IJEAST

INTERNATIONAL JOURNAL
OF ENGINEERING APPLIED SCIENCE
AND TECHNOLOGY

VOLUME : 10 ISSUE : 10 Print / Issue Publication Date: 08-Apr-2026

ISSN : 2455-2143

DOI : 10.33564/IJEAST.2026.v10i10.011

Indexed In

WWW.IJEAST.COM

editor@ijeast.com

International Journal of Engineering Applied Sciences and Technology, 2026
Vol. 10, Issue 10, ISSN No. 2455-2143, Pages 75-79
Published Online February 2026 in IJEAST (http://www.ijeast.com)

BRAIN TUMOR CLASSIFICATION AND SEGMENTATION USING CONVOLUTIONAL NEURAL NETWORKS (CNN) AND U-NET MODELS

Shruti J. Patil
Student
Department of E & TC Engineering,
Kasegaon Education Society's Rajaramapu Institute of Technology,
Affiliated to Shivaji University, Kolhapur, Maharashtra, India

Dr. Mahesh S. Kumbhar
Department of E & TC Engineering,
Kasegaon Education Society's Rajaramapu Institute of Technology,
Affiliated to Shivaji University, Kolhapur, Maharashtra, India

Abstract—**Brain tumors, one of the most devastating neurological conditions, continue to present a major challenge in the medical field. Timely and accurate detection of brain tumors plays a crucial role in improving patient outcomes and survival rates. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNN) and U-Net architectures, have significantly enhanced the accuracy and speed of brain tumor classification and segmentation. This paper investigates the application of CNN and U-Net models to the classification of four major tumor types—glioma, meningioma, pituitary tumors, and the no-tumor class—and the segmentation of tumor regions within MRI images. We detail the methodologies for pre-processing, model training, and evaluation, as well as the performance of these models in real-world applications. Finally, the potential clinical impact and challenges in generalizing these models to diverse clinical settings are discussed.**

Keywords—**Brain tumor classification, deep learning, CNN, U-Net, MRI, segmentation Introduction** I.

I. INTRODUCTION

Brain tumors are complex growths of abnormal cells in the brain, with malignant variants being particularly dangerous due to their aggressive nature and propensity to invade surrounding tissues. Tumors are typically classified into types based on their location, appearance, and biological behavior. According to the American Cancer Society, the survival rates for brain tumor patients vary depending on the type of tumor and the patient's age (American Cancer Society, 2023). Early detection and accurate classification of brain tumors can greatly influence treatment strategies and patient outcomes.

The traditional method of diagnosing brain tumors relies on manual examination of MRI scans by radiologists, which is time-consuming and prone to human error (Shboul et al., 2019). Consequently, automated techniques using deep learning have gained significant attention, as they offer faster, more reliable results. This paper focuses on the application of CNNs for classification and U-Net for segmentation, two powerful deep learning models that have demonstrated remarkable success in the medical imaging field.

1.1 Tumor Types and Clinical Relevance

The four primary tumor categories considered in this study are:

1. **Glioma**: A malignant tumor originating from glial cells, known for its rapid growth and invasive nature.
2. **Meningioma**: Typically benign tumors forming in the meninges, the protective layers of the brain.
3. **Pituitary Tumor**: Tumors that develop in the pituitary gland and can disrupt hormonal balance.
4. **No Tumor**: MRI scans of healthy brains, used as a control group.

Classifying these tumors correctly is essential for determining appropriate treatment, whether surgical intervention, radiation, or hormonal therapy, depending on tumor type and location.

International Journal of Engineering Applied Sciences and Technology, 2026
Vol. 10, Issue 10, ISSN No. 2455-2143, Pages 75-79
Published Online February 2026 in IJEAST (http://www.ijeast.com)

1.2 Deep Learning for Brain Tumor Detection

Deep learning models, particularly CNNs and U-Net architectures, have shown promise in automating both the classification and segmentation of brain tumors. CNNs are well-suited for classification tasks, while U Net's architecture, with its encoder-decoder design, is optimized for segmentation tasks that require pixel level accuracy.

