iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: II Month of publication: February 2026

DOI: https://doi.org/10.22214/ijraset.2026.77630

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

Brain Tumor Detection from MRI Using Deep Learning

Suryakumar N[1], Dr. K. Santhi[2]
[1]Student, [2]Professor, Department of Information Technology, Dr. N.G.P Arts and Science College, Coimbatore

Abstract: Brain tumors represent one of the most critical neurological disorders, where early and accurate diagnosis is essential for improving patient survival and treatment outcomes. Magnetic Resonance Imaging (MRI) remains the preferred modality for detection due to its high resolution and non-invasive nature. However, manual interpretation of MRI scans is time-intensive, requires specialized expertise, and is prone to variability, particularly when tumor boundaries are indistinct.

This study proposes an automated brain tumor detection and segmentation system leveraging deep learning techniques. The framework integrates EfficientNet for tumor classification and U-Net++ for pixel-level segmentation. MRI images undergo preprocessing steps—resizing, normalization, and noise reduction—to ensure consistency and enhance quality. EfficientNet then extracts high-level features to classify scans into tumor and non-tumor categories with high accuracy. Upon detection, U-Net++ performs precise segmentation, utilizing its nested encoder–decoder architecture and dense skip connections to achieve improved boundary delineation. The system is implemented using Python-based deep learning frameworks, enabling efficient model integration and rapid processing. By reducing reliance on manual interpretation, the proposed solution enhances diagnostic accuracy, minimizes analysis time, and supports early-stage tumor detection. This work demonstrates the practical application of artificial intelligence in medical imaging, offering reliable diagnostic support for radiologists and healthcare institutions.

Keywords: Brain Tumor Detection, MRI Image Analysis, Deep Learning, EfficientNet, U-Net++

I. INTRODUCTION

In recent years, brain tumors have become a major concern in the medical field due to their increasing incidence and high mortality rate. Brain tumors are caused by the abnormal growth of cells within the brain and can severely affect cognitive functions, motor skills, and overall quality of life. Early and accurate detection of brain tumors is crucial for effective treatment planning and improving patient survival rates. However, delayed diagnosis often leads to severe complications and reduced treatment success.

Magnetic Resonance Imaging (MRI) is one of the most commonly used medical imaging techniques for brain tumor diagnosis because of its ability to produce high-resolution images with excellent soft-tissue contrast. Despite its advantages, analyzing MRI scans manually is a complex and time-consuming process that requires experienced radiologists. Manual interpretation may also result in variability and inaccuracies, particularly when tumors are small, irregularly shaped, or have unclear boundaries.

With the rapid advancement of Artificial Intelligence (AI) and Deep Learning, automated image analysis has gained significant attention in medical imaging applications. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in extracting meaningful features from medical images. These models enable accurate classification and segmentation, reducing the dependency on manual analysis and minimizing human error.

This project proposes an automated brain tumor detection and segmentation system using deep learning techniques. The system employs EfficientNet for tumor classification due to its optimized architecture and high accuracy with reduced computational complexity. For precise localization of tumor regions, U-Net++ is utilized, as it enhances segmentation performance through its nested encoder–decoder structure and dense skip connections.

The proposed approach processes MRI images through preprocessing steps such as resizing, normalization, and noise reduction before applying deep learning models. By combining classification and segmentation in a single framework, the system provides both tumor presence identification and accurate tumor boundary detection.

Overall, this project aims to assist radiologists and healthcare professionals by providing a reliable, efficient, and automated diagnostic tool. By integrating advanced deep learning models with medical imaging, the proposed system highlights the practical application of artificial intelligence in improving accuracy, efficiency, and decision-making in modern healthcare diagnostics.

II. LITERATURE REVIEW

Earlier research has investigated the use of traditional image processing and machine learning techniques for brain tumor detection from MRI images. Havaei et al. (2017) proposed a tumor segmentation method using conventional CNN architectures, which showed improved accuracy compared to handcrafted feature-based approaches. However, the model struggled with precise tumor boundary detection and required extensive computational resources.

