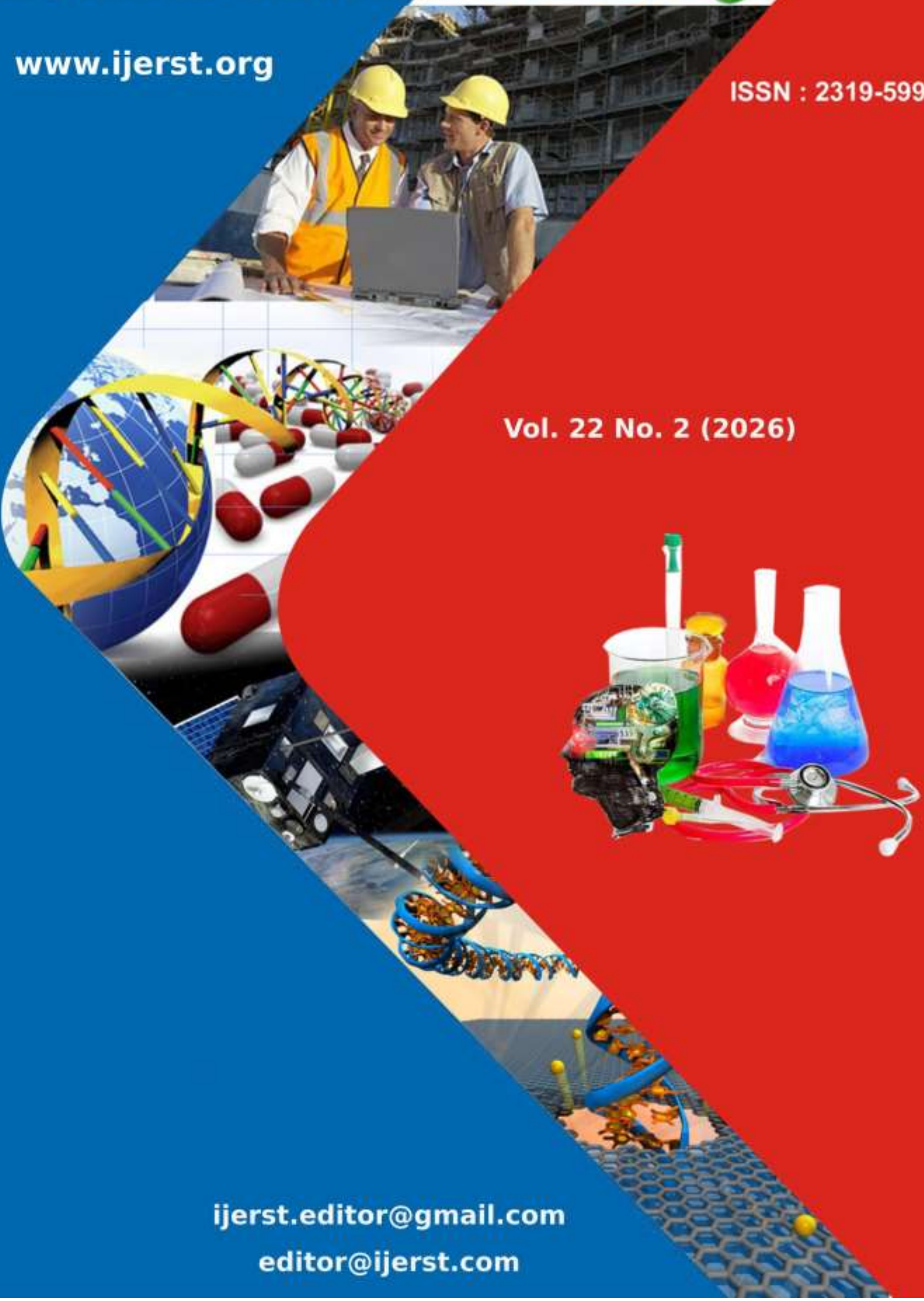
International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991



Vol. 22 No. 2 (2026)

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com
Vol. 22, No. 2, 2026

Peer Reviewed, Referred & Indexed Journal

Brain Tumor Segmentation in MRI Imaging Using an Efficient U-Net LITE Model

Mr. G. Ravi Chandra[1]|Ganta Venkata Ramana[2]|Bejawada Yakshitha[3]|Chamarthi Nagalakshmi[4]|Katta Teja Krishna[5].

