iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: https://doi.org/10.22214/ijraset.2026.80889

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 IV Apr 2026- Available at www.ijraset.com

Brain Tumor Detection System

Arpit Tyagi[1], Anjali Tomar[2], Arin Lamba[3]
Data Science MIET, Meerut, India

Abstract: Deep-Learning Applied to early identification of brain tumors: An introductory review of the state-of-the-art(s) in under 30 minutes. Brain tumors represent an increasing public point-health concern with about 250000 new cases all over the globe annually and approximately 150000 deaths every year. Since late diagnosis significantly reduces the chance of survival, medical experts are resorting to computerized image analysis to enhance rapidity and clarity in detection of results of MRI surveys.

Demarcation of tumors which is done by hand is not only time- consuming but also shows high variability among experts. Third, small lesions, varying contrast and tortuous brain structure, which appear in conventional segmentation found in the traditional techniques of segmenting the brain, such as thresholding and watershed and the use of wavelet transforms, makes the brain hard to segment.

The convolutional networks become contempo- rary and can learn tumor-specific patterns with direct learning with data: To-date models to proposal: Accurate irregularity RPN A Faster-CNN one that initially proposes candidate regions (RPN) which are then classified as glioma, meningioma, or pituitary.

This approach has been tested on a publicly available MRI dataset and achieved the results shown below; The average of the responses of the detection and classification processes show that the algorithms have a precision of 75.18 percent with glioma, 89.45 percent with meningioma, and 68.18 percent with pituitary tumors. The total mean average precision (mAP) of the model achieved was 77.60 percent with all tumor types.

Index Terms: The Important Words: YOLOv11, Brain tumor identification based on AI, Medical imaging, computational processing, Brain tumors, MRI, Medical image segmentation.

I. INTRODUCTION

Majority of studies have been dedicated to medical im- age segmentation in recent years. The simplified architecture proposed has a training accuracy of 98.51 and a validation accuracy of 97.10 which was attained without applying any region-based prior segmentation methods [1]. Even though the YOLO-based models provide real-time speed, earlier mod- els (YOLOv8-v) had a weakness in segmentation accuracy especially in the case of small tumors. More recent hybrid constructions result in trying to make model more precise but have problems with scalability and practical application [2].

The proposed work presents the framework of automated brain tumor identification and segmentation with deep learn- ing, powered by YOLOv11, where the based network is called CSP DarkNet to enhance feature extraction, SPPF neck enhances the performance of the former with optimizing fea- tures, and an anchor-free detection head improves the current performance [6].

The next step of tumor detection and classification methods should be automated to get minimal diagnosis time and the chances of human error in the process of decision-making. A number of conventional image segmentation methods have been availed to divide brain tumor regions. This paper is structured in the way that, Section II includes a review of the literature related to the topic and Section III gives a list of the steps of image data preprocessing and the proposed Faster R-CNN model to be utilized in detecting brain tumors in MRI [3][13]. Such tricks can advance and shape the medical imaging in the era of innovative systems which can enhance patient care.

The method of YOLO allows to identify and localize the objects in one run and simultaneously and accurately work with the whole image by performing the processing through the network [9]. Severe diseases that can consume the central nervous system (CNS) have been the equivalent of a significant challenge when it comes to diagnosis, analysis, and the creation of the most successful treatments [18]. The need to mitigate the problem is conditioned by the fearful statistical tendencies recorded during recent years [13].

Brain tumor has over 10 per cent more frequently become common in the last 20 years, which has further burnt the already scarce health services [5]. To cover this increasing is- sue, an efficient and simplified detection solution is suggested to support with early diagnosis, and lessen clinical workload [4][5].

Tumors of the brain are still one of the most serious and deadly types of cancers. When it comes to glioblastoma, the most aggressive form, about two-thirds of adult patients succumb to the disease within two years of its diagnosis [3]. Moreover, brain cancer is thought to be the deadliest solid tumor of children and it is a significant challenge to the field of pediatric oncology. Locke, even after the survivors become adults, the long-term side effects of such treatments as chemotherapy, radiations and surgical procedures, are usually permanent since they are exposed in their developing years [16].