With the advancement of deep learning, Pereira et al. (2018) developed a CNN-based classification system for identifying brain tumors from MRI scans. Their approach achieved higher classification accuracy than traditional methods, but it focused mainly on tumor presence detection and did not provide accurate segmentation of tumor regions.

To improve segmentation performance, Zhou et al. (2019) introduced U-Net++, an enhanced version of the U-Net architecture with nested and dense skip connections. The model demonstrated superior segmentation accuracy on medical imaging datasets, including brain MRI scans. However, the study did not integrate a dedicated classification model for tumor detection.

More recently, Tan and Le (2020) proposed EfficientNet, a scalable deep learning architecture that achieves high accuracy with fewer parameters. While EfficientNet has been successfully applied in various medical image classification tasks, its combined use with advanced segmentation networks like U-Net++ for brain tumor analysis has been relatively limited.

These studies highlight the potential of deep learning for brain tumor detection while also revealing gaps in integrating efficient classification and precise segmentation within a unified framework. The proposed system addresses these limitations by combining EfficientNet for tumor classification and U-Net++ for accurate tumor segmentation.

From the review of existing literature, it is clear that most systems focus only on food identification or calorie estimation. The proposed AI-Powered Food Nutrition Analyzer aims to overcome these limitations by offering detailed nutritional information through a deep learning–based, web-enabled solution.

III. PROBLEM STATEMENT

In the modern healthcare environment, accurate and early diagnosis of brain tumors remains a significant challenge. Brain tumors often exhibit complex characteristics such as varying sizes, irregular shapes, and indistinct boundaries, making their identification from MRI scans difficult. A lack of timely and precise diagnosis can result in delayed treatment, negatively affecting patient outcomes and survival rates.

Existing approaches for brain tumor detection primarily rely on manual interpretation of MRI images by radiologists. Although effective, this process is time-consuming, highly dependent on clinical expertise, and prone to variability due to human fatigue and subjective judgment.

Some automated methods based on traditional image processing or basic machine learning techniques are limited in accuracy and struggle to generalize across different tumor types and imaging conditions.

While deep learning-based systems have shown promising results in medical image analysis, many existing solutions focus either on tumor classification or segmentation alone. Such systems may fail to provide both reliable tumor detection and accurate localization of tumor regions, which are essential for clinical decision-making and treatment planning. Additionally, some deep learning models require extensive computational resources, reducing their practicality in real-world clinical settings.

Therefore, there is a need for an automated, efficient, and accurate brain tumor detection system that can analyze MRI images with minimal human intervention.

The proposed approach aims to address these challenges by integrating EfficientNet for robust tumor classification and U-Net++ for precise tumor segmentation. This system seeks to support radiologists by improving diagnostic accuracy, reducing analysis time, and enabling early and reliable brain tumor detection.

IV. METHODOLOGY

The methodology of the proposed brain tumor detection system is organized into several structured stages, starting from MRI image acquisition and progressing toward classification, segmentation, and final output generation. The system integrates medical image preprocessing techniques with advanced deep learning architectures to ensure accurate, reliable, and efficient tumor detection.

A. MRI Image Acquisition

Brain MRI images are collected from publicly available and clinically relevant datasets to ensure diversity and reliability. The dataset consists of both tumor and non-tumor MRI scans, including different tumor types such as glioma, meningioma, and pituitary tumors.

These images are obtained in standard MRI formats, allowing seamless integration with deep learning frameworks. The inclusion of multiple tumor categories ensures that the model learns varied tumor patterns, improving its ability to generalize to real-world clinical cases.

B. Image Preprocessing

Before feeding the MRI images into the deep learning models, preprocessing steps are applied to enhance image quality and consistency. All images are resized to a fixed resolution to maintain uniform input dimensions for training and testing. Noise reduction techniques are used to eliminate imaging artifacts, while intensity normalization ensures consistent pixel value distribution across the dataset. In addition, data augmentation techniques such as rotation, flipping, and scaling are applied to increase dataset variability and reduce overfitting. These preprocessing steps play a crucial role in improving model robustness and overall performance.

