limited.	100%
46	Muhammad Hameed Siddiqi, Mohammad Azad, Yousef Alhwaiti	2022	The model underwent training and evaluation using logistic regression	Logistic regression assumes a linear relationship between the features and the log-odds of the outcome. If the true relationship is nonlinear, this could impact the model's accuracy and predictive capabilities, also used linear discriminant analysis (LDA) that employed for dimensionality reduction, there might still be potential redundancy in the selected features, impacting the model's efficiency and interpretability.	96.6%
47	Syrine Neffati, Mohsen Machhout	2022	The innovative MRI classifier utilizing Downsized Kernel Principal Component Analysis	The combination of Downsized Kernel Principal Component Analysis (DKPCA) and Artificial Neural Network (ANN) can result in a model with complex	it is more accurate in classifying MRI

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			(DKPCA) in conjunction with an Artificial Neural Network (ANN). The aim is to effectively classify brain MRIs as either pathological or normal.	decision-making processes, making it challenging to interpret why certain classifications are made. Interpretability is crucial in medical applications for gaining trust and understanding from healthcare professionals.	
48	Ferdaus Anam Jibon, Mayeen Uddin Khandaker, Mahadi Hasan Miraz, Himon Thakur, Fazle Rabby, Nissren Tamam, Abdelmoneim Sulieman, Y S Itas, Hamid Osman	2022	The distinguishing cancerous and non-cancerous brain tumors from MRI images is using Log Polar Transformation and convolutional neural networks.	Implementing both DKPCA and ANN can be computationally intensive, especially for large datasets. This may pose challenges in terms of scalability and practical deployment in real-world healthcare settings, where efficiency is crucial.	96%
49	Nikhil Pateria, Dilip Kumar, Sunil Kumar	2021	Various image classification techniques are used over MRI images to classify abnormal cells or tissues, such as tumors .	The some advanced classification techniques, especially deep learning models, can be computationally demanding. Deploying such models in resource-constrained environments may pose challenges.	In the context of machine learning models, the goal is typically to achieve higher accuracy.
50	Hind Rustum Mohammed and Lamyaa Fahem Katran	2019	Hybrid Method for Detection Tumor using Genetic Algorithm and Swarm Optimization after Wavelet Domain Filtering Then uing Marr-Hilerth	The Genetic Algorithm and Particle Swarm Optimization techniques used in the proposed method may come with computational complexity, making the approach resource-intensive and potentially slow for practical real-time applications.	93%
51	Lamyaa Fahem Katran and Hind Rustum Mohammad	2019	Hybrid Method for the Detection of Brain Tumor Image Using Improving K-Mean and Hybrid Multilevel Image Fusion	The performance of K-Means and hybrid image fusion methods often depends on tuning parameters. The article should discuss the sensitivity of results to parameter choices and how these choices were made.	95%

 ISSN NO: 2770-4491
Date of Publication:30-10-2023

52	Wang, Jun, Tong Zheng, Peng Lei, and Xiao Bai.	2018	Ground target classification in noisy SAR images using convolutional neural networks by SAR	Unnecessary complexity	82%
53	Cao, Qiong, Yanfei Zhong, Ailong Ma, and Liangpei Zhang.	2018	Urban Land Use/Land Cover Classification Based on Feature Fusion Fusing Hyperspectral Image and Lidar Data by LiDAR	Hard to tune parameters	82%
54	Singh, Rajesh, and Rajiv Gupta	2016	"Improvement of classification accuracy using image fusion techniques. Using PCA for classification	Over fitting	98.71%
55	Riri, Hicham, Abdelmajid Elmoutaouakkil, Abderrahim Beni-Hssane, and Farid Bourezgui.	2016	Curriculum learning method CNN	semi-supervised classification problem time complexity	90%
56	Xiao et al	2013	K nearest neighbors (KNN) and conventional Fuzzy connected C-mean (FCM).	Incorrectly assigning non-CSF pixels to the cluster is an issue that arises. To address this problem, a global mask is applied to remove unwanted pixels. As a result, the extracted region remains intact	100%
57	Nandagopal & Rajamony	2013	SVM is used for segmentation. A combination of WST and WCT is used for feature extraction. Genetic algorithm is used to select the optimal texture feature. PNN is used for classification.	Whenever there is a modification in the image dataset, a new training set is required for the Gaussian SVM classifier. This approach is specific to CT images.	97.5%

ISSN NO: 2770-4491
Date of Publication:30-10-2023

58	Kalbhani et al	2013	2D DWT of the input image is calculated fist. Then the features are extracted by PCA and LDA. The extracted feature are applied to KNN and SVM classifier for classification.	They are unable to capture asymmetry concerning the polarity of previous values.	97.62%
59	Sumitra and Saxons	2013	Uses a neural network technique for the classification of MRI images. The feature extraction is done by using PCA	The accuracy of over-discriminant is low. It's not possible to determine a unique feature vector.	73%
60	Deepa and Devi	2012	This methods exploit the capability of back propagation and Radial Basis Function neural network function to classify brain image.	Challenges arise when trying to select the optimal features for distinguishing between classes.	98.6%