The detection of brain tumors is based more on the advanced technique of image processing to analyze the MRI scans. Here, every image is segmented in grid SxS and a series of bounding boxes (m) are created to estimate and detect the presence of tumors. Other recent papers have been using the YOLO (You Only Look Once) architecture to address many brain tumor- based segmentation and detection challenges, and have shown a high potential on medical imaging picture collections [14].

A number of image segmentation algorithms have been utilized in this field such as thresholding, point transformation, wavelet transformation, watershed algorithms and the traditional meth- ods [8]. It is noticeable that the outcomes of the YOLO-based models are much better when compared to previous state-of- the-art methods, and it is more precise and efficient in terms of detection and the segmentation process [11].

Epidemiological reports indicate that in all cases of cancer, brain tumors respond to about 1.50 percent of the total cases though it causes an almost 3 percent of all deaths related to cancer diseases. Computed tomography (CT) and Magnetic resonance imaging (MRI) has become a very important diag- nostic modality because of its great capability of differentiating soft tissues making it very effective in the detection and analysis of abnormalities occurring in the brain [15].

Surveys suggest that by 31st December, 2019, 1,323, 1221 people in the United States lived with brain tumor and other CNS tumors [12]. It is supposed to make AI practical, human- centered and truly helpful by connecting the research, real-life application, and social contribution [11][17].

The discovery of this research underlines an opportunity of YOLO-based models to be incorporated into diagnostic systems that may fit into Portable IVC, with the advantage of performing more a quicker med examination [10]. The problem of Bain tumor detection has remained a significant problem in the discipline of neurology and oncology which requires the system to continuously improve its imaging quality, the effectiveness of computational algorithms, and the quality of real-time analysis procedures to be more precise in its diagnosis [12].

II. RESEARCH OBJECTIVES

This research will be primarily aimed at designing, design- ing and evaluating an intelligent system, able to detect brain tumor and license plates through the recent achievements in deep learning, with the emphasized focus on the YOLOv11 framework. To achieve this broad objective, the paper sets a number of definite goals that were meant to harness the de- velopment process, provide adequate performance in detection and to determine the overall effectiveness and reliability of the system in practice:

A. To Identify Brain Tumor in an Actual Time

Each fill the research question that on MRI pictures the location of brain tumor can be accurately identified and tracked down using a computer vision structure must be capable of running on a computer with an open-source version of the YOLOv11 training code. The model must be able to distin- guish between different types of tumors: glioma, meningioma, and pituitary, and its performance should be checked by the existing public data and actual clinical data using MRI.

B. To optimize the Performance of Detection by means of Improved Preprocessing Models

In order to create a sophisticated preprocessing sequence with intensity normalization, contrast boosting, and various data enhancement functions, such as image rotating, image mirrors, and brightness adjustment. The goal is to enhance stability of the system as well as guarantee proper localization of tumors in heterogeneous datasets of MRI images.

C. To sustain High Performance in different Clinical Settings

To examine model robustness to various imaging variations, e.g., noisy MRI inputs, low-contrast visuals and varying image resolutions.