C. Tumor Classification Using EfficientNet

The classification stage utilizes the EfficientNet architecture to determine whether a tumor is present in a given MRI scan. EfficientNet is selected due to its compound scaling approach, which optimally balances network depth, width, and resolution to achieve high accuracy with lower computational cost.

Transfer learning is employed by initializing the model with pre-trained weights, enabling efficient feature extraction and faster convergence during training. The model analyzes the MRI images and classifies them into tumor or non-tumor categories with high reliability, serving as the first diagnostic decision stage in the system.

D. Tumor Segmentation Using U-Net++

For MRI images identified as tumor-positive, the system proceeds with tumor segmentation using U-Net++. This advanced architecture features a nested encoder–decoder structure with dense skip connections that enhance feature propagation and reduce the semantic gap between network layers. By preserving both low-level and high-level features, U-Net++ enables precise pixel-level segmentation of tumor regions. The output is a detailed segmentation mask that accurately highlights the tumor’s location, shape, and boundaries within the MRI scan.

E. Model Training and Optimization

During the training phase, appropriate loss functions are applied to optimize both classification and segmentation performance. The classification model is trained using categorical cross-entropy loss, while the segmentation model employs Dice loss or Intersection over Union (IoU) loss to maximize overlap accuracy between predicted and actual tumor masks. Optimization algorithms such as the Adam optimizer are used to enhance convergence efficiency. Learning rate scheduling and validation monitoring are implemented to prevent overfitting and ensure stable training.

F. Performance Evaluation

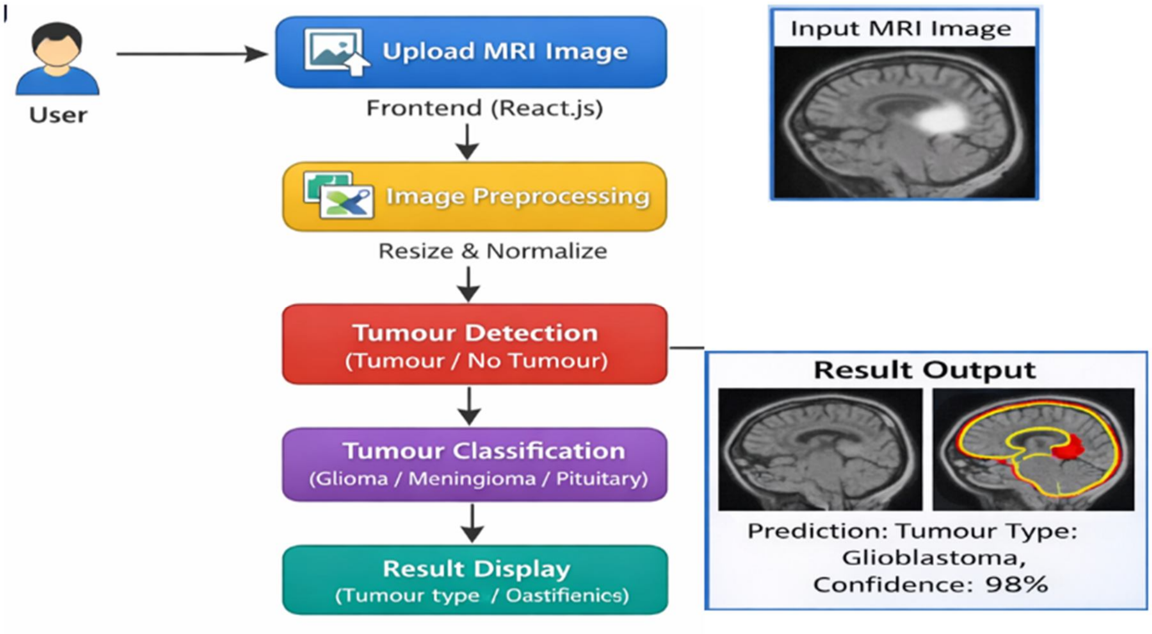
The performance of the proposed system is evaluated using standard metrics to ensure comprehensive assessment. Classification results are measured using accuracy, precision, recall, and F1-score, while segmentation quality is evaluated using Dice coefficient and IoU metrics.

