World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Review Article)

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# A survey on brain MRI segmentation

Kavitha Soppari [1], Sravya Putnala [2, *], Sai Srujana Borala [2] and Sai Kumar Gondhi [2]

*[1] Professor and Head, Department of CSE (Artificial Intelligence & Machine Learning), ACE Engineering College, Hyderabad, Telangana, India.*
*[2] IV B. Tech students, Department of CSE (Artificial Intelligence & Machine Learning), ACE Engineering College, Hyderabad, Telangana, India.*

World Journal of Advanced Research and Reviews, 2024, 21(03), 1702–1710

Publication history: Received on 08 February 2024; revised on 16 March 2024; accepted on 19 March 2024

Article DOI: https://doi.org/10.30574/wjarr.2024.21.3.0813

## Abstract

Neurological disorders pose a significant challenge in medical diagnostics, requiring accurate and efficient analysis of brain Magnetic Resonance Imaging (MRI) scans. This study introduces a novel approach for enhanced neurological diagnosis through the application of deep learning techniques to automate the segmentation of brain structures in MRI images. The proposed method leverages the power of convolutional neural networks (CNNs) to extract intricate patterns and features from complex neuro imaging data. The research involves the development and training of a deep learning model capable of accurately delineating key anatomical regions, such as the cortex, hippocampus, and ventricles. The model is trained on a large data set of annotated MRI scans, optimizing its performance through rigorous validation processes. The utilization of deep learning enables the algorithm to learn and generalize from diverse imaging data, improving its adaptability to variations in patient demographics and scanner characteristics. To evaluate the effectiveness of the proposed approach, comprehensive experiments are conducted on a diverse set of MRI datasets, encompassing various neurological conditions. Quantitative metrics, including Dice coefficient and Hausdorff distance, are employed to assess the segmentation accuracy compared to ground truth annotations. Additionally, the clinical relevance of the automated segmentation is validated through collaboration with neurologists and radiologists. The results demonstrate that the deep learning- enabled segmentation method consistently outperforms traditional image processing techniques, providing more accurate and reliable segmentation results. The proposed approach not only streamlines the diagnostic process but also has the potential to uncover subtle abnormalities that may be overlooked by manual inspection. In conclusion, the integration of deep learning into the segmentation of brain MRI scans presents a promising avenue for enhancing neurological diagnosis. The automated and precise delineation of brain structures contributes to the efficiency and accuracy of diagnostic workflows, ultimately improving patient outcomes and facilitating timely interventions in the realm of neurological disorders.

**Keywords:** Neurological disorders; Medical diagnostics; Magnetic Resonance Imaging (MRI); Deep learning techniques; Automated segmentation; Convolutional neural networks (CNNs); Anatomical regions; Diverse imaging data; Quantitative metrics; Diagnostic workflows.

## 1. Introduction

Medical image segmentation is a crucial aspect of medical imaging, seeking to partition an input image into distinct segments that align closely with the region of interest (RoI). The primary objectives include representing the input image meaningfully for anatomical studies, identifying the RoI, and aiding in treatment planning by assessing tumor size and determining radiation therapy dosage. This process significantly enhances the analysis of medical images by highlighting and isolating critical regions. In the medical domain, image segmentation finds diverse

