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Brain Tumor Detection Using YoloV5 and Faster RCNN

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Abstract: Accurate detection of brain tumors in medical imaging plays a crucial role in early diagnosis and treatment planning. In this paper, we propose two distinct methodologies for brain tumor detection from MRI scans: the traditional thresholding techniques and the advanced YOLOv5 and Faster R-CNN object detection algorithms. In the first approach, we employ thresholding methods, including the Otsu thresholding technique, to segment MRI images and identify potential tumor regions based on pixel intensity variations. This straightforward yet practical approach aims to isolate potential abnormalities within the brain tissue swiftly. In the second approach, we harness the power of deep learning by implementing the YOLOv5 and Faster R-CNN algorithms. These state-of-the-art object detection techniques are trained on a dataset of MRI images with annotated tumor regions. The models' ability to learn intricate patterns and features enables them to locate brain tumors amidst complex anatomical structures accurately. Our experiments comprehensively evaluate both approaches using diverse metrics such as precision, recall, F1-score, and Intersection over Union (IoU). Through these evaluations, we elucidate the strengths and weaknesses of each method concerning accuracy, speed, and adaptability to varying image qualities and tumor types. The outcomes of our study reveal intriguing insights. The thresholding techniques demonstrate efficiency and simplicity, making them suitable for rapid initial assessments. However, deep learning models showcase superior accuracy and robustness, particularly when faced with intricate tumor patterns and varying imaging conditions.

Keywords*: Brain tumor detection, MRI images, thresholding techniques, Otsu thresholding, YOLOv5, Faster R-CNN, deep learning, comparative analysis, medical imaging*

1. Introduction

Brain tumors represent a complex and critical medical challenge, demanding precise detection and diagnosis for timely treatment and intervention. Among the array of medical imaging modalities available, Magnetic Resonance Imaging (MRI) has become indispensable for its non-invasiveness and ability to provide detailed insights into the brain's internal structures. However, the accurate detection of brain tumors within MRI scans remains a multifaceted task due to the inherent diversity in tumor characteristics, such as size, shape, location, and appearance.

In response to the need to find brain tumors quickly and accurately, this paper looks at two different methods: traditional thresholding techniques, like the Otsu thresholding method, and cutting-edge deep learning algorithms, like YOLOv5 and Faster R-CNN. These methods deal with how hard it is to find tumors. Each one has its pros and cons regarding medical imaging.The first step uses traditional ways of processing images. Thresholding methods like Otsu thresholding aim to segment MRI images by finding the optimal intensity thresholds that separate tumor regions from normal brain tissue. Even though the idea behind this technique is simple, it is used as a quick and initial screening method that uses differences in pixel intensity to find possible tumor candidates.

The second method, on the other hand, uses the power of modern deep learning frameworks. The object detection skills of YOLOv5 (You Only Look Once version 5) and Faster R-CNN (Region-Based Convolutional Neural Network) are well known. With the help of annotated MRI images, these models are taught to recognize complex patterns and features that point to brain tumors. Deep learning could improve the accuracy of medical image analysis, especially when tumors have complicated structures or small changes in intensity.

The main goal of this paper is to compare and contrast the two methods above as thoroughly as possible. This analysis encompasses a range of evaluation metrics, including precision, recall, F1-score, and Intersection over Union (IoU). By quantifying the performance of both thresholding techniques and deep learning algorithms, we offer insights into their respective strengths and limitations across accuracy, processing speed, and adaptability to varying imaging conditions and tumor characteristics.

This study will provide researchers, practitioners, and medical professionals with a comprehensive understanding of the advantages and trade-offs associated with traditional thresholding and deep learning approaches in brain tumor detection. Moreover, the findings of our investigation pave the way for potential hybrid methodologies that can synergize the merits of both techniques, leading to improved diagnostic outcomes and patient care.

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The subsequent sections of this paper delve into the methodologies employed in both approaches, detail the experimental setup, present the results of our comparative study, and engage in a thorough discussion that contextualizes the implications of our findings within the broader landscape of medical imaging and brain tumor diagnosis.