Comparative analysis with existing methods is conducted to validate the effectiveness of the proposed framework. These evaluation metrics confirm the reliability and robustness of the system in detecting and segmenting brain tumors.

G. Output Visualization

The final output of the system includes a clear classification result indicating the presence or absence of a brain tumor. In tumor-positive cases, the segmented tumor region is visually overlaid on the original MRI image to assist radiologists in identifying the affected area. The output is designed to be clear, interpretable, and clinically meaningful, supporting medical professionals in accurate diagnosis and treatment planning.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue II Feb 2026- Available at www.ijraset.com

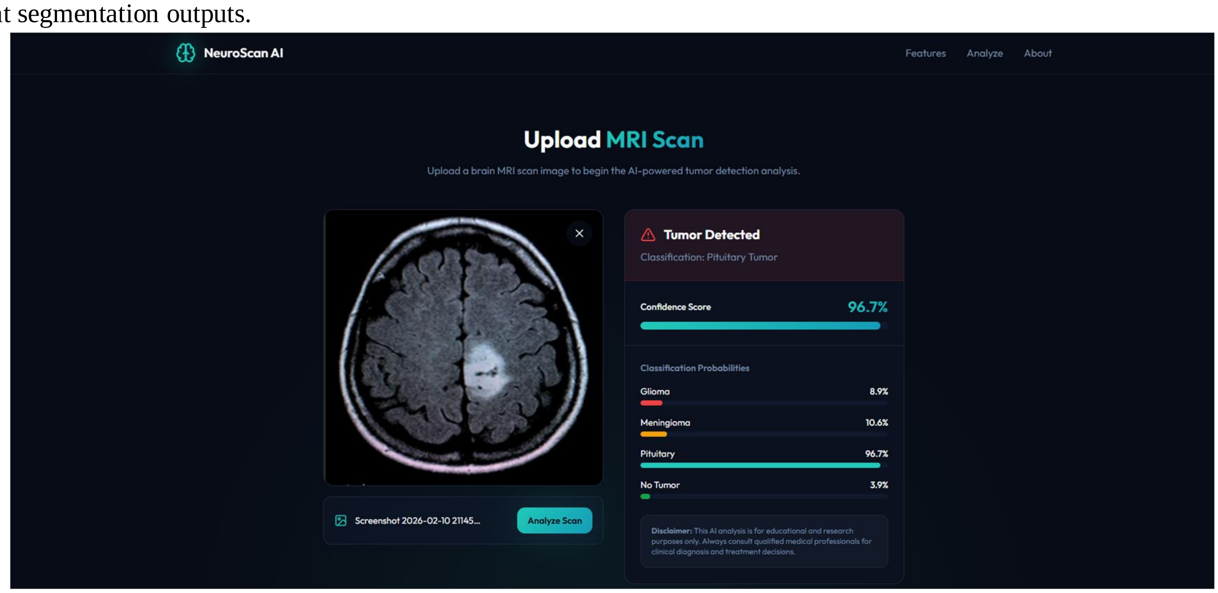


V. RESULTS AND DISCUSSION

The proposed brain tumor detection system was evaluated using a diverse set of MRI brain images, including both tumor and non-tumor cases. The dataset contained different tumor types such as glioma, meningioma, and pituitary tumors, allowing the model to learn a wide range of tumor patterns. Experimental results demonstrate that the deep learning-based approach is effective for automated brain tumor analysis.

The EfficientNet classification model achieved an average accuracy of approximately **95%** in distinguishing tumor and non-tumor MRI images. The high accuracy indicates that EfficientNet is capable of extracting meaningful features from MRI scans and reliably identifying the presence of brain tumors. The model also showed strong performance in terms of precision and recall, reducing false positive and false negative predictions.