* Corresponding author: Sravya Putnala

applications, including delineating brain tumor boundaries in MRI images. The demand for robust medical image segmentation algorithms is high due to a scarcity of expert manpower in this specialized field. Early models for image segmentation relied on traditional image processing approaches, such as thresholding, edge-based techniques, and region-based methods. Thresholding categorized pixels based on pixel value ranges, while edge-based techniques classified pixels as edged or non-edged using filters. Region-based segmentation separated neighboring pixels with similar values and grouped pixels with dissimilar values. However, these traditional approaches faced challenges due to limitations in the medical image acquisition process, pathology types, and biological variations. Brain MRI segmentation presents unique challenges due to constraints in the image procurement procedure, the nature of brain pathology, and biological variations. Additionally, the analysis of brain MRI images demands expertise, and there is a shortage of medical imaging professionals specializing in neuro imaging. In recent years, deep learning networks have significantly contributed to the development of advanced image segmentation models, including those specifically designed for brain MRI segmentation. Deep neural networks have demonstrated high accuracy rates on various popular datasets, surpassing traditional methods. Image segmentation techniques can be broadly categorized into semantic segmentation and instance segmentation. Semantic segmentation, within the context of brain MRI, involves classifying pixels in the image and assigning each pixel to a specific class, aiding in the understanding of different brain structures. Instance segmentation aims to detect and delineate each individual object of interest within the brain MRI, providing a more detailed understanding of the neuro anatomy. The evolution from traditional image processing methods to deep learning networks has significantly advanced the field of medical image segmentation, including its application to brain MRI. These advancements are crucial for improving the accuracy and efficiency of neuro imaging analysis, addressing the shortage of expert manpower in neuroimaging, and ultimately enhancing patient care through more informed diagnoses and treatment planning for neurological conditions.

## 2. Literature review

The research centered on a thorough investigation into the effectiveness of various methodologies within the domain. By scrutinizing pertinent research papers, the aim was to assess a multitude of approaches and techniques employed in these areas. This process sought to reveal the nuanced intricacies and advancements within the field.

**A. Sengur, U. Budak, Y. Akbulut, M. Karabatak, and E. Tanyildizi et al. [1]** This survey explores the application of neutrosophic sets in medical image segmentation. Neutrosophic set theory is an extension of classical set theory that handles indeterminate and uncertain information. The paper provides an overview of various techniques and methodologies in the field of neutrosophic medical image segmentation. It discusses the challenges and opportunities presented by neutrosophic sets in improving the accuracy and robustness of medical image segmentation, which is a crucial step in medical image analysis. The survey covers key concepts, methodologies, and applications, offering insights into the potential of neutrosophic sets in enhancing the segmentation of medical images for diagnostic and treatment purposes. In the last decade, considerable attention has been directed towards neutrosophic sets (NS) as a generalization of interval fuzzy sets in the computer vision and machine learning communities. This heightened interest has led to a proliferation of applications, particularly in image processing tasks. The focus of this review is on the utilization of NS in medical image segmentation, a well-established process in image processing that involves dividing an input image into distinct regions with homogeneous pixel properties. The surveyed literature indicates a widespread application of NS-based segmentation approaches across various medical imaging modalities, including breast ultrasounds, liver computed tomography, brain CT, dermoscopy, retinal, eye angiography, and dental X-ray images. Additionally, NS has found significant utility in optical image segmentation, particularly in the context of texture image segmentation. In these applications, NS is commonly employed for tasks such as denoising and image enhancement. The surveyed literature reveals a prevailing trend wherein NS is frequently utilized for either improving image quality through contrast enhancement and noise reduction or segmenting images into regions of interest and background. The review introduces several prominent NS-based medical image segmentation approaches, elucidating the methodologies applied and presenting detailed outcomes. Throughout the discussion, the inherent limitations of NS-based segmentation in medical imaging are highlighted. The chapter concludes by synthesizing key findings and offering insights into the current state of NS-based segmentation in medical imaging. Furthermore, future perspectives are outlined to guide forthcoming research endeavors in this evolving field.

**G. Litjens, T. Kooi, B. E. Bejnordi et al. [2]** In this comprehensive survey, the authors review the extensive applications of deep learning in medical image analysis. Deep learning has emerged as a powerful tool for extracting complex patterns and features from medical images, leading to significant advancements in diagnosis and treatment planning. The paper discusses various deep learning architectures and techniques employed in medical image analysis, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs). It also addresses challenges such as the need for large annotated datasets and interpretable models. The survey provides a valuable resource for researchers, clinicians, and practitioners interested in the state-of-the-art applications of deep learning in medical image analysis. Deep learning algorithms, particularly convolutional networks, have swiftly emerged as the preferred methodology for analyzing medical images. This review paper comprehensively examines key deep learning concepts relevant to medical image analysis, encapsulating insights from over 300 contributions in the field, with a focus on recent publications. The scope encompasses the application of deep learning in diverse tasks such as image classification, object detection, segmentation, registration, and others. The paper provides succinct overviews of studies within specific application areas, including neuro, retinal, pulmonary, digital pathology, breast, cardiac, and musculoskeletal domains. The synthesis concludes with a summary encapsulating the current state-of-the-art, coupled with a critical discussion addressing open challenges. Furthermore, the paper outlines prospective directions for future research in the dynamic landscape of medical image analysis employing deep learning methodologies.