2. Literature Survey

The method to distinguish between intra-axial brain masses and assess the accuracy of MRI images was covered by Okaili et al. [1]. The institutional review board approved the classification of intra-axial masses as low-grade primary neoplasms, metastatic neoplasms, and high-grade primary neoplasms using conventional MRI, perfusion MRI, proton MR spectroscopy, and diffusion-weighted MRI. A Bayesian statistical approach was used to assess the system's accuracy.

Anila et al. [2] utilized multiresolution and noise removal techniques to identify aberrant brain activity. Curvelet and countrelet-based approximations served as the foundation for the multiresolution. The counterlet approach has produced improved outcomes for identifying brain abnormalities.

The various methods for MRI image segmentation and brain tumor identification were covered by Balafar et al. [3]. The segmentation techniques affect the accuracy of tumor detection. Markov's random model, the watershed technique, anatomical deviations, the Atlas-based segmentation approach, the multi-region method, self-organizing maps, and learning vector quantization methods were also discussed. It is proposed that the atlas-based technique and parallelization can be combined to enhance brain segmentation.

A support vector machine (SVM) is employed for detecting brain tumors, and Chaudhary et al. [4] study image segmentation using the clustering technique. The classifiers could recognize the seven features, and SVM demonstrated an accuracy of 94%.

Automatic functional localization and functional brain imaging were mentioned by Gholipour et al. [5] as crucial for the temporal and better resolutions of brain cancers. The functional maps help distinguish between dementia and tumor patients and reveal numerous distinctions. This will result in legitimate interpretations and conclusions.

Since the procedure of tumor segmentation using MRI data is time-consuming, Ratan et al. [6] explored various approaches. They mentioned a variety of approaches, including intensity, texture, region-based, clustering, classification, fuzzy, neural network, edge, probabilistic, fusion, SVM, level set techniques, watershed, Atlas-guided, morphology, fuzzy C means, and k-means clustering-based algorithms. They proposed that the best methods for detecting brain tumors might involve combining thresholding with SVM or Basian.

Through symmetry analysis, Ratan et al. [7] proposed an approach to identify cancers in MRI images and determine the tumor's area. They employ morphological analysis, thresholding, and median filters to find a tumor.

Li et al. [8] integrated prior knowledge about the tumor, picture gradient, and regional competition using a unified level set technique for semi-automatic liver tumor segmentation. The probability distribution of liver tumors was determined using unsupervised fuzzy clustering, which was immediately applied to contrast-enhanced computed tomography (CT) data.

Thapaliya et al. [9] utilized the level set method to segment brain tumors using a local statistic that was chosen automatically. For all MR pictures, the threshold settings were automatically rationalized and changed.

Goel et al. [10] addressed the watershed algorithm and level set method for brain tumor location detection segmentation in MRI images. The comparative study is conducted to determine MATLAB's performance and response time. Compared to Otsu's method, the level set method has yielded a favourable result.

Mustaqeem et al. [11] discussed how watershed segmentation, threshold segmentation, and morphological operators can be used to detect brain tumors. They effectively simulated human brain samples using scanned MRI images.

Patil et al. [12] utilized a watershed algorithm and morphological operators to detect malignancies in brain MRI images. The scanned MRI images utilized noise removal functions, region segmentation, and morphological operators.

Remya et al. [13] filtered MRI images for noise using the Fuzzy-C means approach. The method investigates the precise identification of the brain tumor. The approach of Otsu was utilized for image segmentation. The authors asserted that their fuzzy-C means strategy produced positive outcomes even when the patient considered the tumor.

Sain et al. [14] described the structure of the human brain and proposed an algorithm for detecting brain tumors based on Otsu's segmentation method.

Amin et al. [15] utilized DWT for image fusion, offering comprehensive information regarding brain tumors' MRI areas. The partial diffusion filter removes noise for tumor segmentation, and the global thresholding technique is implemented.