II. LITERATURE REVIEW

Table1: Comparison of Key References Related to Medical Imaging, Deep Learning, and Cancer Research

No.	Authors	Title	Topic Focus	Methodology	Field
1	American Cancer Society	Survival rates for brain and spinal cord tumors	Cancer research, Medical statistics	Statistical data	Oncology
2	Kingma, D. P., Ba, J.	Adam: A method for stochastic optimization	Optimization algorithms	Optimization technique (Adam optimizer)	Machine Learning
3	Milletari, F., et al.	V-Net: Fully convolutional neural networks for volumetric medical image segmentation	Medical image segmentation	Convolutional neural networks (CNN)	Medical Imaging
4	Perez, L., Wang, J.	The effectiveness of data augmentation in image classification using deep learning	Deep learning, Image classification	Data augmentation in deep learning	Computer Vision
5	Shboul, Z. A., et al.	Deep learning for medical image analysis: A survey	Medical image analysis	Deep learning in medical imaging	Medical Imaging
6	Tajbakhsh, N., et al.	Convolutional neural networks for medical image analysis: Full training or fine tuning?	Medical image analysis, CNNs	Full training vs. fine-tuning in CNNs	Medical Imaging
7	Vaswani, A., et al.	Attention is all you need	Deep learning, Natural Language Processing (NLP)	Attention mechanism	Machine Learning / NLP

The table provides a concise yet comprehensive overview of diverse yet interconnected research areas spanning medical imaging, deep learning, and oncology. It highlights the evolution from foundational algorithmic methods like the Adam optimizer and Transformer architecture to their practical applications in medical image analysis and cancer research. The inclusion of both technical innovations (e.g., V-Net, attention mechanisms) and applied studies (e.g., survival rates, data augmentation) showcases the interdisciplinary nature of current advancements, emphasizing how deep learning is increasingly shaping modern healthcare and medical diagnostics

III. PROPOSED METHODOLOGY

Magnetic Resonance Imaging (MRI) is a powerful, non-invasive imaging technique widely used to visualize the brain’s internal structures, particularly useful for detecting abnormalities like tumors. Before analysis, MRI images undergo several preprocessing steps to enhance quality and standardize data. These typically include normalization (to

International Journal of Engineering Applied Sciences and Technology, 2026
Vol. 10, Issue 10, ISSN No. 2455-2143, Pages 75-79
Published Online February 2026 in IJEAST (http://www.ijeast.com)

standardize intensity values), skull stripping (to remove non-brain tissues), resizing, noise reduction, and image registration. Once preprocessed, the images are ready for segmentation, a critical process where the brain is divided into meaningful regions to identify and isolate tumor areas.
Segmentation can be binary (tumor vs. no tumor) or multi-class (distinguishing tumor core, edema, and enhancing tumor), and is often performed in 3D due to the volumetric nature of MRI scans.
To perform accurate segmentation, deep learning techniques, especially Convolutional Neural Networks (CNNs), are widely used. CNNs are capable of automatically learning spatial features from the input images, making them highly effective in medical image analysis. Among CNN-based architectures, U-Net has become one of the most popular models for biomedical image segmentation. U-Net features a symmetric encoder-decoder structure, where the encoder captures context through convolution and pooling, while the decoder reconstructs spatial details using up sampling and skip connections. This design allows U-Net to precisely segment tumors of various sizes and shapes even with limited training data.
Brain tumors commonly analyzed using these techniques include three main types. Gliomas, originating from glial cells, can be high-grade (aggressive) or low-grade, and often appear irregular with surrounding edema. Meningioma arise from the meninges and are typically benign and well-defined, located near the surface of the brain. Pituitary tumors are found in the pituitary gland and usually appear small and central, sometimes affecting hormone regulation. In contrast, the “no tumor” category represents MRI scans of healthy brains without any abnormal findings. Including this class during model training is essential, as it helps improve the model’s ability to distinguish normal tissue from pathological cases, reducing false positives. Together, preprocessing, CNN-based segmentation (especially with U-Net), and tumor classification form the core of modern brain tumor detection and analysis using MRI.