**X. Liu, L. Song, S. Liu, and Y. Zhang et al. [3]**Published in the journal Sustainability, this paper provides a review of deep learning-based methods for medical image segmentation. The authors survey and summarize the advancements in the field, focusing on techniques that utilize deep learning for accurate and efficient segmentation of medical images. The review covers recent developments up to the year 2021, shedding light on the sustainability aspect of these methods and their potential impact on enhancing medical image analysis applications. As an emerging biomedical image processing technology, medical image segmentation has significantly advanced sustainable medical care and has become a pivotal research focus in computer vision. The paper delves into the realm of medical image segmentation, specifically centered on the application of deep learning. It initiates by presenting the fundamental concepts and characteristics of medical image segmentation based on deep learning, elucidating its research status, and providing a comprehensive overview of the three primary methods along with their inherent limitations. The discourse extends to the future developmental trajectory of this field. The paper meticulously examines various pathological tissues and organs, highlighting the nuances and classic segmentation algorithms specific to each. Despite the notable achievements in recent years, challenges persist in medical image segmentation based on deep learning. Issues such as sub-optimal segmentation accuracy, limited data set size, and low resolution impede the fulfillment of clinical requirements. The review concludes by offering a comprehensive overview of current methods in medical image segmentation based on deep learning, aiming to assist researchers in addressing the prevailing challenges in this domain.

**M. H. Hesamian, W. Jia, X. He, and P. Kennedy et al. [4]** Published in the Journal of Digital Imaging, this paper explores deep learning techniques employed in medical image segmentation, highlighting both achievements and challenges in the field. The authors discuss the progress made by deep learning methods in improving the accuracy and efficiency of medical image segmentation tasks. Additionally, they address the existing challenges and potential avenues for future research in order to overcome limitations and enhance the applicability of deep learning in medical image segmentation. Deep Learning Techniques for Medical Image Segmentation: Achievements and Challenges Deep learning has firmly entrenched itself as a reliable tool for image segmentation, particularly in the realm of medical imaging where it serves as a crucial initial step in the diagnosis and treatment process. This article provides a meticulous examination of prevalent methodologies that leverage deep learning techniques for medical image segmentation. The focus lies in critically assessing these approaches, shedding light on their effectiveness and applicability within the medical context. By delving into the nuances of these methods, the article contributes to a comprehensive understanding of the landscape where deep learning-based image segmentation plays a pivotal role. A fundamental aspect of the article involves elucidating the significant role of deep learning in separating homogeneous areas within medical images. This segmentation process stands as a critical component in the broader diagnostic and treatment pipeline. The article not only underscores the widespread adoption of deep learning in this domain but also emphasizes its indispensable nature as the initial step, setting the stage for subsequent medical interventions. Through this exploration, the article offers insights into the integral role played by deep learning- based image segmentation in enhancing the efficiency and accuracy of medical diagnosis and treatment. In addition to reviewing existing methodologies, the article dedicates attention to the challenges inherent in deep learning-based medical image segmentation. By summarizing the most common obstacles encountered, the article contributes to the identification of areas where improvements and innovations are imperative. Furthermore, the article goes beyond highlighting challenges and takes a proactive stance by suggesting potential solutions, offering a valuable resource for researchers and practitioners navigating the complex terrain of medical image segmentation using deep learning techniques.