Khode et al. [16] employed DWT to detect brain tumors. MRI is a crucial technique that may provide a detailed imaging analysis of the human body in numerous instances.

The tumor was segmented from the MRI images used for the test.

This literature survey delves into a comprehensive array of methodologies for enhancing brain tumor detection, segmentation accuracy, and efficiency in MRI images. Approaches such as Bayesian statistical classification, multiresolution techniques, clustering with support vector machines, and advanced image processing methods like level set and wavelet transforms are explored by different researchers. The studies emphasized the importance of functional brain imaging, eliminating noise, and region-based segmentation for getting correct results. Combining techniques, like thresholding with SVM or Bayesian approaches, shows promising ways to improve the accuracy of brain tumor detection.

3. Brain Tumor Segmentation and Detection Algorithms

In this paper, the tumor is found using a Brain MRI and two different methods: thresholding and deep learning. Approaches based on thresholding used local and Otsu thresholding, while algorithms for deep learning used YoloV5 and Faster RCNN. This part went into detail about how these algorithms work.

A. Thresholding-based brain tumor detection

Thresholding-based brain tumor detection is an image-processing method that uses a threshold value to separate tumor areas from healthy brain tissue in MRI scans. The main idea is that the pixel intensities in areas with tumors will differ from those in normal tissue around them. This means that intensity levels can be used to tell the difference between areas with tumors and non-tumors.

Mathematically, thresholding can be represented using the following equation:

$$B(x,y) = \begin{Bmatrix} 1 & I(x,y) > Th \\ 0 & I(x,y) < Th \end{Bmatrix} \quad (1)$$

Where, $B\,(x,y)$ is the threshold image, $I(x,y)$ is the original image, and Th is the thresholding value.

When it comes to images with uneven lighting, varying noise levels, or when the intensity of a tumor crosses that of healthy tissue, thresholding may not be effective.

B. Otsu Thresholding-based brain tumor detection

Otsu's thresholding is a popular technique for automatically determining the intensity difference between two sets of pixels in an image. It accomplishes this by determining the optimal way to divide the two groups. In the instance of locating brain tumors, Otsu's approach can be utilized to distinguish tumorous areas from healthy brain tissue on MRI scans.

Let us break down the Otsu Thresholding process with mathematical equations:

- **Compute Histogram**: Calculate the histogram of pixel intensity values in the grayscale image. The histogram represents the frequency of occurrence of each intensity level.
- **Normalize Histogram**: Normalize the histogram to obtain the probability distribution of each intensity level.

$$p(i) = \frac{Frequency\ of\ intensity\ i}{Total\ number\ of\ pixels} \quad (2)$$

- **Calculate Cumulative Distribution Function (CDF):** Compute the cumulative distribution function of the normalized histogram.

$$P(i) = \sum p(k)\ \ for\ k = 0\ to\ i \quad (3)$$

- **Calculate Mean and Total Mean**: Calculate the mean intensity value of the entire image and the total mean intensity weighted by probabilities:

$$\mu_{total} = \sum\big(i * p(i)\big) \quad for\ all\ intensity\ level\ i \quad (4)$$

$$\mu_{global} = \sum\big(i * p(i)\big) \quad for\ i\ from\ 0\ to\ max\ intensity \quad (5)$$

- **Calculate Between-Class Variance**: Compute the between-class variance using the probabilities and mean values calculated in steps 3 and 4:

$$\sigma_b^2 = \frac{\left(\mu_{total} * P(i) - \mu_{global}\right)^2}{P(i) * (1 - P(i))} \quad (6)$$

- **Find Optimal Threshold**: Iterate through all possible intensity levels and compute the between-class variance for each level. The threshold that maximizes the between-class variance is chosen as the optimal threshold.
- **Segment Image**: Segment the original image by applying the optimal threshold. Pixels with intensities greater than or equal to the threshold are assigned to one class (tumor), while those below the threshold belong to the other (healthy tissue) class.