III. LITERATURE REVIEW

Author(s) & Year	Method / Model Used	Key Findings / Contributions
Dipu et al. (2021)	CNNs and transfer learning-based models	Findings have shown that more in depth models with optimum parameters are more accurate. Convolutional neural networks trained with the use of MRI scans achieve higher classification rates than other traditional machine learning algorithms.
Qarni et al. (2025)	YOLOv11-based detection and segmentation framework	The system provided localization real-time precision and the detailed segmentation. The fact that YOLOv11 has high inference efficiency and low tumor detection capabilities can make it very effective in performing clinical imaging tasks.
Bhanothu et al. (2020)	Deep CNN for MRI tumor detection and classification	The model was very accurate when classifying different tumors. Hierarchy of features in this direction made the method better generalize across dissimilar MRI modalities.
Thota and Prasad (2024)	INCS (Intelligent Neural Classification Strategy)	The model used combined the features of features learning and adaptive decision tuning to maintain an unvarying detection accuracy to noisy and low-quality MRI images.
Koshti et al. (2022)	CNN-based automated detection system	Through this a full automation framework was designed that included preprocessing up to classification giving a simplified, clinic ready solution that performed well at the diagnosis.
Goswami and Dixit (2020)	Image segmentation techniques (thresholding, clustering, deep learning)	The study examined several segmentation approaches and it was shown that segmentation accuracy is very important in the accurate classification of tumors.
Babu et al. (2021)	Survey of ML and DL-based detection methods	It was found that CNN-based deep learning models are always superior to the traditional methods in tumor detection and classification.
Agrawal and Goel (2023)	ML models using SVM and ANN	It was effective but limited by manual detection of features and, as a result, the benefit deep learning models like YOLO in automatic learning of features was demonstrated.

IV. PROPOSED METHOD

This paper presents the multi-step method of MRI-real time brain tumor analysis, which will include preparing and pre-processing datasets, designing the YOLOv11 model, and training.

A. Datasets Preparation

The dataset used in the study was the BRAIN-TUMOR on Roboflow Universe, which comprised 834 labelled MRI images, divided into 70 percent training, 15 percent validation and 15 percent test images. Principles of data augmentation- including flipping and 90 degrees rotation-scaled up the dataset to include 1,960 images which enhanced the model robustness and generalization.

B. Pre-processing

All the pictures were pre-processed to a 640x640 resolution prior to training to adjust them to the target format required by the YOLOv11 engine. Embedded EXIF metadata was used to automatically perform orientation correction so as to make the database consistent.

C. R-CNN Model Faster Architecture.

Faster R-CNN architecture [15] will consist of the three main components that are the Region Proposal Network (RPN), Region of Interest (RoI) pooling and the Region-based Convolution Neural Network (R-CNN) which collectively leads to the detecting of objects. A base convolution network is first used to extract features whereby the input image is subjected to a base convolution network in the form of a tensor.

D. Proposed Detection Framework.

The section gives an outline of detection model design and training. The tumor that is a back-end of the system is the model. It is mainly used to process the MRI images and make them either tumor-positive or tumor-negative. The model makes use of transfer learning, which is realized in retraining customized layers atop a pretrained network, to become tumor- detection task.

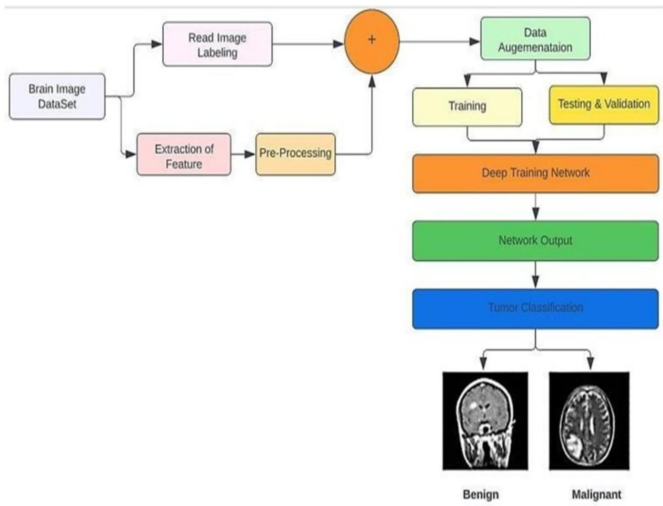


Fig. 1. Detection Model

E. Evaluation

The system is verified according to the general measures: IOU (Intersection over Unions): Checks Intersections of boxes between true and predicted ones. Precision and Recall: Mea- sured how well and how well the model locates the tumor regions. F1-Score: This gives a unison between recall and precision to determine the overall performance. FPS (Frag- mentations Per Second): The parameter contains real-time efficiency and responsiveness of the detecting system.