**S. M. Anwar, M. Majid, A. Qayyum, M. Awais, M. Alnowami, and M. K. Khan et al . [5]**Published in the Journal of Medical Systems, this paper presents a comprehensive review of medical image analysis techniques using convolutional neural networks (CNNs). The authors survey the literature up to 2018, summarizing the applications and advancements of CNNs in various medical imaging tasks, including segmentation, classification, and detection. The review provides insights into the strengths and challenges of CNN-based approaches in medical image analysis, aiming to guide researchers and practitioners in the field. The domain of biomedical engineering has witnessed significant strides, positioning medical image analysis at the forefront of research and development endeavors. This scientific discipline entails resolving clinical issues through the scrutiny of images generated in clinical practice. The overarching goal is to adeptly and efficiently extract pertinent information, thereby enhancing the efficacy of clinical diagnoses. An instrumental driver behind recent advancements in medical image analysis is the integration of machine learning techniques, particularly the application of deep learning. This methodology harnesses neural networks to autonomously learn features, a departure from conventional approaches reliant on manually crafted features, a complex task fraught with challenges. Notably, deep convolutional networks, a subset of deep learning techniques, have emerged as a prominent tool for medical image analysis, finding application in segmentation, abnormality detection, disease classification, computer-aided diagnosis, and retrieval. This study delves into a comprehensive exploration of the contemporary landscape of medical image analysis, specifically focusing on the utilization of deep convolutional networks. The review encapsulates the current state-of-the-art methodologies, providing insights into their applications across diverse areas within medical image analysis. The multifaceted roles encompass segmentation, abnormality detection, disease classification, and computer-aided diagnosis, underscoring the versatility of deep convolutional networks in addressing varied aspects of medical image analysis. Within this discourse, the study also accentuates the challenges inherent in employing these techniques, shedding light on potential obstacles and complexities that researchers and practitioners may encounter. As the review unfolds, it systematically emphasizes the challenges and potential inherent in the deployment of deep convolutional networks for medical image analysis. By elucidating the obstacles, the study contributes to a nuanced understanding of the intricacies involved in implementing these techniques. Simultaneously, it underscores the vast potential that deep convolutional networks hold, showcasing their capacity to revolutionize medical image analysis. This dual perspective provides a balanced and insightful overview, guiding future research endeavors in this dynamic intersection of biomedical engineering and deep learning.

**H. C. Shin et al. [6]** This paper, published in the IEEE Transactions on Medical Imaging, focuses on the application of deep convolutional neural networks (CNNs) for computer-aided detection. The authors delve into the architectures of CNNs, data set characteristics, and the role of transfer learning in enhancing the performance of computer-aided detection systems. The study contributes valuable insights into the design considerations and methodologies employed in leveraging deep CNNs for the detection of medical conditions through image analysis. Significant strides in image recognition owe much to the expansive availability of large-scale annotated datasets and the deployment of deep convolutional neural networks (CNNs). The efficacy of CNNs lies in their capability to glean data-driven, hierarchical features from extensive training data, a characteristic vital for image analysis. However, the translation of these advancements to the medical imaging domain encounters challenges, notably the scarcity of comprehensively annotated datasets akin to ImageNet. This paper delves into the realm of medical image classification using CNNs, focusing on four key techniques: training CNNs from scratch, leveraging pre-trained CNN features, employing unsupervised CNN pre-training with supervised fine-tuning, and implementing transfer learning, specifically fine-tuning CNN models pre-trained on natural image datasets for medical image tasks. The study unfolds by exploring and evaluating diverse CNN architectures, varying from 5 thousand to 160 million parameters and differing in the number of layers. A critical aspect of the paper involves an empirical evaluation of three pivotal factors in the application of deep convolutional neural networks to computer-aided detection (CAD) problems. The investigation encompasses an in-depth analysis of various CNN architectures, scrutinizing models with parameter ranges from 5 thousand to 160 million and different layer configurations. The study also assesses the impact of data set scale and spatial image context on performance, shedding light on essential considerations for optimizing CNN-based CAD systems. Furthermore, the paper investigates the utility of transfer learning from pre-trained ImageNet, specifically through fine-tuning, elucidating scenarios in which this approach proves beneficial. The specific CAD problems examined are thoraco-abdominal lymph node (LN) detection and interstitial lung disease (ILD) classification. The comprehensive empirical evaluation and nuanced CNN model analysis presented in this paper contribute valuable insights to the domain of medical image analysis, particularly in the context of computer-aided detection. The research achieves state-of-the-art performance in mediastinal LN detection and reports pioneering five-fold cross-validation classification results for predicting axial CT slices with ILD categories. The findings and methodologies outlined herein serve as a foundation for designing high-performance CAD systems across diverse medical imaging tasks, emphasizing the applicability and transferability of insights gained from this study.