For tumor localization, the U-Net++ segmentation model produced accurate pixel-level segmentation results. The model achieved a high Dice coefficient and Intersection over Union (IoU), demonstrating its ability to precisely delineate tumor boundaries. The nested architecture and dense skip connections of U-Net++ helped preserve spatial information, resulting in clearer and more consistent segmentation outputs.



©IJRASET: All Rights are Reserved

The combined use of EfficientNet and U-Net++ improved overall system performance compared to models that perform only classification or segmentation independently. The system was able to detect tumors at early stages and highlight affected regions effectively, which can assist radiologists in diagnosis and treatment planning.

Overall, the experimental results confirm that the proposed system provides reliable and accurate brain tumor detection and segmentation. The approach reduces manual effort, improves diagnostic consistency, and demonstrates the practical applicability of deep learning techniques in real-world medical imaging scenarios.

Aspect	Traditional CNN Model	Proposed System (EfficientNet + U-Net++)
Architecture Design	Standard convolutional layers with pooling and fully connected layers	EfficientNet for classification with compound scaling + U-Net++ for segmentation
Feature Extraction	Automatically extracts features but may require deeper networks for better accuracy	Advanced feature extraction using optimized scaling (depth, width, resolution)
Computational Efficiency	May require high parameters for improved performance	Achieves high accuracy with fewer parameters and optimized computation
Classification Performance	Good accuracy depending on network depth and dataset size	Higher accuracy due to transfer learning and optimized architecture
Segmentation Capability	Basic CNN does not perform segmentation effectively	U-Net++ provides precise pixel-level tumor segmentation
Tumor Localization	Limited or indirect localization	Accurate tumor boundary detection with nested skip connections
Overfitting Control	Requires regularization and large datasets	Improved generalization with data augmentation and efficient scaling

VI. CONCLUSION

The proposed brain tumor detection system demonstrates that deep learning techniques can be effectively applied to analyze MRI brain images. By combining EfficientNet for tumor classification and U-Net++ for precise segmentation, the system accurately identifies the presence of brain tumors and highlights affected regions. MRI images can be processed automatically with minimal human intervention, making the system practical and efficient for clinical use. Overall, the proposed approach provides a reliable and automated tool that can assist radiologists in early diagnosis, improve diagnostic accuracy, and support better treatment planning in healthcare environments.

VII. FUTURE WORK

In the future, the proposed system can be enhanced in several ways to further improve its performance and clinical applicability. Detection accuracy can be increased by training the models on larger and more diverse multi-modal MRI datasets, including T1, T2, FLAIR, and contrast-enhanced images. Incorporating advanced data augmentation and attention mechanisms may also help in identifying small or low-contrast tumors more effectively.