6. Transfer learning

The increasing number of transfer learning approaches in brain MRI applications highlights the perceived significance of this field. Transfer learning is necessary due to the heterogeneity in large datasets that combine MR images from multiple studies and acquisition centers, each with different imaging protocols and scanner hardware. Furthermore, transfer learning simplifies training in new environments, thereby increasing the clinical applicability of machine learning. Prominent datasets readily available to researchers have significantly advanced specific applications, such as Alzheimer's diagnostics/prognostics and tumor segmentation. The availability of pretrained convolutional neural networks (CNNs) has also played a role in the popularity of transfer learning. Pre training a CNN or utilizing a pretrained CNN and fine-tuning it on target domain data emerged as the most widely adopted approach for transfer learning. Additionally, studies exploring different fine-tuning strategies on ImageNet-pretrained CNNs reported higher accuracy when fine-tuning all parameters, not just the last layers as in many other approaches. While several studies addressed relevant issues in the medical imaging community, such as privacy, it is worth noting that only two brain-specific approaches, coincidentally, did not employ CNNs. Furthermore, the surveyed studies often lacked in-depth analysis of their solutions after applying transfer learning. For instance, instance-based approaches seldom interpreted image weights, feature-based approaches did not compare various feature spaces with other methods, and the majority of parameter-based approaches relied on assumptions to determine which parameters to share. The importance of improving algorithms' ability to generalize heterogeneous and large datasets will likely continue to drive the adoption of transfer learning in MR brain imaging. The need for such extensive databases is likely to encourage collaborations among research institutions and the development of

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privacy-preserving methods that circumvent the need for data sharing. In medical imaging, particularly in MRI (Magnetic Resonance Imaging), transfer learning has been proven to be effective due to the limited availability of labeled medical data [61-62-63-64]. There are some transfer learning models that have been used for MRI image classification tasks as show in table 3.

Table3. Some models of transfer learning that use for classification MRI

models	Tasks
ResNets	• pertained on large image datasets (e.g., ImageNet). • Fine-tuned on MRI images for specific classification tasks, such as tumor detection or disease diagnosis.
VGG	• Similar to ResNets, VGG models pretrained on ImageNet can be fine-tuned for MRI classification tasks.
3D CNNs	• 3D CNN architectures like C3D (Convolutional 3D) or VoxResNet can capture spatial information in 3D MRI data. • Pretrained on large 3D datasets, these models can be adapted for specific classification tasks, such as brain tumor detection.
U-Net	• Originally designed for image segmentation, U-Net architectures can also be repurposed for image classification tasks. • U-Net can learn to segment relevant regions from MRI scans and classify them into different classes.
DenseNet	• DenseNet architectures, pretrained on general image datasets, can be fine-tuned for MRI image classification tasks. • They capture dense connections between layers, aiding in learning intricate patterns.

7. Conclusion

The impact of deep learning on the analysis of MRI images is nothing short of revolutionary. This powerful fusion of artificial intelligence and medical imaging has ushered in a new era, transforming the landscape of diagnostic medicine. The ability of deep learning algorithms to discern intricate patterns and extract meaningful features has elevated the precision and efficiency of MRI image analysis to unprecedented levels. The implications are profound, promising not just theoretical advancements but tangible improvements in patient outcomes. Swift and accurate diagnoses, personalized treatment plans tailored to individual health profiles, and the potential for early detection of diseases are among the significant contributions of deep learning to the field. Yet, this transformative journey is not without its challenges. The need for extensive datasets, the demand for interpretability in complex models, and ethical considerations related to data privacy underscore the ongoing necessity for research and innovation. As we navigate this uncharted territory, collaboration among researchers, clinicians, and policymakers becomes paramount to unlock the full potential of deep learning. In essence, the impact of deep learning on MRI image analysis transcends the realm of technological innovation; it signifies a paradigm shift with far-reaching consequences for healthcare. The convergence of artificial intelligence and medical imaging is not just a collaboration of technologies but a gateway to possibilities that can reshape healthcare systems. By steadfastly addressing challenges and fostering collaborative initiatives, we are on the path to a future where deep learning not only enhances efficiency but also brings about a more empathetic and accessible healthcare landscape, ultimately transforming patient outcomes for the better. Despite the increased attention and relatively promising results achieved by researchers in the field of MRI-based deep learning, several pressing issues and challenges persist due to various constraints. Two key challenges stand out:

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Date of Publication:30-10-2023

- Limited Dataset Size and Class Imbalance: The efficacy of deep learning is often correlated with the size of the dataset used for training. However, due to the intricate and costly nature of MRI image acquisition, dataset sizes are often constrained in numerous applications.
- Choosing Appropriate Architecture and Hyperparameters: The selection of an appropriate deep learning architecture and the corresponding hyperparameters remains an enigma. Current knowledge about the strengths and weaknesses of various architectures is rudimentary among most researchers. Thus, identifying the optimal architecture for a specific application remains unresolved. Even when an architecture is chosen, setting the ideal hyperparameters remains a challenge. Currently, trial-and-error based on experimental experience is the predominant approach to address these concerns.

Given the ongoing evolution of medical big data, the constraints related to MRI dataset sizes are expected to diminish. Simultaneously, as comprehension of deep learning architectures advances, the process of selecting the right architecture and tuning hyperparameters for specific applications will likely become more feasible. Ultimately, it's reasonable to anticipate that deep learning applications in the domain of MRI images will achieve even more significant strides in the future.

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