**N. Tajbakhsh et al. [7]**Also published in the IEEE Transactions on Medical Imaging, this paper explores the use of convolutional neural networks (CNNs) for medical image analysis. The authors specifically investigate the trade-off between training CNNs from scratch and fine-tuning pre- trained models for medical image analysis tasks. The study discusses the advantages and limitations of each approach and provides insights into the optimal strategies for leveraging CNNs in the context of medical image analysis. Initiating the training of a deep convolutional neural network (CNN) from scratch poses a formidable challenge, demanding extensive labeled training data and specialized expertise for ensuring convergence. An alternative approach gaining traction involves fine-tuning pre-trained CNNs using datasets derived from large sets of labeled natural images. However, the considerable disparities between natural and medical images raise concerns about the efficacy of knowledge transfer in this context. This paper addresses a pivotal question in medical image analysis: Can pre-trained deep CNNs, with adequate fine-tuning, obviate the need for training a deep CNN from scratch? The study encompasses four distinct medical imaging applications across radiology, cardiology, and gastroenterology, involving classification, detection, and segmentation across three different imaging modalities. A comprehensive examination of the experiments consistently reveals several key findings. Firstly, the use of pre-trained CNNs, coupled with appropriate fine-tuning, consistently outperforms or performs on par with CNNs trained from scratch. Secondly, fine-tuned CNNs exhibit enhanced robustness to variations in the size of training sets compared to their scratch-trained counterparts. Thirdly, the optimal choice between shallow and deep tuning is contingent on the specific application, challenging the notion of a one-size-fits- all approach. Lastly, the paper introduces a layer-wise fine-tuning scheme that proves to be a practical and effective strategy for optimizing performance based on the available data for a given application. In conclusion, the findings of this study significantly contribute to the discourse on deep CNNs in medical image analysis. The demonstrated effectiveness of pre-trained CNNs with fine- tuning offers a promising avenue to circumvent the challenges associated with training from scratch. The insights gained from the layer-wise fine-tuning scheme provide a valuable practical approach for tailoring CNNs to specific medical imaging applications, taking into account the nuances of available data. This research not only advances the understanding of CNNs in the medical domain but also presents practical strategies for optimizing their performance in real-world scenarios.