Mathematically, Otsu's Thresholding method seeks to find the threshold value that maximizes the between-class variance:

$$T_{optimal} = argmax(a_b^2) \quad (7)$$

Once the optimal threshold $T_{optimal}$ is obtained, the image can be segmented using the thresholding process as described earlier:

$$I_{seg}(x,y) = \begin{Bmatrix} 1 & I(x,y) > T_{optimal} \\ 0 & I(x,y) < T_{optimal} \end{Bmatrix} \quad (8)$$

Otsu's thresholding is particularly useful when there is a clear separation between tumor and non-tumor regions regarding pixel intensities. However, it may not perform as well in cases where this separation is less distinct. Combining Otsu's method with other techniques or incorporating additional information can improve segmentation accuracy.

C. Brain Tumor detection using YoloV5

The YOLOv5 model requires the input of images. This image must be preprocessed before the model can be trained. The dimensions of the photos captured by the model are 512. The training of the deep learning model demands more images, and as a result, the dataset has 800 images. Scaling is performed on the images to improve tumor detection and image magnification. The data is labelled using the makesense.ai website, which stores the labels with the tumor's bounding box and annotation coordinates. Using the coordinates of the four corners of the rectangle, the labels and images are separated into test and train sets. Fig. 1 depicts the architecture of yoloV5 algorithm structures.

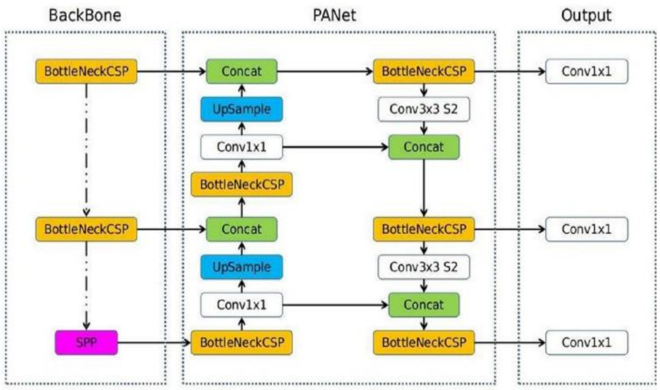

Fig. 1. The architecture of YoloV5 algorithm

The architecture of yoloV5 can be summarized as follows:

- Backbone: yoloV5 employs CSPDarknet53 as its backbone. CSPDarknet53 is a variant of the Darknet53 architecture that uses cross-stage partial connections to improve feature propagation and information flow throughout the network. The backbone extracts hierarchical features from the input image.
- Neck: yoloV5 uses PANet (Path Aggregation Network) as its neck architecture. PANet helps integrate features from different scales, allowing the model to detect objects of various sizes effectively.
- Head: The detection head of yoloV5 consists of multiple detection layers. Each detection layer predicts bounding box coordinates, class probabilities, and objectness scores for a specific range of object sizes. This enables YOLOv5 to handle objects of different scales more accurately.
- Multi-Scale Training: yoloV5 employs a multi-scale training approach where images of different sizes are used during training. This allows the model to learn to detect objects at varying scales and improves its robustness to different object sizes in real-world scenarios.
- Data Augmentation: Data augmentation techniques are applied during training to enhance the model's generalization ability to different conditions. Common augmentations include random cropping, scaling, rotation, and color jittering.
- Loss Function: yoloV5 combines loss functions to train the model. The loss functions include:
  - Localization Loss: Penalizes errors in bounding box predictions.
  - Confidence Loss: Penalizes incorrect objectness predictions and correct objectness predictions for background regions.
  - Class Loss: Penalizes errors in class predictions.