F. Refinement and Optimization

This part of the work underlines the improvement of the system in terms of accuracy, efficiency, and user-friendliness, which encompasses three significant improvement processes.

1) *Hyperparameter Tuning:* This step entailed setting hy- perparameters of YOLOv11 like learning rate, batch size, the number of epochs, and input resolution to ensure that the precision of the detected objects is balanced with real- time. Motivation of anchor boxes, threshold values, and loss weighting further increased the tumor detection accuracy and minimized erroneous predictions.
2) *Computer-assisted Clinical Deployment:* The trained model is designed in a way that it is very easy to deploy on cloud servers and hospital systems through optimizing its computational efficiency. Quantization, pruning and ONNX conversion are some of the techniques used to reduce the size of the model and make it faster without compromising on diagnostic accuracy. Also, an encrypted cloud storage is added to enable the storage of MRI information, analysis findings, and patient information in a safe manner to serve purposes of remote access and management of archives.
3) *Improved Diagnostic Interface/ Reporting Dashboard:* The system consists of simplified diagnostic dashboard en- abling clinicians to post MRI scans, view tumor detection findings with confidence measurements of their findings, and produce automatic diagnostic reports. It also assists in tracking of the case history, determinists trend and visualization, and use of data insight to enhance clinical decision support.

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 IV Apr 2026- Available at www.ijraset.com

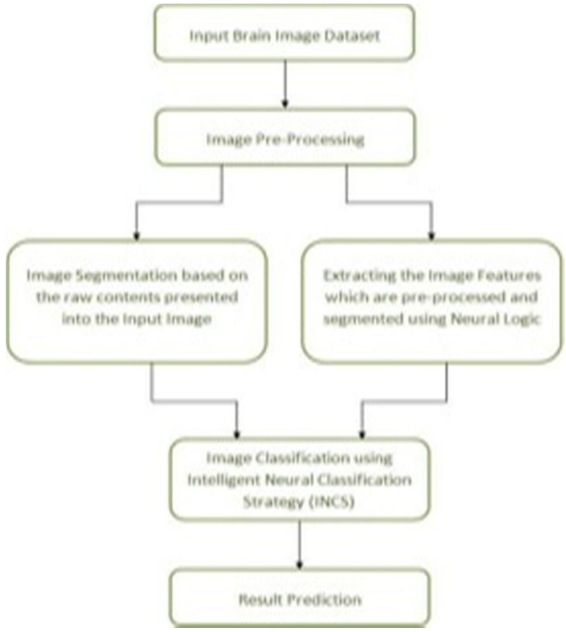


Fig. 2. Refinement and Optimization

V. RESULTS

The suggested model was found to have a good localization accuracy, the precision of 95.83, the recall of 91.85, the F1- score of 93.48, the mAP 0.5 of 96.48 and 77.75:0.95. It provides significant accuracy and speed improvements over current YOLO-based methods. The model used in training was the YOLOv11 large (yolo11l.pt) on a custom dataset of brain MRI (tumor and non-tumor) in a custom dataset. The datasets were diverse in terms of MRI sequences and tumor features and had a wide range of imaging artifacts, which guaranteed the improvement of model robustness.

A. Proposed Tumor Detection Approach

It was proposed, and it was visible that the detection model was able to correctly classify both MRI scans with brain tumor and without brain tumor and it is highly reliable even in case of variable shapes of tumors, small areas, and low- contrast case with images. These findings verify the model as effective in practical medical imaging settings as far as clinical applications are concerned.