**R. Li et al[8]** Published in the proceedings of the Medical Image Computing and Computer- Assisted Intervention conference, this paper introduces a deep learning-based approach for completing imaging data to enhance the diagnosis of brain diseases. The authors present a method that leverages deep learning techniques to fill in missing or incomplete data in medical images, aiming to improve the accuracy of brain disease diagnosis. The amalgamation of multi-modality brain data for disease diagnosis often enhances diagnostic performance. However, a recurrent challenge in utilizing such multi-modality data lies in its inherent incompleteness, with some subjects lacking certain modalities. Addressing this issue, this work introduces a deep learning framework designed to estimate multi-modality imaging data. The proposed method adopts a convolutional neural network architecture, with two volumetric modalities serving as input and output. Notably, the network is endowed with a substantial number of trainable parameters, facilitating the capture of intricate relationships between the input and output modalities. Through training on subjects with complete modalities, the network becomes adept at predicting the output modality based on the input modality. The efficacy of this approach is evaluated on the Alzheimer's Disease Neuroimaging Initiative (ADNI) database, specifically focusing on MRI and PET images as input and output modalities, respectively. Encouragingly, the results demonstrate the superior performance of the proposed method compared to previous approaches. The significance of this work extends beyond the proposed framework's application to Alzheimer's Disease Neuro imaging Initiative (ADNI) database. By tackling the common issue of incomplete multi-modality data, the method contributes to the broader landscape of medical imaging and diagnostic research. The adoption of a convolutional neural network architecture, renowned for its capability in capturing complex relationships within data, positions this framework as a robust solution for estimating missing modalities. The empirical evaluation on ADNI further substantiates the method's effectiveness, showcasing its ability to outperform existing methods in handling incomplete multi- modality brain data. In the realm of disease diagnosis, particularly in neuro imaging, the integration of multi-modality data is pivotal for enhancing diagnostic accuracy. However, the inherent challenge of incomplete data necessitates innovative solutions. This work not only proposes a deep learning-based framework tailored for estimating missing modalities but also provides empirical evidence, through ADNI database evaluation, of its superior performance compared to existing methodologies. The contributions of this research extend to the broader field of medical imaging, shedding light on effective strategies for handling incomplete multi-modality data in the pursuit of more accurate and reliable disease diagnosis.

**A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi et al[9]**This survey paper provides an overview of recent architectures of deep convolutional neural networks (CNNs). Published in Artificial Intelligence Review, the authors review and analyze various CNN architectures that have been proposed in recent years. The survey aims to summarize the key features, advancements, and applications of these architectures, providing insights into the current landscape of deep CNNs. The Deep Convolutional Neural Network (CNN) stands out as a specialized neural network type, exhibiting exceptional performance in various Computer Vision and Image Processing competitions. Its applications span diverse domains, encompassing Image Classification and Segmentation, Object Detection, Video Processing, Natural Language Processing, and Speech Recognition. The remarkable learning prowess of deep CNNs is attributed to their utilization of multiple feature extraction stages, enabling automatic learning of data representations. The surge in research on CNNs is propelled by the abundance of available data and advancements in hardware technology, resulting in the emergence of intriguing deep CNN architectures. Several avenues for enhancing CNNs have been explored, including the adoption of different activation and loss functions, parameter optimization, regularization techniques, and architectural innovations. However, the most substantial improvements in the representational capacity of deep CNNs stem from innovative architectural approaches. The survey delves into the intrinsic taxonomy present in recent deep CNN architectures, offering a systematic classification of innovations into seven distinct categories. These categories revolve around spatial exploitation, depth, multi-path information processing, width, feature-map exploitation, channel boosting, and attention mechanisms. Notably, the survey emphasizes the growing popularity of architectural strategies that exploit spatial and channel information, manipulate the depth and width of the architecture, and engage in multi-path information processing. Additionally, the notion of employing a block of layers as a structural unit garners attention as a promising avenue for architectural innovation. By providing a comprehensive overview of recent advancements, the survey sheds light on the evolving landscape of deep CNN architectures. The exploration of recent innovations in deep CNN architectures within the survey is anchored in a thorough understanding of CNN components, current challenges, and applications. The categorization into seven distinct classes elucidates the diverse strategies employed to enhance CNNs, offering a structured perspective on the evolving landscape. The survey not only encapsulates the state-of-the-art developments but also provides insights into the foundational elements of CNNs, current obstacles faced, and the wide-ranging applications across various domains. This comprehensive overview positions the survey as a valuable resource for researchers, practitioners, and enthusiasts navigating the dynamic field of deep CNNs.