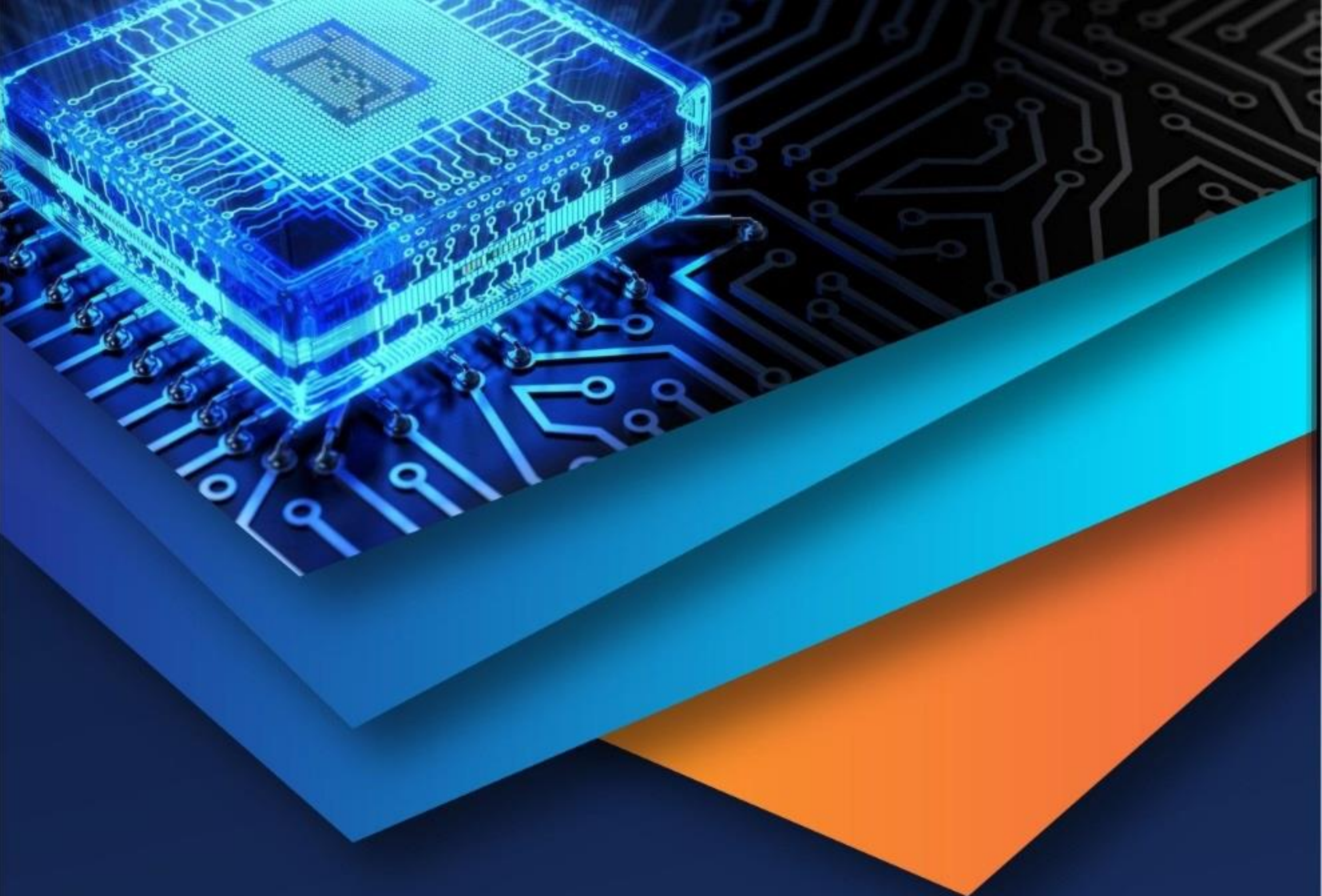
The segmentation performance can be refined by integrating 3D deep learning models to capture volumetric tumor information and improve boundary accuracy. Additional features such as tumor grading, growth tracking over time, and survival prediction could be incorporated to support advanced clinical decision-making. Integrating the system with hospital information systems and real-time clinical workflows would further enhance its usability and impact in real-world healthcare environments.

REFERENCES

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

[2] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, “UNet++: A Nested U-Net Architecture for Medical Image Segmentation,” IEEE Transactions on Medical Imaging, vol. 39, no. 6, pp. 1856–1867, 2020.

[3] M. Tan and Q. V. Le, “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks,” Proceedings of the 36th International Conference on Machine Learning (ICML), pp. 6105–6114, 2019.
[4] H. Havaei, A. Davy, D. Warde-Farley, et al., “Brain Tumor Segmentation with Deep Neural Networks,” Medical Image Analysis, Elsevier, vol. 35, pp. 18–31, 2017.
[5] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, “Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images,” IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1240–1251, 2016.
[6] F. Chollet, Deep Learning with Python, 2nd edition, Manning Publications, 2021.
[7] M. Abadi et al., “TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems,” arXiv preprint arXiv:1603.04467, 2016.
[8] Keras, “Keras: Deep Learning for Humans,” Accessed on: Jan. 27, 2026.
[9] PyTorch, “PyTorch: An Open Source Machine Learning Framework,” Accessed on: Jan. 27, 2026.
[10] Kaggle, “Brain MRI Images for Brain Tumor Detection,” Accessed on: Jan. 27, 2026.



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)