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Analysis of axial T2 TSE images using deep learning reconstruction in MRI of brain tumors

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ABSTRACT

Magnetic Resonance Imaging (MRI) Brain examinations often encounter uncooperative patients, necessitating rapid scanning techniques that yield optimal results. To address this challenge, advanced technologies such as deep learning can be leveraged to accelerate scan time, reduce noise, and enhance image precision. This study aims to evaluate the disparity in MRI Brain image quality with and without deep learning in tumor cases to achieve superior diagnostic imaging. Employing a quantitative experimental approach, this research analyzed a sample of 30 patients collected from January to February 2025. Three Radiologist Specialists assessed the images using a questionnaire based on the Visual Grading Analysis (VGA) method. The obtained responses were statistically examined through Cohen's Kappa consistency test and Wilcoxon Signed-Rank Test. Findings revealed a statistically significant difference in image information between deep learning-assisted and conventional MRI scans. In T2 TSE sequences, deep learning reconstruction demonstrated superior anatomical visualization of the Gray Matter, White Matter, Lateral Ventricles, Basal Ganglia, and Parafalx Cerebri. However, in brain tumor pathology visualization, conventional MRI exhibited sharper and more distinct tumor delineation. Although deep learning-enhanced T2 TSE sequences reduced scan duration and improved overall image quality, they provided suboptimal diagnostic information in tumor cases.

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INTRODUCTION

Brain tumors are abnormal proliferations of cells or tissues within or around the brain that can lead to fatal outcomes. These tumors are classified into two main types: primary and secondary (Suta et al., 2019). Primary brain tumors originate directly from brain cells and include intrinsic neoplasms such as gliomas, astrocytomas, oligodendrogliomas, medulloblastomas, and pituitary tumors (Hulmansyah, 2020). Meanwhile, secondary brain tumors emerge as metastases from malignancies in other body regions (Gianzurriell et al., 2023). The incidence of brain tumors has been rising annually, with approximately 300 new diagnoses reported each year in Indonesia. These tumors affect both adults and children, yet public awareness regarding early symptoms remains limited(Kiryu et al., 2023). To prevent progression to advanced stages, early detection is crucial, necessitating vigilance among both medical professionals and the general population (Febrianti et al., 2020). One of the most effective diagnostic modalities for identifying brain tumors is Magnetic Resonance Imaging (MRI), which provides detailed imaging for neurological assessment) (Gianzurriell et al., 2023; Hulmansyah, 2020). MRI is widely utilized for detecting conditions such as multiple sclerosis, infarcts, hemorrhages, infections, trauma, and metastatic diseases (Westbrook, 2014).

Magnetic Resonance Imaging (MRI) is a non-invasive imaging technique that employs strong magnetic fields and radiofrequency waves to generate high-resolution anatomical visuals without utilizing ionizing radiation (Hendrati & Wyantuti, 2020.; Jatmiko, 2021). This modality is highly sensitive, painless, and free from adverse effects, making it particularly useful for soft tissue evaluations (Hendrati & Wyantuti, 2020.; Jatmiko, 2021). The assessment of pathological conditions through MRI relies on sectional imaging in coronal, sagittal, and axial planes, depending on the anatomical site and suspected abnormalities (Sriyatun et al., 2020). Brain MRI imaging sequences incorporate standard and advanced techniques, including Turbo Spin Echo (TSE), Diffusion Weighted Imaging (DWI), Fluid Attenuated Inversion Recovery (FLAIR), Magnetic Resonance Angiography (MRA), and Magnetic Resonance Venography (MRV) (Faisal et al., 2024; Putri et al., 2021). Among these, Turbo Spin Echo (TSE) sequences are frequently employed due to their efficiency in reducing scan duration by utilizing extended echo train lengths (ETL) (Prabawati et al., 2015). This sequence applies 90^o excitation pulses followed by multiple 180^o rephasing pulses, generating several spin echoes per repetition time (TR) (Westbrook, 2014). T2-weighted imaging, essential in clinical protocols, provides enhanced contrast for analyzing cerebral anatomy, cerebrospinal fluid (CSF) spaces, and parenchymal lesions (Sartoretti et al., 2021).