**Zhang W et al. [10]** This paper, published in NeuroImage, focuses on the segmentation of isointense infant brain images using deep convolutional neural networks (CNNs). The authors propose a methodology that leverages CNNs to perform segmentation on multimodal images, addressing the challenges associated with isointensity in infant brain imaging. The study contributes to the understanding of deep learning applications in handling complex imaging characteristics specific to pediatric brain images. The segmentation of infant brain tissue images, specifically into white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF), holds paramount importance for investigating early brain development in both health and disease contexts. The isointense stage, typically occurring around 6-8 months of age, presents a significant challenge in segmentation as WM and GM exhibit comparable intensity levels in T1 and T2 MR images. Existing methods for tissue segmentation in this stage are limited, primarily relying on single T1 or T2 images or their combination. This paper introduces a novel approach employing deep convolutional neural networks (CNNs) to address the segmentation challenges in the isointense stage. Leveraging multi- modality MR images, including T1, T2, and fractional anisotropy (FA), the proposed CNN architecture generates segmentation maps as outputs. The model's architecture incorporates multiple intermediate layers that apply convolution, pooling, normalization, and other operations to capture intricate and highly nonlinear mappings between inputs and outputs. The effectiveness of the proposed CNN-based approach is empirically assessed by comparing its performance with commonly used segmentation methods on manually segmented isointense stage brain images. The results demonstrate the superior performance of the proposed model in infant brain tissue segmentation, outperforming existing methods. Notably, the integration of multi-modality images yields a significant improvement in performance, underscoring the advantage of leveraging diverse imaging information for more accurate and robust segmentation outcomes. This research not only addresses the specific challenges of isointense stage segmentation but also contributes to the broader landscape of medical image segmentation methodologies, particularly in the context of infant brain tissue analysis. In the domain of infant brain tissue segmentation, where challenges arise due to isointensity in T1 and T2 MR images, this paper introduces a pioneering approach based on deep convolutional neural networks (CNNs). By utilizing multi-modality information from T1, T2, and FA images, the proposed CNN architecture surpasses existing methods, as evidenced by empirical comparisons on manually segmented isointense stage brain images. The integration of various imaging modalities emerges as a crucial factor, demonstrating the significance of leveraging complementary information for enhanced segmentation performance. This research not only addresses specific challenges in infant brain tissue segmentation but also contributes valuable insights to the broader field of medical image analysis, highlighting the efficacy of deep learning methodologies in overcoming complex segmentation tasks.

## 3. CNN for medical image segmentation

Convolutional Neural Networks (CNNs) have become a powerful tool in medical image segmentation, specifically for identifying and delineating structures in complex medical images. These networks leverage convolutional layers to extract hierarchical features, capturing intricate patterns. Pooling layers aid in dimension reduction, retaining crucial information through mechanisms like max pooling. A common architectural design for medical image segmentation involves an encoder-decoder framework. The encoder captures contextual information, while the decoder reconstructs the segmented output. Skip connections are often used for accurate segmentation, preserving details during upsampling. CNNs find extensive applications in medical imaging, including tumor and organ segmentation in modalities like MRIs and CT scans. They contribute to precise delineation, aiding in diagnosis, treatment planning, and surgery. In addition to structural segmentation, CNNs play a crucial role in lesion detection and segmentation in medical images. They are also employed for cell segmentation in histopathology images, enhancing pathology analysis.

Despite their benefits, deploying CNNs in medical image segmentation poses challenges. Ensuring quality and quantity of training data is crucial, and interpretability of CNN decisions is an ongoing concern. Computational resources for training deep CNNs are substantial, leading researchers to explore techniques like transfer learning. In conclusion, CNNs represent a forefront technology in medical image segmentation, providing automated solutions for various healthcare applications. Their potential to extract meaningful features from complex medical images could revolutionize diagnosis, treatment planning, and patient care.