B. Region Localization and Box-Based Marking

The YOLOv11 model was found to be able to localize tumors with accuracy, marking with end-boxes the location of the abnormal masses in the MRI scan. The identified regions, which had been refined by post- and pre-processing operations, including normalization, augmentation and non- maximum suppression, were further refined by the segmen- tation or OCR module to become more useful in clinical diagnosis and quantitative analysis.

C. Model Evaluation Parameters

The model showed good accuracy measures (high precision, recall, and F1-scores), which proved that its detection is consistent. IoU scores confirmed the exact coincidence of the predicted tumor area with the actual one whereas FPS analyses confirmed the system suitability to be used in real- time medicine.

D. Evaluation

Comparison to Past Based on YOLOv11 model is superior to the older versions, such as YOLOv3, YOLOv4, YOLOv5, YOLOv7 and YOLOv8 by achieving higher accuracy, more classifier-stable training behavior, and identifying smaller tu- mor segmentation. Such improvements allow the system to be more flexible, and reliable in clinical imaging setting.

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 IV Apr 2026- Available at www.ijraset.com

TABLE I
ANALYSIS OF PERFORMANCE OF VALIDATION

Classes	Targets	Recall	Precision	F1-score	mAP@0.5:0.95	mAP@0.5
All	23	0.76	0.81	0.77	0.56	0.82
No	13	0.76	0.82	0.75	0.58	0.84
Yes	10	0.78	0.80	0.79	0.58	0.83

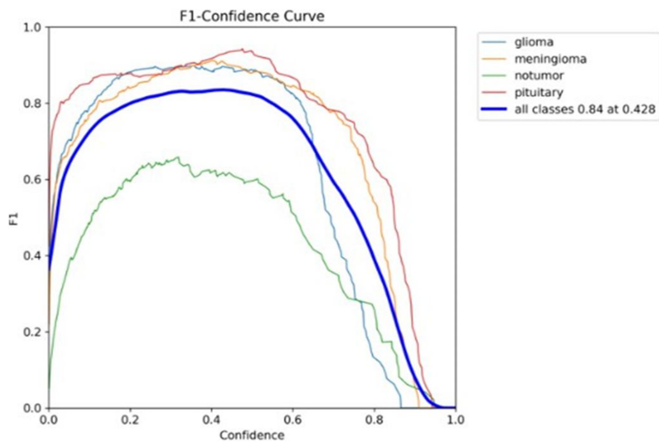


Fig. 3. Prediction accuracy of the test data.

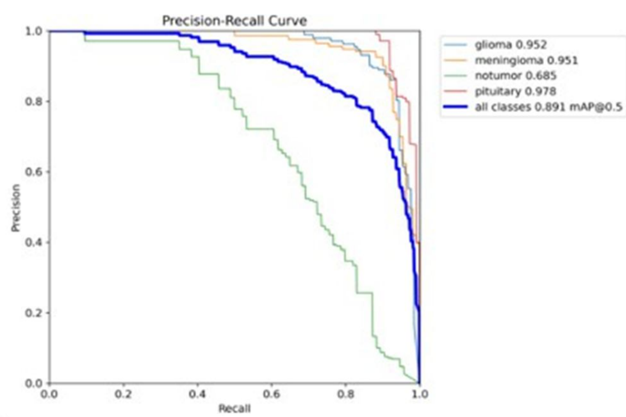


Fig. 4. The legend of the Precision-Recall plot signifies. The Area Under the Curve (AUC) of each of the images evaluated.

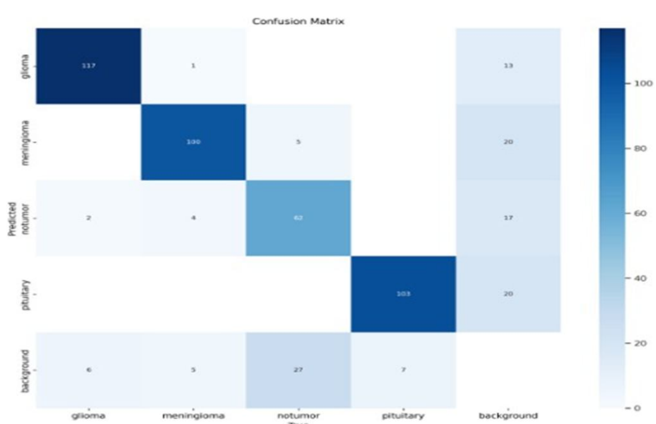


Fig. 5. Prediction on test confusion matrix.