Despite its diagnostic efficacy, prolonged MRI acquisition time often induces patient discomfort, resulting in suboptimal image quality and limited diagnostic utility (Susanto et al., 2016). To address this issue, advancements in modern technology, particularly deep learning-based approaches, have been explored for optimizing scan efficiency(Pardosi & Lubis, 2019). Deep learning techniques can significantly overcome the limitations of conventional MRI imaging by enhancing image reconstruction, improving signal-to-noise ratio (SNR), and reducing motion artifacts, which are common challenges in brain tumor detection (Inaoka et al., 2024). Conventional MRI often struggles with prolonged scan durations, susceptibility to motion artifacts, and low contrast in tumor visualization. Deep learning-based algorithms address these challenges by reconstructing high-quality images from undersampled data, allowing for faster acquisition without sacrificing diagnostic accuracy. Moreover, deep learning can facilitate automated lesion segmentation, classification, and quantitative analysis, aiding radiologists in more precise tumor assessment. Deep learning, an advanced subset of artificial intelligence (AI), surpasses conventional machine learning methodologies in recognizing patterns and objects with superior accuracy (Primartha, 2018). As a multi-layered neural network framework, deep learning refines image reconstruction by minimizing noise and enhancing visualization quality (Islami, 2020.; Nugroho et al., 2020). Research by Inaoka et al., (2024) demonstrated that deep learning-enhanced MRI images exhibited improved anatomical visualization and reduced artifacts compared to low-field conventional MRI. Similarly, studies indicate that deep learning-assisted image reconstruction effectively decreases acquisition time while maintaining high image fidelity (Xie et al., 2024). These techniques have been widely applied in imaging the spine, knee, and shoulder (Kaniewska et al., 2022); however, most existing literature focuses on retrospective studies addressing undersampling issues. Notably, research on deep learning-driven reconstruction for brain MRI, particularly in tumor assessment using TSE sequences, remains scarce, highlighting a significant research gap that warrants further investigation.

Given these considerations, this study aims to analyze the impact of deep learning integration in MRI Brain imaging for tumor cases, specifically by evaluating image quality and diagnostic information derived from standard acquisition versus deep learning-enhanced reconstruction. The objective is to determine whether deep learning can facilitate acquisition time reduction without compromising diagnostic accuracy, thereby offering an innovative solution for optimizing MRI workflows in neuro-oncology.

RESEARCH METHOD

This quantitative research employs an experimental approach to examine the optimal imaging information differentiation between deep learning-based processing and conventional methods. Data acquisition was conducted between January and February 2025 at the Radiology Department of Dr. Sardjito General Hospital, Yogyakarta, utilizing a Philips 1.5 Tesla MRI scanner. The study focuses on assessing deep learning-enhanced and non-deep learning processing in TSE T2-weighted axial sequence imaging. A total of 30 patients presenting with clinical indications of tumors and undergoing MRI brain scans were included as subjects. The imaging parameters utilized in this investigation are as follows:

Table 1. T2 TSE axial MRI brain sequence parameters

Parameters	MRI Brain
TR	5380
TE	101
Slice thickness (mm)	4.0
FOV (mm)	220
Disc Factor	20%

Note: TR = Time Repetition; TE = Time Echo; FOV = Field of View; NEX = Number of Excitation

MRI images were acquired using standardized protocols and stored in DICOM format. Post-acquisition, images were processed in two different ways: one set underwent deep learning-based image enhancement, while the other retained conventional processing. The deep learning model used was a neural network-based denoising and contrast enhancement algorithm optimized for MRI sequences. Image preprocessing included normalization and standardization before evaluation by radiologists.

Quantitative assessment in this study utilized a questionnaire evaluated by three Radiologist through the Visual Grading Analysis (VGA) method, encompassing gray matter, white matter, lateral ventricles, basal ganglia, parafalx cerebri, and brain tumors, rated on a three-point Likert scale. Each radiologist independently assessed MRI Brain images in the T2 TSE Axial sequence, both processed with deep learning and without deep learning, in tumor cases comprising 60 images—30 utilizing deep learning and 30 without deep leaning.