**Table 1** Overview of Techniques and Methodologies for Brain MRI Segmentation,highlighting the pros and cons of each approach

| Paper | Year | Technique/Methodology | Pros | Cons |
|---|---|---|---|---|
| [1] | 2019 | Neutrosophic Sets in Medical Image Segmentation | Addresses uncertainty, indeterminacy | Limited coverage of recent advancements |
| [2] | 2017 | Deep Learning in Medical Image Analysis | Comprehensive survey, covers multiple modalities | Focuses on developments up to 2017 |
| [3] | 2021 | Deep Learning-Based Medical Image Segmentation | Reviews recent methods, focuses on sustainability | Specifics on sustainability could be more detailed |
| [4] | 2019 | Deep Learning Techniques for Medical Image Segmentation | Comprehensive overview, discusses achievements and challenges | Limited discussion on specific challenges |
| [5] | 2018 | CNNs in Medical Image Analysis | In-depth review, covers various applications | Limited discussion on challenges and future directions |
| [6] | 2016 | Deep CNNs for Computer-Aided Detection | Discusses CNN architectures, dataset characteristics, and transfer learning \| | Limited discussion on dataset challenges |
| [7] | 2016 | CNNs for Medical Image Analysis: Full Training or Fine-Tuning? | Investigates training strategies for CNNs in medical image analysis | Limited discussion on specific applications |
| [8] | 2014 | Deep Learning-Based Imaging Data Completion for Brain Disease Diagnosis | Improves brain disease diagnosis using deep learning | Limited discussion on broader applications |
| [9] | 2020 | Survey of Recent Architectures of Deep CNNs | Comprehensive survey of recent CNN architectures | Limited depth in the analysis of architectures |
| [10] | 2015 | Deep CNNs for Multimodality Isointense Infant Brain Image Segmentation | Addresses isointensity challenges in infant brain imaging | Specific to isointense infant brain image segmentation |

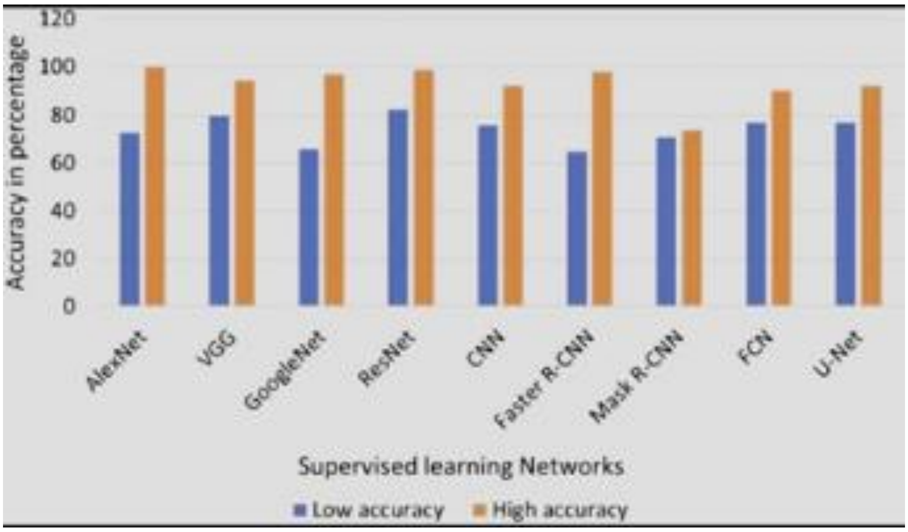


**Figure 1** Accuracy Graph of Different Supervised Learning Networks

## 4. Conclusion

In conclusion, the field of brain MRI segmentation using deep learning has made substantial progress, showcasing its potential to revolutionize medical image analysis. Ongoing research efforts focus on addressing challenges, improving generalization across diverse datasets, and integrating deep learning models into clinical workflows for real-world impact. As the field continues to evolve, advancements in deep learning techniques are likely to contribute further to the precision and efficiency of brain MRI segmentation in clinical practice.

## Compliance with ethical standards


### *Acknowledgments*

We would like to thank our guide Dr. Kavitha Soppari, Head of the Department of CSE (Artificial Intelligence & Machine Learning), Ace Engineering College . Also, we are extremely grateful to her for her continuous support and invaluable time.


### *Disclosure of conflict of interest*

The authors have no conflicts of interest to declare. All co-authors have seen and agreed with the contents of the manuscript and there is no financial interest to report.

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