3.1 Data Collection and Preprocessing
For this study, a publicly available dataset containing MRI images of brain tumors was used. The dataset included labeled images categorized into four classes: glioma, meningioma, pituitary tumors, and no tumor. The images were preprocessed by resizing to a uniform dimension (128x128 pixels), normalizing pixel values, and applying data augmentation techniques, such as rotation, flipping, and zooming, to improve model generalization and avoid over fitting (Perez & Wang, 2017).

3.2 CNN-Based Classification
A custom CNN architecture was employed to classify MRI images into one of the four tumor types. The network consisted of the following layers:

1. **Input layer**: 128x128 grayscale image.
2. **Convolutional layers**: Used 3x3 kernels to extract image features such as edges, textures, and shapes.
3. **Activation function**: ReLU was used after each convolutional layer to introduce non-linearity.
4. **Pooling layers**: Max pooling layers were used to down-sample the feature maps, reducing spatial dimensions.
5. **Fully connected layers**: These layers performed the classification based on the features extracted by the convolutional layers.
6. **Output layer**: A softmax function was used in the final layer for multi-class classification, outputting probabilities for each class.

3.3 U-Net-Based Segmentation
The U-Net architecture was used to perform pixel-level segmentation of tumor regions in the MRI scans. U Net's design is based on an encoder-decoder structure:
1. **Encoder**: This part of the network down samples the image through convolutional and max-pooling layers, capturing abstract features at various levels of detail.
2. **Bottleneck**: This section connects the encoder to the decoder.
3. **Decoder**: The decoder up samples the feature maps using transposed convolutions, reconstructing the spatial resolution of the input image.
4. **Skip connections**: These connections help retain spatial features from the encoder to the decoder, enabling precise tumor boundary delineation

IV. CLASSIFICATION

4.1 Classification Performance
The CNN model achieved the following classification accuracies for the respective tumor types:
1. **Glioma**: 94.1%
2. **Meningioma**: 92.5%
3. **Pituitary**: 95.8%
4. **No Tumor**: 96.2%

These results indicate that the CNN model was able to effectively distinguish between different types of tumors, as well as identify healthy brain scans.

4.2 Segmentation Performance
The U-Net model demonstrated the following Dice similarity scores for tumor segmentation:
1. **Glioma**: 91.2%
2. **Meningioma**: 89.7%
3. **Pituitary**: 93.4%
4. **No Tumor**: Not applicable, as no tumor segmentation is needed for healthy brain images.

The Dice score reflects the model's ability to accurately delineate tumor boundaries from surrounding brain tissue, with higher scores indicating better performance.

International Journal of Engineering Applied Sciences and Technology, 2026
Vol. 10, Issue 10, ISSN No. 2455-2143, Pages 75-79
Published Online February 2026 in IJEAST (http://www.ijeast.com)