To ensure data reliability, inter-observer agreement was measured using Cohen's Kappa consistency test. Prior to statistical analysis, normality testing was conducted to determine the appropriate statistical method. Given the ordinal nature of the VGA scores and the paired comparison design, the Wilcoxon Signed-Rank Test was applied to determine whether there is a difference in image information between the use of deep learning and non-deep learning in the T2 TSE Axial sequence. This evaluation aimed to discern whether deep learning processing provides statistically superior diagnostic information for MRI Brain images in tumor cases.

RESULTS AND DISCUSSIONS

The demographic characteristics of the study participants are presented in Table 2, which categorizes them based on gender and age. This information provides an overview of the distribution of MRI brain patients diagnosed with tumors, highlighting variations in gender composition and age range.

Table 2. Sample characteristics based on gender and age

Category	Number	Percentage (%)
Gender		
Male	10	33.3%
Female	20	66.7%
Total	30	100%
Age Group		
21-40 years	2	6.7%
41-80 years	28	93.3%
Total	30	100%

Based on Table 2, this study involved 30 MRI Brain patients diagnosed with tumors, with 33.3% being male and 66.7% female. In terms of age distribution, 6.7% of patients were aged 21-40 years, while the majority, 93.3%, were between 41-80 years old.

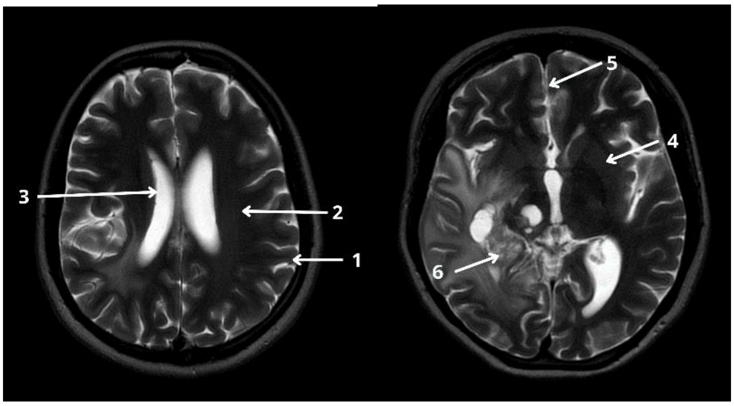

Figure 1. (a) distinctly illustrates; (b) clearly highlights

The six axial MRI brain anatomical images evaluated by respondents are depicted in Figure 1. Image (a) distinctly illustrates the Gray Matter (1), White Matter (2), and Lateral Ventricle (3), whereas image (b) clearly highlights the Basal Ganglia (4), Parafalcine Cerebri (5), and Tumor (6). This study examines the variance in anatomical detail discernibility between MRI brain axial T2 TSE sequence images processed with deep learning and those obtained without its application in tumor cases. The evaluation was conducted through a structured questionnaire completed by three board-certified radiologists, assigning scores based on clarity: 1 (“Indistinct or Poorly Defined”), 2 (“Clearly Visible”), and 3 (“Most Distinct”). To determine the objectivity level of the assessments across the two imaging techniques, inter-rater agreement was measured using Cohen’s Kappa statistical test.

Table 3. Cohen's kappa test value results

	Respondent	Respondent	Respondent
Cohen’s Kappa	1 & 2	1 & 3	2 & 3
	0,974	0,956	0,930

Based on Table 3, the Cohen's Kappa test yielded a value exceeding 0.80. According to Samudra et al., (2025), a Cohen's Kappa coefficient below 0.20 indicates poor agreement, 0.21–0.40 signifies fair concordance, 0.41–0.60 represents moderate consistency, 0.61–0.80 denotes substantial agreement, and 0.81–1.00 reflects near-perfect alignment. This result implies that the consensus among the three respondents is exceptionally strong. Consequently, Respondent 1 was selected for further analysis due to their extensive tenure as a radiologist specialist. Subsequent evaluation employed the Wilcoxon test, as the dataset comprises ordinal variables. This non-parametric statistical approach assesses whether there is a significant disparity in anatomical imaging information when utilizing deep learning compared to conventional methods. The findings from the Wilcoxon test are presented in Table 4.