[1,2,3,4,5]Department of CSE-AI, Chalapathi Institute of Engineering and Technology, LAM, Guntur, Andhra Pradesh, India

ABSTRACT: Brain tumor detection is a critical task in medical image analysis, as early and accurate diagnosis plays an important role in effective treatment planning and improving patient survival rates. Magnetic Resonance Imaging (MRI) is widely used for identifying brain abnormalities, but manual analysis by radiologists can be time-consuming and prone to human error. In existing systems, Convolutional Neural Networks (CNN) have been used for tumor detection; however, they often face limitations in precisely identifying tumor boundaries. To address this issue, this study proposes a brain tumor segmentation approach using a lightweight U-Net architecture (UNet-Lite). The proposed model is designed to efficiently segment tumor regions from MRI images by utilizing an encoder–decoder structure with skip connections that preserve spatial information and improve segmentation accuracy. The system is trained and evaluated on a dataset of brain MRI images to automatically detect and highlight tumor regions. Experimental results demonstrate that the proposed UNet-Lite model provides improved accuracy and better segmentation performance compared to traditional CNN-based approaches. The automated system can assist radiologists by providing faster and more reliable tumor detection, reducing diagnostic errors and enhancing clinical decision-making. This work highlights the effectiveness of deep learning-based segmentation techniques in medical imaging and their potential to support early diagnosis and treatment of brain tumors.

Keywords: Brain Tumor Segmentation, Magnetic Resonance Imaging (MRI), Deep Learning, UNet-Lite, Medical Image Analysis, Convolutional Neural Networks.

1.INTRODUCTION

Brain tumors are one of the most serious and life-threatening neurological disorders that affect the normal functioning of the brain. They occur due to the abnormal growth of cells in the brain tissues, which can interfere with vital brain activities such as memory, movement, and sensory functions. Early detection and accurate diagnosis of brain tumors are essential for effective treatment planning and improving the survival rate of patients. Medical imaging techniques play a significant role in identifying brain abnormalities, among which Magnetic Resonance Imaging (MRI) is widely used because it provides detailed and high-resolution images of brain structures. MRI scans help doctors visualize soft tissues clearly, making them highly useful for detecting tumors and other brain-related diseases. However, manually analyzing MRI images to identify and outline tumor regions is a complex, time-consuming, and error-prone process. It also depends heavily on the expertise and experience of radiologists. As the number of medical images continues to increase, there is a growing need for automated systems that can assist in the accurate detection and segmentation of brain tumors. In recent years, advancements in artificial intelligence and deep learning have greatly improved medical image analysis. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated high performance in tasks such as image classification, detection, and segmentation. These techniques can automatically learn important features from medical images and accurately identify tumor regions. Automated brain tumor segmentation helps in precisely locating the tumor boundaries, which is essential for diagnosis, treatment planning, and monitoring disease progression. Therefore, developing efficient and reliable automated methods for brain tumor segmentation from MRI images has become an important research area in the field of medical image processing.Brain tumor segmentation is an important task in medical image analysis that helps doctors identify abnormal tumor regions in brain MRI scans. Early and accurate detection of brain tumors is essential for effective diagnosis, treatment planning, and improving patient survival rates. In traditional approaches, Convolutional Neural Networks (CNN) have been used for tumor detection, but they may not accurately segment the exact tumor boundaries. This project proposes a UNet-Lite deep learning model for efficient brain tumor segmentation in MRI images. The UNet-Lite architecture uses an encoder–decoder structure with skip connections to capture both spatial and contextual information from medical images. The model automatically analyzes MRI scans and highlights the tumor regions with higher accuracy. The dataset of brain MRI images is used to train and validate the segmentation model. The system performs preprocessing, model training, and prediction to identify tumor areas. Performance is evaluated using metrics such as accuracy, precision, recall, and F1-

score. The proposed UNet-Lite model improves segmentation performance compared to traditional CNN-based methods and helps support faster and more reliable medical diagnosis.

2. LITERATURE SURVEY

[1] The study recommends a CNN (Convolution Neural Network)-based automatic segmentation approach, which uses small 33 kernels to perform the segmentation. This method combines two processes into one, allowing for efficient segmentation and classification. CNN is a machine learng technology that derives from NN (Neural Networks) and uses a layer-based approach to classification outcomes. The proposed techniques consist of the following stages: (1) data collection; (2) pre-processing; (3) average filtering; (4) segmentation; (5) feature extraction; and (6) CNN by means of classification and identification. Important connections and patterns in the data can be extracted using DM (data mining) techniques. [2] This review walked readers through the fundamentals of brain tumors, where to find data, how to improve it, how to enhance it, how to segment it, extract features for classification, how to use deep learning, transfer those features, and how to use quantum machine learning to analyze it. This overview also includes the benefits, drawbacks, advances, and forthcoming trends of all relevant literature for detecting brain cancers. [3] When applied to disease detection, machine learning techniques such as SVM, KNN, Naive Bayes, and Decision tree can improve decision-making speed while simultaneously decreasing the number of false positives. Python is discussed as a realistic implementation language for these algorithms. Cancer, diabetes, epilepsy, heart attack, and other major disorders are all diagnosed with the help of these algorithms.