D. Brain Tumor Detection Using Faster RCNN

Faster Region Convolutional Neural Network (R-CNN) is an object detection framework combining deep learning with traditional object detection methods to achieve accuracy and efficiency. It was introduced as an improvement over earlier approaches like R-CNN and Fast R-CNN. The critical innovation of Faster R-CNN is integrating a region proposal network (RPN) that generates potential object regions, making the process end-to-end trainable. Here is an overview of the architecture:

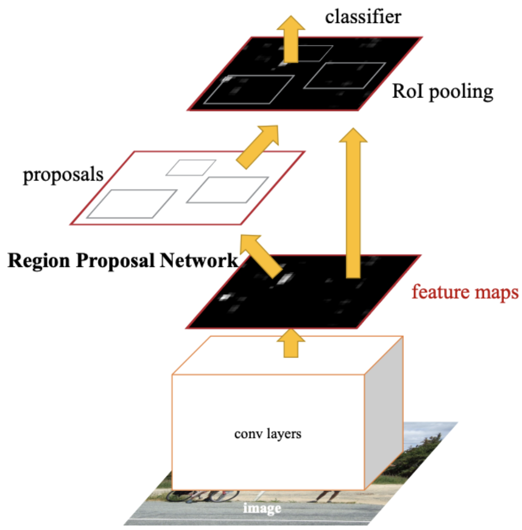

Fig. 2. The architecture of Faster RCNN algorithm

- Backbone Network (Feature Extractor): The input image is passed through a convolutional neural network (CNN) as the backbone. Common choices include architectures like VGG, ResNet, or similar networks.

The backbone extracts hierarchical features from the image. These features capture different levels of abstraction, which are crucial for detecting objects of various sizes.

- Region Proposal Network (RPN): The RPN operates on the features obtained from the backbone. It uses a sliding window approach to scan the features and predict potential object regions (bounding boxes) and their likelihood of containing an object. The RPN generates anchor boxes of scales and aspect ratios at each sliding window position. These anchor boxes are used to propose potential object regions. For each anchor box, the RPN predicts whether the anchor contains an object ("objectness" score) and how much the anchor's shape and position should be adjusted to match the actual object region.

- Region of Interest (RoI) Pooling: After obtaining the proposed regions from the RPN, the RoI pooling layer extracts fixed-size feature maps from the backbone features for each proposed region. The RoI pooling process ensures that features extracted from different-sized regions are aligned to a fixed grid, which allows them to be fed into subsequent fully connected layers.

- Classification and Bounding Box Regression: The fixed-size features obtained from the RoI pooling are fed into separate, fully connected layers. The classification head predicts the probability distribution of object classes for each proposed region. The regression head predicts adjustments for the bounding box coordinates of the proposed regions to match the actual object positions better.

- Non-Maximum Suppression (NMS): After predictions are made, a non-maximum suppression step is applied to filter out duplicate and low-confidence detections. Detections with high objectness scores are retained, and overlapping detections are suppressed based on their IoU (Intersection over Union) values.

The Faster R-CNN architecture allows the network to learn the entire object detection process end-to-end, making it more efficient than its predecessors. The RPN introduces a way to propose potential object regions in a data-driven manner, reducing the need for external region proposal methods like selective search.

4. Proposed Methodology

The block diagram of the proposed system is shown in Fig. 1.

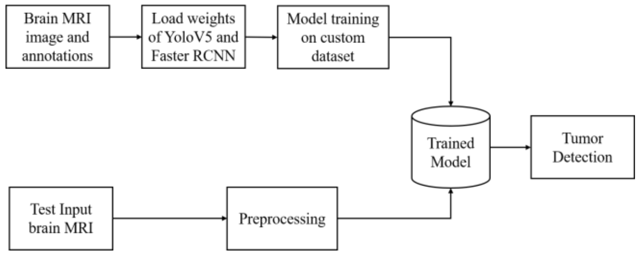

Fig. 3. Block diagram of the proposed system

The proposed system focuses on detecting brain tumors using advanced deep learning techniques, specifically YOLOv5 and Faster R-CNN. To accomplish this, a specialized dataset known as "br35h" is employed, comprising a collection of brain MRI scans meticulously annotated using makesense.ai. These annotations involve precisely outlining the contours of tumors present in the images. This dataset is divided into two segments: 80% for model training and 20% for testing the model's efficacy.