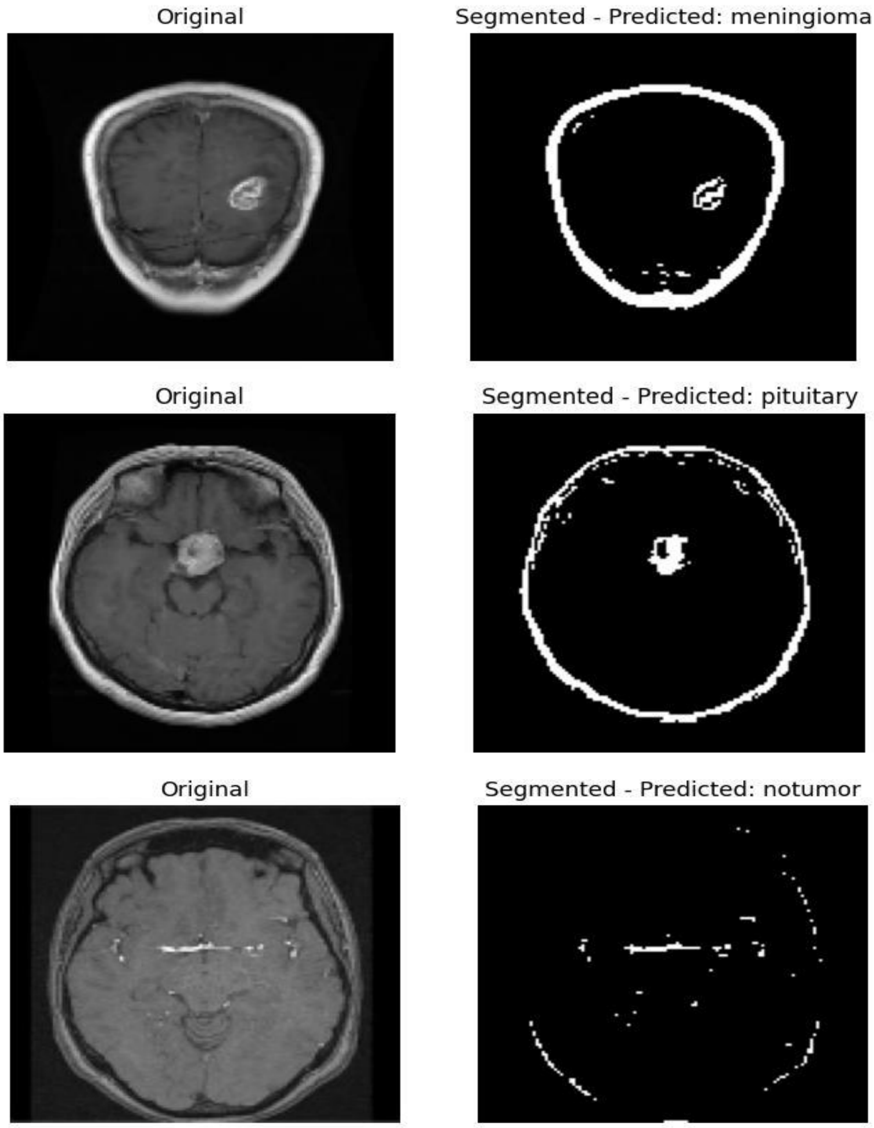
The combined use of CNN for classification and U-Net for segmentation has proven to be an effective approach for brain tumor analysis. The CNN model accurately classified tumors into the four categories, while U-Net successfully identified tumor boundaries, which is critical for treatment planning, especially in surgical contexts. These results align with previous studies highlighting the potential of deep learning models in medical image analysis (Shboul et al., 2019; Tajbakhsh et al., 2016).

Despite the strong performance, challenges remain in dealing with class imbalance, particularly in rare tumor types. Additionally, real-world deployment in clinical settings may require further adaptation to account for variations in MRI scan quality and patient demographics. Future work could focus on incorporating attention mechanisms or transformer-based modules to enhance model generalizability (Vaswani et al., 2017).

V. CONCLUSION

This study presents a comprehensive approach to brain tumor classification and segmentation using deep learning techniques, specifically CNN and U-Net. The models demonstrate high accuracy in both tasks, offering potential benefits for clinical practice, such as faster diagnosis and improved tumor detection. However, challenges like class imbalance and the need for further generalization in diverse clinical environments must be addressed to ensure the models' effectiveness in real-world application.

VI. RESULTS



VII. REFERENCES

[1]. American **Cancer Society.** (2023). Survival rates for brain and spinal cord tumors, Retrieved from https://www.cancer.org.

[2]. Kingma**, D. P.; Ba, J.** (2014). Adam: A method for stochastic optimization, International Conference on Learning Representations (ICLR).