Table 4. Results of the wilcoxon test of differences in overall anatomical information on MRI brain

Sequence	Mean Rank	Significance (p-value)	Interpretation
T2 TSE Axial without Deep Learning	58.72		
T2 TSE Axial with Deep Learning	69.51	0.001	Significant Difference

Based on Table 4, the Wilcoxon test conducted at a 95% confidence level indicates a significance value of $p < 0.001$ across the anatomical structures analyzed. This confirms a statistically significant difference between T2 TSE axial sequences with and without deep learning. Furthermore, the mean rank of the T2 TSE sequence utilizing deep learning is higher than that of the conventional T2 TSE sequence, suggesting that deep learning-enhanced T2 TSE provides superior MRI brain imaging quality. These results align with research conducted by Xie et al., (2024), which demonstrated that deep learning applications significantly improve MRI scan contrast and noise reduction, ultimately leading to better clinical diagnosis accuracy.

Table 5. Wilcoxon test results for anatomical information in T2 TSE axial sequences with and without deep learning

Anatomy	Sequence	Mean Rank	Significance (p-value)
Gray Matter	T2 TSE without Deep Learning	9.50	
	T2 TSE deep learning	12.24	0.001
White Matter	T2 TSE without Deep Learning	10.00	
	T2 TSE Deep learning	12.30	0.001
Ventrikel Lateral	T2 TSE without Deep Learning	11.50	
	T2 TSE deep learning	13.29	0.001
Ganglia Basalis	T2 TSE without Deep Learning	8.50	
	T2 TSE deep learning	13.07	0.001
Parafalx Cerebri	T2 TSE without Deep Learning	7.50	
	T2 TSE deep learning	11.58	0.001
Brain Tumor	T2 TSE without Deep Learning	11.32	
	T2 TSE deep learning	9.63	0.006

Table 5 presents the Wilcoxon test results for anatomical information extracted from MRI brain scans using the T2 TSE axial sequence, both with and without deep learning. The significance values for Gray Matter ($p = 0.001$), White Matter ($p = 0.001$), Lateral Ventricle ($p = 0.001$), Basal Ganglia ($p = 0.001$), and Parafalcine Cerebri ($p = 0.001$) indicate a statistically significant enhancement in anatomical detail when deep learning is applied. The brain tumor evaluation yielded a p-value of 0.006, still demonstrating a significant difference at a 95% confidence level. These findings highlight that deep learning integration in MRI enhances anatomical visualization, particularly in pathological cases such as brain tumors, reinforcing its potential in clinical radiological assessments.

The imaging data underwent evaluation by three independent observers, followed by Cohen's Kappa test to assess inter-observer agreement. The analysis yielded a Cohen's Kappa coefficient exceeding 0.80, indicating strong concordance among evaluators. Specifically, the mean agreement between Observer 1 and Observer 2 reached 0.974, while Observer 1 and Observer 3 demonstrated an agreement of 0.956. Similarly, the consensus between Observer 2 and Observer 3 was 0.930. As per Samudra et al. (2025), Cohen's Kappa values below 0.20 suggest poor agreement, 0.21-0.40 indicate fair reliability, 0.41-0.60 reflect moderate agreement, 0.61-0.80 represent good concordance, and values from 0.81 to 1.00 denote an excellent level of consistency. These results confirm a high degree of agreement among the observers.