3.SYSTEM ARCHITECTURE

The system architecture for brain tumor segmentation in MRI imaging is designed as a structured pipeline that integrates data acquisition, preprocessing, model training, and evaluation to achieve accurate and efficient tumor detection. Initially, MRI images are collected and preprocessed through resizing to a uniform dimension of 256×256 pixels and normalization of pixel values to ensure consistency and improved model convergence. The dataset is then divided into training and validation sets for effective learning and performance assessment. In the existing approach, Convolutional Neural Networks (CNNs) are used to extract features and perform basic segmentation, whereas the proposed system employs a lightweight U-Net Lite architecture with an encoder–decoder structure and skip connections to enhance spatial feature preservation and segmentation accuracy. The model is trained using the Adam optimizer and binary cross-entropy loss, with techniques such as early stopping and model checkpointing to prevent overfitting.

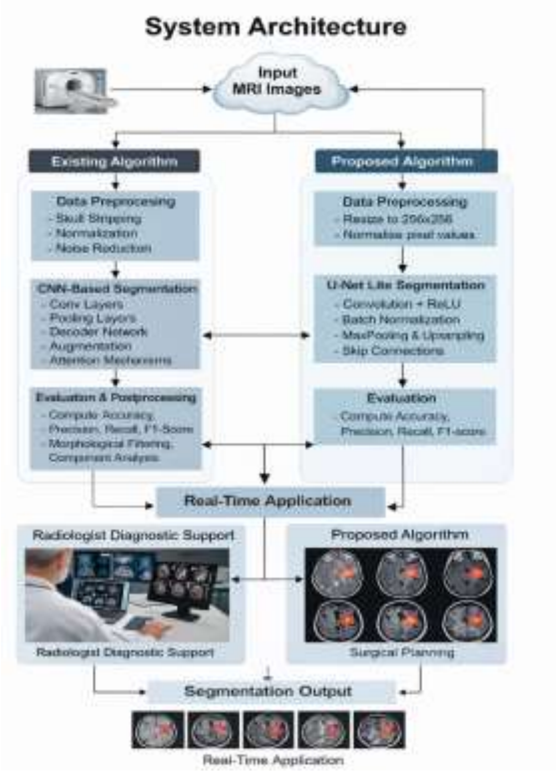


Fig 1: System Architecture

3.1 METHODOLOGY

The methodology for brain tumor segmentation in MRI imaging follows a systematic pipeline that integrates both existing and proposed algorithmic approaches to ensure accurate and efficient detection. Initially, MRI datasets along with corresponding tumor masks are acquired from reliable medical imaging sources. The collected data undergoes preprocessing, which includes resizing images to a standard dimension, normalization of pixel values, and application of data augmentation techniques to enhance dataset diversity and reduce overfitting. In the model development stage, the existing approach utilizes Convolutional Neural Networks (CNNs) to extract hierarchical features and perform basic segmentation, while the proposed method employs a lightweight U-Net Lite architecture with an encoder–decoder structure and skip connections for precise tumor boundary detection. The models are trained using appropriate optimization techniques and loss functions to ensure convergence and performance stability. In the evaluation stage, the performance of both models is assessed using metrics such as accuracy, precision, recall, and F1-score to compare effectiveness.

3.2 Dataset Acquisition: The dataset consists of MRI images and corresponding tumour masks, resized to 256×256 pixels for consistency. It is split into 80% training and 20% validation, with normalization applied to improve model stability and learning efficiency.

3.3 Data Prep-rocessing: All MRI images and masks are resized to 256×256 and normalized to a 0–1 range. Masks are converted into binary format, and data generators are used to efficiently load and pre-process image-mask pairs in batches.

3.4 Model Development:A CNN model and a lightweight U-Net architecture are developed for segmentation. U-Net LITE uses an encoder–decoder structure with skip connections, Adam optimizer, and training strategies like early stopping for better performance.

3.5 U-Net LITE Algorithm: The U-Net LITE model processes images using a lightweight encoder–decoder design with skip connections. It is trained using Adam optimizer and binary cross-entropy loss with batch-wise data feeding and model checkpointing.

3.6 Performance Evaluation: The proposed U-Net LITE model outperforms the CNN model in accuracy, precision, recall, and F1-score. It provides better tumor boundary detection with reduced errors and faster computation, making it suitable for real-time use.

4.DESIGN AND CONSTRUCTION

The design and construction of the proposed brain tumor segmentation system using the U-Net Lite model are structured to ensure efficiency, accuracy, and scalability for medical image analysis. The system is designed with a modular architecture consisting of data input, preprocessing, model processing, and output visualization components. MRI images along with their corresponding tumor masks are first collected and organized, followed by preprocessing steps such as resizing to 256×256 pixels, normalization of pixel values, and conversion of masks into binary format. The core component of the system is the U-Net Lite model, which is constructed using a lightweight encoder–decoder architecture with convolutional layers, batch normalization, max-pooling for feature extraction, and upsampling layers with skip connections for precise reconstruction of tumor regions. The model is trained using the Adam optimizer and binary cross-entropy loss function, with techniques such as early stopping and checkpointing to enhance performance and prevent overfitting. During construction, a data generator is implemented to efficiently handle large datasets through batch processing. The final system is capable of processing unseen MRI images and generating accurate tumor segmentation masks, which are visually represented for clinical interpretation. This design ensures reduced computational complexity while maintaining high segmentation accuracy, making it suitable for real-time medical applications.