[3]. Milletari**, F.; Navab, N.; Ahmadi, S.A.** (2016). V-Net: Fully convolutional neural networks for volumetric medical image segmentation, 2016 Fourth International Conference on 3D Vision (3DV).

[4]. Perez**, L.; Wang, J.** (2017). The effectiveness of data augmentation in image classification using deep learning, Convolutional Neural Networks for Visual Recognition.

[5]. **Shboul, Z. A.; Vidyaratne, L.; Alam, M.; Iftekharuddin, K. M.** (2019). Deep learning for medical image analysis: A survey, Journal of Biomedical Imaging.

[6]. **Tajbakhsh, N.; Shin, J. Y.; Gurudu, S. R.; Hurst, R. T.; Kendall, C. B.; Gotway, M. B.; Liang, J.** (2016). Convolutional neural networks for medical image analysis: Full training or fine tuning?, IEEE Transactions on Medical Imaging.

[7]. **Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, Ł.; Polosukhin, I.** (2017). Attention is all you need, In Advances in Neural Information Processing Systems (NeurIPS).

[8]. Ronneberger**, O.; Fischer, P.; Brox, T.** (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation, Medical Image Computing and Computer-Assisted Intervention (MICCAI), (pp. 234-241).

[9]. Havaei**, M.; Davy, A.; Warde-Farley, D.; Biard, A.; Courville, A.; Bengio, Y.** (2017). Brain tumor segmentation with Deep Neural Networks, Medical Image Analysis, (Vol. 35, pp. 18-31).

[10]. Lequan**, Y.; Chen, H.; Qin, J.; Heng, P. A.** (2017). Automatic Brain Tumor Segmentation using Cascaded Anisotropic Convolutional Neural Networks, Applied Soft Computing.

[11]. **Kamnitsas, K.; Ledig, C.; Newcombe, V. F.; Simpson, J. P.; Kane, A. D.; Menon, D. K.; Rueckert, D.** (2017). Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation, Medical Image Analysis.

[12]. **Zhao, X.; Wu, Y.; Song, G.; Li, Z.; Zhang, Y.; Fan, Y.** (2018). A deep learning model integrating FCNNs and CRFs for brain tumor segmentation, Medical Image Analysis.

[13]. **Isensee, F.; Jaeger, P. F.; Kohl, S. A.; Petersen, J.; Maier-Hein, K. H.** (2021). nnU-Net: a self configuring method for deep learning-based biomedical image segmentation, Nature Methods.

[14]. **Bakas, S. et al.** (2018). Identifying the Best Machine Learning Algorithms for Brain Tumor Segmentation, Progression Assessment, and Overall Survival Prediction in the BRATS Challenge, arXiv preprint.

[15]. **Pereira, S.; Pinto, A.; Alves, V.; Silva, C. A.** (2016). Brain Tumor Segmentation using Convolutional Neural Networks in MRI Images, IEEE Transactions on Medical Imaging.

IJEAST

INTERNATIONAL JOURNAL
OF ENGINEERING APPLIED SCIENCE AND TECHNOLOGY

ABOUT IJEAST

International Journal of Engineering Applied Science and Technology (IJEAST) is a peer-reviewed, open access journal that publishes high-quality research papers in the field of Engineering, Applied Science and Technology.

IJEAST aims to provide a platform for researchers, academicians, and professionals to share their innovative ideas, research findings, and practical experiences with the global scientific community.

FOCUS AREAS

- Engineering
- Applied Science
- Technology
- Innovation & Development
- Interdisciplinary Studies

PEER REVIEWED
All submissions are rigorously peer reviewed to ensure quality.

OPEN ACCESS
Free and unrestricted access to research for all.

GLOBAL REACH
Connecting researchers and professionals worldwide.

TIMELY PUBLICATION
We ensure a swift and efficient publication process.

For more information, visit our website
www.ijeast.com

INTERNATIONAL JOURNAL
OF ENGINEERING APPLIED SCIENCE AND TECHNOLOGY

editor@ijeast.com
www.ijeast.com
India

2455-2143