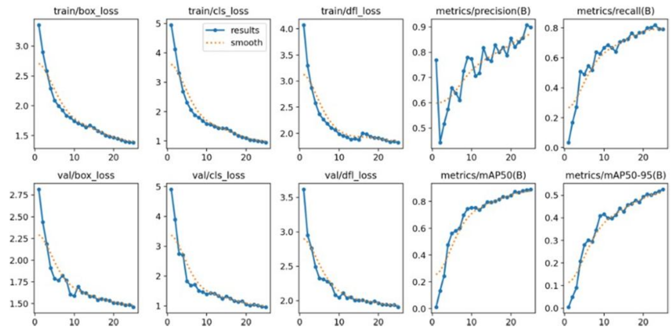


Fig. 6.

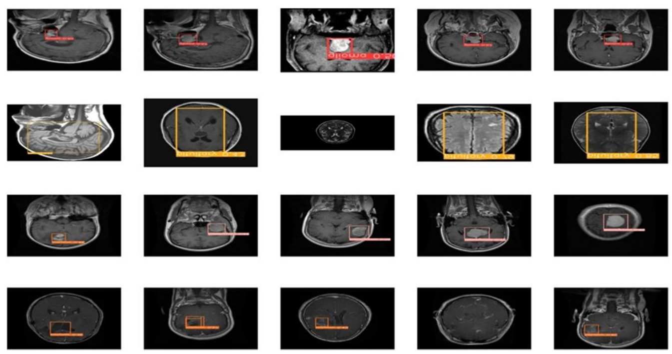


Fig. 7. Results Obtained After Testing the Model on Tumor Data

VI. CONCLUSION

This research result validates the potential of deep learning algorithms to predict the presence of brain tumors with high precision and sensitivity in case of MRI scans. The system is able to localize with high precision and in real-time a variety of MRI conditions and forms of tumors using the YOLOv11 model. Also, preprocessing and augmentation of the data is effective to increase the accuracy and the generalization of the system to be used in a wider range of clinical environments. The YOLOv11-based detection system is faster and more accurate than previous versions, so it is more appropriate to use in the clinical practice. It assists by automatically identifying the location of tumor in order to reduce the workload of radiologist, reduced diagnostic error, and early intervention due to which brain tumor patients can have a better chance to survive. The system can be extended to scan 3D MRI images in the future, segmentation models to facilitate a better delineation of the boundaries, and connected to the working system of hospitals to aid in real-time diagnosis. The study eventually helps in the development of effective and dependable AI-driven diagnosis instruments to the clinical practice.

REFERENCES

[1] N. M. Dipu, S. A. Shohan and K. M. A Salam, "Brain Tumor De- tection Using Various Deep Learning Algorithms," 2021 International Conference on Science Contemporary Technologies (ICSCT), Dhaka, Bangladesh, 2021.

[2] A. M. Qarni, S. Anwar and G. M. Khan, "YOLOv11-Based Brain Tumor Detection and Segmentation for Clinical Decision Support," 2025 International Conference on Emerging Technologies in Electronics, Computing, and Communication (ICETECC), Jamshoro, Pakistan, 2025.

[3] Y. Bhanothu, A. Kamalakannan and G. Rajamanickam, "Detection and Classification of Brain Tumor in MRI Images using Deep Convolutional Network," 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2020.