Subsequent statistical examination using the Wilcoxon test aimed to determine discrepancies in anatomical image quality between T2 TSE sequences with and without deep learning. The obtained p-value (< 0.05) signified a statistically significant distinction in imaging outcomes for MRI Brain Axial tumor cases. Table 6 reveals that the mean rank for the T2 TSE sequence without deep learning stood at 58.72, whereas the corresponding value for deep learning-enhanced sequences reached 69.51. This suggests that T2 TSE images reconstructed with deep learning exhibit superior anatomical representation. These findings align with prior research, which demonstrated that deep learning techniques significantly enhance image quality (Inaoka et al., 2024), thereby improving anatomical visualization.

Further Wilcoxon tests for distinct anatomical structures revealed statistically significant variations in image detail for Gray Matter (p = 0.001), White Matter (p = 0.001), Lateral Ventricles (p = 0.001), Basal Ganglia (p = 0.001), Parafalx Cerebri (p = 0.001), and Brain Tumor (p = 0.006). These findings indicate that MRI Brain Axial T2 TSE sequences reconstructed with deep learning provide more refined anatomical details compared to conventional sequences. Deep learning-based MRI reconstruction has been demonstrated to reduce scan duration in TSE imaging (Xie et al., 2024). This technology operates using a self-supervised learning framework to enhance image quality without necessitating additional scan data (Jung et al., 2022; Lee et al., 2023). Previous studies indicate that T2 TSE Axial scan times may be reduced by up to 65% with deep learning (Gassenmaier et al., 2021). Consequently, shorter scanning durations minimize patient movement, mitigating motion-related artifacts.

Wilcoxon test results for each anatomical region further substantiate the advantages of deep learning-enhanced imaging. The mean rank values for deep learning sequences were: Gray Matter (12.24), White Matter (12.30), Lateral Ventricles (13.29), Basal Ganglia (13.07), and Parafalx Cerebri (11.58). In contrast, standard T2 TSE sequences yielded lower mean rank values: Gray Matter (9.50), White Matter (10.00), Lateral Ventricles (11.50), Basal Ganglia (8.50), and Parafalx Cerebri (7.50). These findings reinforce the superiority of deep learning-augmented imaging in anatomical depiction. Prior research highlights that inter-observer agreement in evaluating spinal canal stenosis, vertebral structures, and foraminal narrowing significantly improves with NSA1 deep learning technology (Kiryu et al., 2023). However, tumor imaging yielded different results, with the mean rank for deep learning being 9.63, compared to 11.32 for standard sequences. Pardosi and Lubis A.A (2019) noted that noise reduction techniques employed in deep learning can inadvertently obscure tumor details, leading to diminished clarity in pathological assessment.

Implementation of deep learning-based MRI TSE reconstruction has been shown to enhance clinical imaging by reducing scan time, improving image fidelity, and maintaining diagnostic reliability comparable to conventional TSE (Suh et al., 2024). Although the present study did not focus specifically on tumor pathology visualization, findings indicate that deep learning reconstruction contributes to artifact reduction through expedited scanning. This corroborates prior findings by Gassenmaier et al., (2021), which suggest that integrating deep learning in MRI imaging can reduce scan durations, leading to decreased patient discomfort and improved clinical workflow efficiency.

CONCLUSION.

This study shows that there is a significant difference in MRI imaging information with and without the use of deep learning. In anatomical structures such as Gray Matter, White Matter, Lateral Ventricles, Basal Ganglia, and Parafalx Cerebri, the use of deep learning produces clearer and higher-quality images compared to those without deep learning. However, in cases of tumor pathology, the research findings indicate that images obtained without deep learning are actually more informative. Therefore, in brain MRI examinations for tumor cases, the use of deep learning is not always necessary, as it may reduce the clarity of information needed for tumor pathology analysis. Further research is recommended to evaluate the effectiveness of deep learning in other imaging modalities beyond MRI, such as CT scans, to determine its broader applicability in medical imaging. Additionally, the findings of this study can contribute to the development of more refined deep learning algorithms by optimizing their ability to enhance anatomical structures while preserving critical pathological details, particularly in tumor cases. Future studies could focus on algorithm improvements that adapt dynamically to different imaging needs, ensuring that deep learning aids rather than hinders diagnostic accuracy.

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