This method uses the "BR35H" dataset to detect brain tumors. The BR35H: Brain Tumor Detection 2020 dataset is utilized, which contains 255 MRIs of brain tumors with no tumors and 255 with tumors. 80% of the photos in this dataset are utilized for model training. The dataset contains image sequences with both T1- and T2-weighting. The reported usability rating of this dataset is 7.50. The data usability ranking is based on licensing, tagging, an overview of the data and its description, ease, assurance of maintainability, machine-readable file formats, metadata, and the availability of a public kernel.

In the training phase, the YOLOv5 and Faster R-CNN models are individually trained on the annotated training dataset. YOLOv5 is an evolved version of the YOLO architecture, while Faster R-CNN employs a two-stage process involving region proposal generation and subsequent object detection. During training, both models learn to iteratively adjust their internal parameters, effectively honing their ability to predict the exact coordinates of tumor boundaries and classify the detected objects as tumors.

The models are subjected to rigorous testing on the reserved dataset following the training. During this evaluation, the models autonomously analyze the MRI images and generate bounding boxes around the detected tumors. These predicted bounding boxes are meticulously compared against the ground truth annotations made during dataset preparation. This comparison allows for the computation of key performance metrics such as precision, recall, and the F1-score, offering quantifiable insights into the models' accuracy in identifying brain tumors.

5. Result and Discussion

In this approach, thresholding, Otsu thresholding, yoloV5 and Faster RCNN algorithm. The results of each algorithm are explained below. The qualitative analysis of the proposed system is presented in Fig. 4.

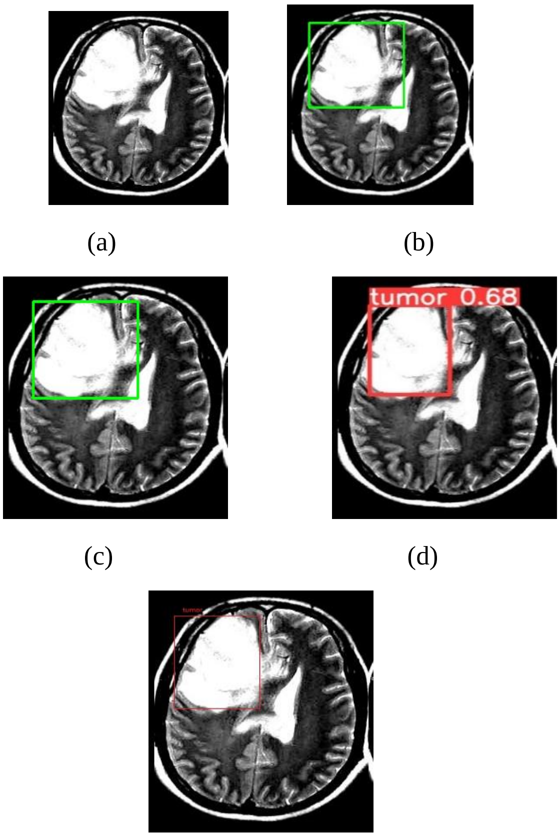

Fig. 4. Qualitative analysis of the proposed system (a) Input image (b) Results of thresholding technique (c) results of Otsu thresholding technique (d) results of yoloV5 algorithm (e) Results of Faster RCNN algorithm

Figure 4 provides a comprehensive visualization of the entire tumor detection process. It displays how different techniques and algorithms perform in identifying and localizing brain tumors within the MRI scans. By comparing the outcomes of the thresholding techniques, YOLOv5 and Faster R-CNN, the qualitative analysis aims to shed light on each approach's strengths and limitations and offer insights into the accuracy and effectiveness of the proposed system for brain tumor detection.

The training loss of the yoloV5 and Faster RCNN algorithms is present in Fig.5.