[4] M. V. Madhu Thota and B. R. Prasad, "INCS: A Novel Brain Tumor Detection Methodology Design Based on Deep Learning Assisted Intel- ligent Neural Classification Strategy," 2024 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), Chennai, India, 2024,

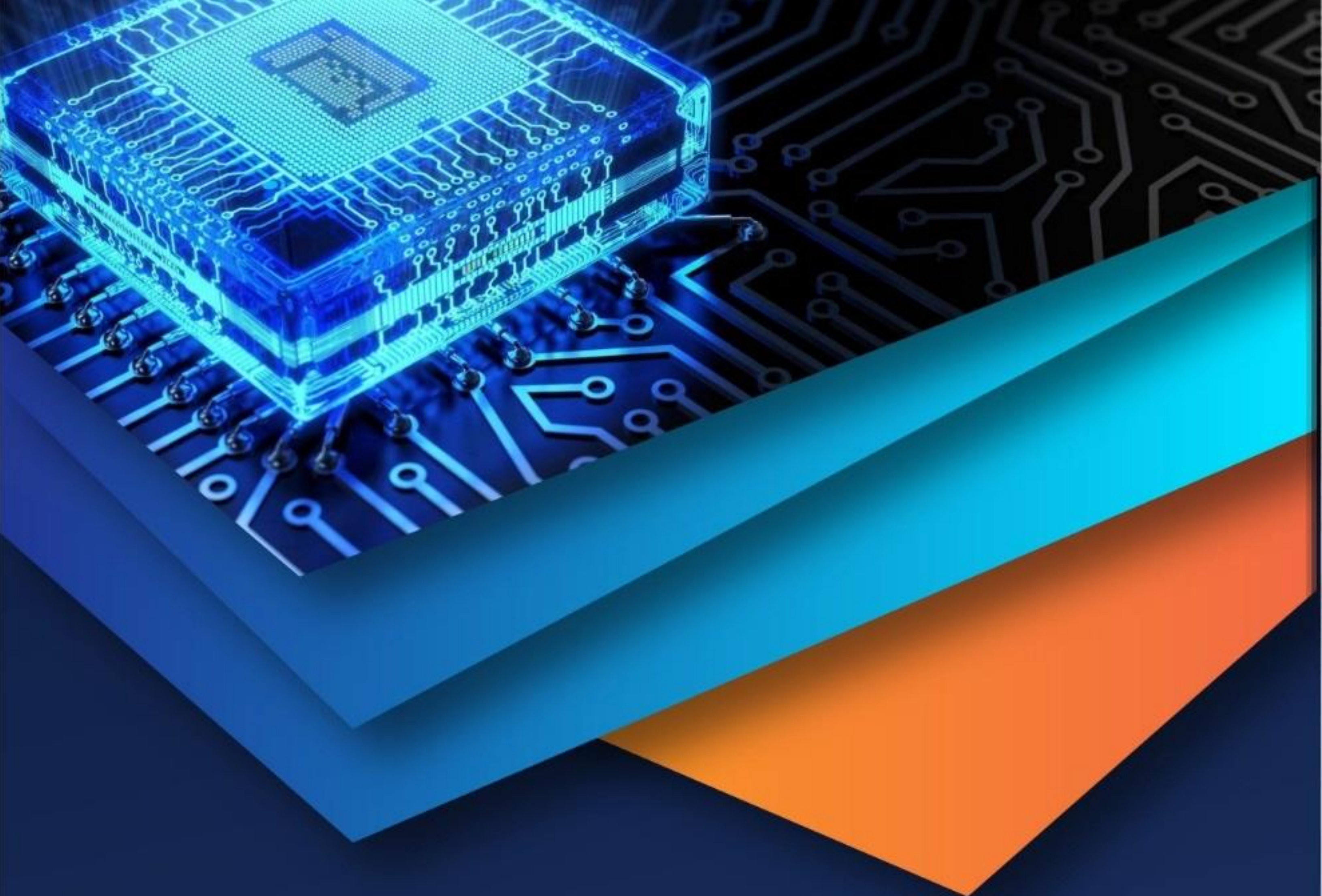
[5] S. Koshti, V. Degaonkar, I. Modi, I. Srivastava, J. Panambor and A. Jagtap, "Brain Tumor Detection System using Convolutional Neural Network," 2022 IEEE Pune Section International Conference (PuneCon), Pune, India, 2022.