5. RESULTS AND DISCUSSION

The proposed brain tumor segmentation system using the U-Net-LITE model was implemented and evaluated using MRI brain images. The dataset was divided into training and validation sets to train the deep learning model and evaluate its performance. During the training process, the model learned to identify tumor regions by extracting important spatial features from MRI images. The experimental results show that the proposed UNet-Lite model performs better in segmenting tumor regions compared to the existing CNN-based approach. The model achieved high performance with evaluation metrics such as Accuracy, Precision, Recall, and F1-Score. The segmentation results clearly highlight the tumor regions in MRI images, demonstrating the effectiveness of the encoder–decoder architecture with skip connections used in UNet-Lite. Compared to traditional CNN methods, UNet-Lite provides improved localization of tumor boundaries and better pixel-level classification. The lightweight architecture also reduces computational complexity while maintaining high segmentation accuracy. The generated accuracy and loss graphs indicate stable training and good generalization performance on validation data.

Fig 2: Python Environment

Figure 2: shows the project is developed using Python, TensorFlow, and Flask. A virtual environment is used to manage dependencies.

Fig 3: HOME PAGE

Figure 3show that the Home Page provides a simple and user-friendly interface. It includesnavigation options like login and registration. Users can easily access different features of the system.

Fig 4: User Registration

Figure 5 shows that the new user must register to login. Here users should provide Name, Username, Password, Age, Email and Location.

Fig 5: Loading Scanning Image

Figure 5 shows the Brain Tumor Scanning Images used in this project. It contains scanning data required for prediction and is loaded using Python. The images are given to predict the tumor.

Fig 6: Output Prediction

Fig 6 shows the output of the Tumor prediction system, where the result is displayed as “Original MRI”, “Ground Truth Mask”, “Prediction Probability” and “Predicted Contours” with Confidence Score: 1.09%. The prediction is obtained using the trained hybrid model after processing the input. This enables early identification of Tumor and assists in timely diagnosis. The system provides fast and reliable results.

6. CONCLUSION

In this study, a brain tumor segmentation system for MRI images was developed using the UNet-Lite deep learning architecture. Traditional CNN-based methods used in existing systems are effective for classification but often struggle to accurately identify tumor boundaries. To overcome this limitation, the proposed UNet-Lite model utilizes an encoder–decoder structure with skip connections, enabling more precise segmentation of tumor regions. The experimental results show that the proposed model can effectively detect and segment brain tumors with improved accuracy and reliability. The automated segmentation approach reduces the need for manual analysis and helps radiologists perform faster and more accurate diagnoses. the proposed UNet-Lite based system demonstrates strong potential in medical image analysis and can serve as a supportive tool for early brain tumor detection and treatment planning.

FUTURE SCOPE: Future scope includes integrating Dense Net and Vision Transformer (ViT) architectures to improve feature extraction and capture both local and global tumor patterns more effectively. This hybrid approach can enhance segmentation accuracy, robustness, and generalization for advanced medical imaging applications.

REFERENCES

[1]G. Hemanth, M. Janardhan, L. Sujihelen, “Design and Implementing Brain Tumor Detection Using Machine Learning Approach, 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), 2019

[2] Javaria Amin, Muhammad Sharif, Anandakumar Haldorai, Mussarat Yasmin & Ramesh Sundar Nayak, “Brain tumor detection and classification using machine learning: a comprehensive survey”, Complex & Intelligent Systems, 2021

[3] Pushpa Singh; Narendra Singh; Krishna Kant Singh; Akansha Singh," Diagnosing of disease using machine learning", 2021, Machine Learning and the Internet of Medical Things in Healthcare Pages 89-111, 2021

[4] Chinta Someswararao, R Shiva Shankar, Sangapu Venkata Appaji, Vmnssvkr Gupta, "Brain Tumor Detection Model from MR Images using Convolutional Neural Network, 2020 International Conference on System, Computation, Automation, and Networking (ICSCAN), 2020

[5] D. Divyamary, S. Gopika, S. Pradeeba, M. Bhuvaneswari, "Brain Tumor Detection from MRI Images using Naive Classifier", 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), 2020

[6] Mircea Gurbină, Mihaela Lascu, Dan Lascu, " Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines", 2019 42nd International Conference on Telecommunications and Signal Processing (TSP), 2019