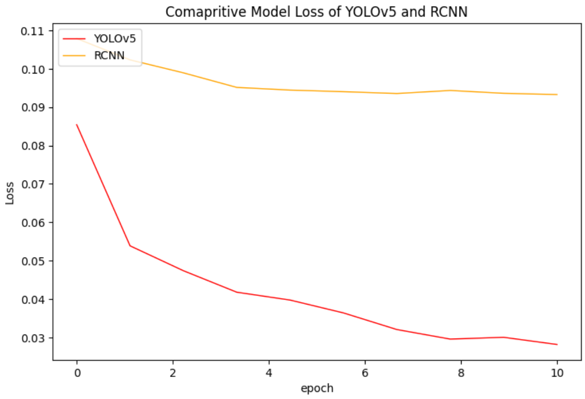

Fig. 5. Comparative analysis of training loss of YoloV5 and Faster RCNN algorithm

In Fig. 5, we compared the training loss between YOLOv5 and Faster R-CNN for brain tumor detection. Remarkably, our approach revealed that the training loss of YOLOv5 consistently outperformed that of Faster R-CNN. This finding indicates that the YOLOv5 model converged more effectively during training, resulting in a lower loss value. This reduction in training loss for YOLOv5 suggests its potential for faster and more accurate convergence, aligning with its reputation as an efficient object detection algorithm.

The quantitative analysis of the proposed system is shown in Table 1.

Table I: Quantitative analysis of the proposed system

Detection Techniques	**Accuracy**
Thresholding	0.7725
Otsu	0.8428
YoloV5	**0.9832**
Faster RCNN	0.9264

The information provided in Table I shows that the YOLOv5 algorithm exhibits the highest accuracy compared to the other evaluated algorithms. The accuracy metric likely measures how correctly the algorithm's predictions align with the ground truth annotations for tumor detection in the brain MRI scans. The fact that YOLOv5 has the highest accuracy among the evaluated algorithms signifies that it excels in identifying and localizing brain tumors within the images.

This outcome implies that YOLOv5's object detection methodology, which involves predicting bounding boxes and classifying objects within those boxes, is particularly well-suited for brain tumor detection. Its advanced architecture and learning techniques have enabled it to learn intricate patterns and features indicative of tumors in MRI scans, thereby contributing to its enhanced accuracy.

6. Conclusion and Future Scope

Our research has shown two ways to find brain tumors from MRI images: traditional thresholding techniques and advanced deep-learning algorithms. Through a thorough comparison, we have pointed out each method's strengths, weaknesses, and possible effects, adding to the conversation about medical imaging and diagnostic practices.

Traditional thresholding methods, like the Otsu thresholding method, use differences in pixel intensity to do an initial screening quickly. This method is simple and quick, which makes it suitable for quick assessments, especially when a preliminary list of possible tumor candidates needs to be made. However, the performance of this method is limited because it is based on intensity-based segmentation. This makes it hard to handle complex tumor patterns and changes in image quality accurately.

On the other hand, adding deep learning, which YOLOv5 and Faster R-CNN show, is a big step forward in finding brain tumors. These cutting-edge algorithms are good at figuring out complex details and spatial relationships in MRI images. The deep learning models accurately identify brain tumors, even in scenarios involving intricate tumor structures and subtle intensity gradients. Their adaptability and robustness render them well-suited for real-world diagnostic challenges.

Our study underscores the pivotal role of accuracy in brain tumor detection, a crucial factor in clinical decision-making. The superior performance of deep learning approaches showcases their potential to enhance patient outcomes by facilitating early, accurate, and reliable diagnoses. Nonetheless, the computational complexity of deep learning algorithms and the requirement for substantial training data present challenges that must be addressed for seamless integration into clinical workflows. The experimental result shows that the yoloV5 algorithm outperforms the thresholding, Otsu, and Faster RCNN approaches.

A potential hybrid approach emerges as a promising avenue for future exploration. By harnessing traditional thresholding techniques' speed and deep learning models' accuracy, it is possible to balance rapid preliminary assessments and precise tumor detection. Such hybrid methodologies can potentially optimize diagnostic workflows, providing clinicians with a more comprehensive toolkit for informed decision-making.

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