[6] A. Goswami and M. Dixit, "An Analysis of Image Segmentation Methods for Brain Tumor Detection on MRI Images," 2020 IEEE 9th International Conference on Communication Systems and Network Technologies (CSNT), Gwalior, India, 2020.

[7] A. E. Babu, A. Subhash, D. S. Rajan, F. Jacob, and P. A. Kumar, "A Survey on Methods for Brain Tumor Detection," International Journal of Engineering Research Technology (IJERT), vol. 10, no. 4, pp. 1– 5,
2021.

[8] K. Agrawal, K. ("Kushagra"), and L. Goel, "Brain Tumor Detection us- ing Machine Learning," International Journal of Computer Applications, vol. 185, no. 9, May 2023.

[9] Ali, A.,Nadeem, M. B., Aziz, M. W., Ashraf, M. W., Mustafa, G. (2025). YOLO-v9-YOLO-v11: Brain Tumor Performance Analysis Using MRI Images. The Asian Bulletin of Big Data Management, 5(3), 135-153.
[10] Chourib, I. (2025). From detection to diagnosis: An advanced transfer learning pipeline using YOLO11 with morphological post-processing for brain tumor analysis for MRI images. Journal of Imaging, 11(8), 282.
[11] Abuhammad, H. Z., ALsaidi, R. A., Alraqad, R. H. (2025, April). Enhancing Brain Tumor Detection with YOLOv11: An Innovative Deep Learning Approach in Medical Imaging. In 2025 1st International Conference on Computational Intelligence Approaches and Applications (ICCIAA) (pp. 1-6). IEEE.
[12] Wahidin, M. F., Kosala, G. (2025, February). Brain Tumor Detection Using YOLO Models in MRI Images.In 2025 International Conference on Advancement in Data Science, E-learning and Information System (ICADEIS) (pp. 1-6). IEEE.
[13] Thakur, M. K., Chauhan, S. (2025, April). Brain Tumor Detection and Classification Using YOLO Algorithms. In 2025 International Conference on Inventive Computation Technologies (ICICT) (pp. 116- 123). IEEE.
[14] Jeyaraj M, P., Kumar M, S. (2025). Automated Brain Tumor Segmen- tation using Hybrid YOLO and SAM. Current Medical Imaging, 21(1), E15734056392711.
[15] Yang, T., Lu, X., Yang, L., Yang, M., Chen, J., Zhao, H. (2025). Application of MRI image segmentation algorithm for brain tumors based on improved YOLO. Frontiers in Neuroscience, 18, 1510175.
[16] Hechkel, W.,Missaoui, R., Helali, A. (2025, February). Early Diagnosis of Alzheimer's Disease Using YOLOv11 Deep Learning Model in MRI Scans. In 2025 IEEE 22nd International Multi-Conference on Systems, Signals Devices (SSD) (pp. 599-604). IEEE.
[17] Elgohr, A.T., Elhadidy, M. S., El-geneedy, M., Akram, S., Mousa, M. A. (2025, August). Advancing sign language recognition: a YOLO v. 11-Based deep learning framework for alphabet and transactional hand gesture detection. In Proceedings of the AAAI Symposium Series (Vol. 6, No. 1, pp. 209-217).
[18] Behzadi, S., Sharifrazi, D., Mesbahzadeh, B., Joloudari, J. H., Al- izadehsani, R. (2025). A Lightweight and Robust Framework for Real- Time Colorectal Polyp Detection Using LOF-Based Preprocessing and YOLO-v11n. arXiv preprint arXiv:2507.10864.



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY