Brain Tumor Detection in MRI Using YOLO

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***Abstract*— As recent advancements in image processing and computer vision have transformed the health technology scene of today, improvements in precision diagnostics come with colossal cost and time efficiency. MRI is a necessary tool for the expert team of radiologists, who would be able to detect minor abnormalities in the brain. The present work analyses the YOLOv10 framework of state-of-the-art deep architectures capable of classifying and detecting multiple brain tumors in MRI scans. In this work, we have included three different classes in the dataset: meningiomas, gliomas, and pituitary tumours. For exact tumour segmentation, we are applying advanced preprocessing technique with effective mask alignment. We evaluate YOLOv10 performance against the pre-processed dataset, which generates an optimistic result in tumour detection and classification. Preliminary results indicate a recall score of 0.912 for bounding box detection and 0.914 for mask segmentation with precision scores of 0.941 and 0.938, respectively. These results are therefore indicative of the promise of YOLOv10 in advancing the diagnosis of brain tumors toward better patient care in a clinical context.**

Keywords*— Brain tumour, deep learning, image processing, MRI, YOLO.

I. INTRODUCTION (*HEADING 1*)

Brain cancer is one of the most common destructive diseases, killing thousands of people even in the developed countries. In the United States, this toll is particularly shocking, taking about 20,000 lives to this daunting illness [1]. This refers to uncontrolled growth and the spread of cells within the body. Under normal circumstances, the human body regulates cell growth and multiplication, producing new cells through cell division. When an old or damaged cell dies, they are rapidly replaced with new ones. However, when this well-arranged process fails, abnormal or damaged cells may begin growing inappropriately.

These cells may appear as masses in tissue called tumors. Most brain tumors start in the brain and usually only spread to surrounding the tissues
Out of all these, 70% of brain tumors are benign and the rest 30% are malignant in nature. More than 120 types of brain tumours are identified but some common types are meningioma, glioma, and pituitary tumour. [2], [3]

Deep learning models, especially Convolutional Neural Networks (CNNs), are notable for not requiring manually engineered features for classification tasks. More than 120 different types of brain tumors have been identified to date, with gliomas, meningiomas, and pituitary tumors being the most prevalent. Meningiomas, which originate in the meninges (the membranes surrounding the brain and spinal cord), are the most common primary brain tumors. The International Association of Cancer Registries (IARC) reports that in India alone, over 28,000 people are diagnosed with brain tumors annually, with more than 24,000 deaths attributed to the disease [4-6].

As reported by the International Association of Cancer Registries, over 28,000 individuals are diagnosed with brain tumors annually in India, with more than 24,000 succumbing to the disease each year [7]. CNN can be used very well when having huge datasets, which is quite rare in this medical image field [8], a pre-trained model on some other large dataset to another domain is used for classification [9].

Brain tumors are a consequence of uncontrolled and excessive cell growth which interferes with normal brain function and has serious implications for health, especially in children and adolescents. Over the last few years, brain tumors have been portrayed as one of the major causes of cancer death in all age groups. To be managed properly, it has to be diagnosed in time and with accuracy. One of the tools that medical science uses for diagnostic purposes here is imaging, and MRI comes especially well into the reckoning as one of the important modes of imaging.[10]

Benign tumors, like meningiomas, tend to grow slowly and generally do not invade nearby tissues. In contrast, malignant tumors, such as glioblastomas, often grow quickly, are highly invasive, and are challenging to remove entirely. Brain tumors can directly press on brain structures, which increases intracranial pressure, potentially causing symptoms such as headaches, blurred vision, and alterations in mood and cognitive function [11-13].

The development of machine learning and computer vision has led to the creation of highly effective models, notably Convolutional Neural Networks (CNNs). These advanced models have become capable of addressing complex challenges in Computer-Aided Diagnosis (CAD), including tasks like recognition, classification, segmentation, and detection [14], [15], [16], [17].

Notable algorithms include the Single Shot Multibox Detector (SSD) [18], R-CNN [19], and Fast R-CNN [20].

In one study, the Faster R-CNN algorithm was employed to detect tumors, achieving a mean average precision of 76.60%. Another study proposed a CNN architecture that demonstrated a high tumor classification accuracy of 95.56%. Additionally, a combination of a pre-trained CNN with gray-level co-occurrence matrix (GLCM) [22] features resulted in an accuracy of 96.5%. However, a comprehensive analysis of these results is limited due to the lack of detailed information about the pre-existing tasks in these prior works [23]. Omitting crucial metrics such as, for instance, recall or specific thresholds of detection would make it quite difficult to adequately assess and compare related work and models [23]

II. METHODOLOGY

A. *Data collection:*

Afterward, the process of collecting real-time data for brain tumor segmentation began. This involved manually gathering images and relevant details from Google. Careful attention was given to selecting datasets that met the specific requirements for detailed and accurate analysis. Each chosen image was annotated to ensure that the quality of segmentation would contribute effectively to future steps in lineage analysis and project support.

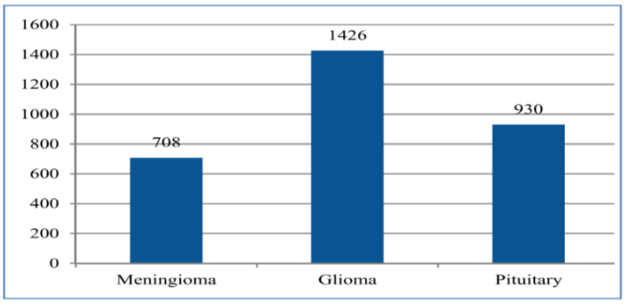

Fig. 1. Distribution of tumour types in dataset

B. *Data Processing*

Each MRI image is being annotated for data processing; decent tool Roboflow is generally designed with the full set of features for image annotation and preprocessing. It meant to draw the bounding box of the whole brain for each frame and then locate the tumor exactly in all the frames. I took care to delineate the tumor boundaries well so that each annotation is a correct representation of how big, how irregularly shaped, and where exactly those common prostatic adenocarcinoma regions of interest are.

Accurate annotations for the MRI images are crucial, as can be seen from this detailed process which involved a deep knowledge and close examination of MRI images to achieve perfect annotations. The good quality dataset produced using this technique was required for modeling effective segmentation of brain tumour and thus added greatly towards the accuracy and reliability of further analysis and research.

Roboflow, a tool designed to simplify image data handling in computer vision projects, provides features for image annotation, dataset versioning, and model training. These capabilities make it easier to develop and deploy machine learning models.

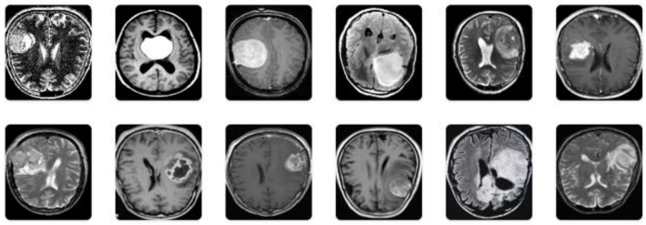

Figure 2.3: Brain tumors images after annotations

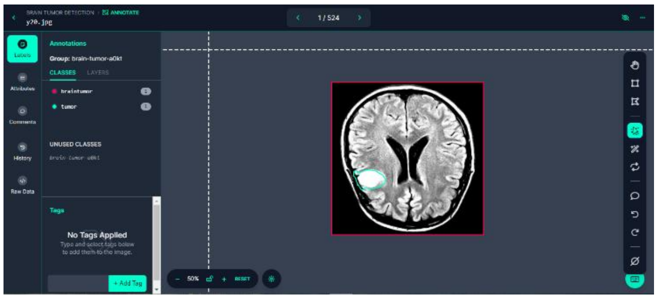

Figure 2.2: Annotating tumor manually

C. *Dataa Selection*

The complete dataset is split into three distinct portions: a training set, a validation set, and a test set, following the necessary pre-processing steps. The training set consists of 2,144 images, which account for approximately 69.97% of the entire dataset.
The validation set contains 827 images, making up 26.99% of the data, while the test set includes 91 images, representing 2.97% of the total. Although each portion of the dataset contains multiple mask annotations, for the purposes of this fine-tuning process, only bounding boxes will be utilized. This approach focuses on bounding boxes to ensure efficient and effective model training, validation, and testing for the specific task at hand.

D. *Model Training*

In this research, the YOLOv10 variant of the YOLO framework is utilized for brain tumor segmentation and classification. The choice of this variant is intended to enable a thorough evaluation of its performance and effectiveness in tackling the challenges associated with tumor detection and classification.
1) YOLO V10 MODEL
With the aim of further improving a better brain tumor segmentation model, I opted for YOLOv10, which is the latest version in the YOLO family and has enhanced object detection capabilities. I first preprocessed and augmented my annotated MRI images with Roboflow to make my dataset diversified and robust. Then, I split my dataset into training, validation, and test subsets to help me evaluate the general performance of my model. I established the architecture of YOLOv10 and adjusted the hyperparameters like learning rate, batch size, and number of epochs for the optimum performance. During the training process, I continuously monitored the performance metrics such as precision, recall,

and mean Average Precision (mAP), how accurate the model in question was about the correctness and made a few adjustments accordingly. Finally, the trained model was tested to validate it with the test set to assure that the model is reliable enough to identify and segment the tumors in the brain. Thus, the final YOLOv10 model is very precise and has high recall; it can thus be very useful for practical medical image analysis applications.

YOLO predicts bounding boxes at three different scales, allowing it to detect objects of varying sizes. These predictions are made using anchor boxes, which help the model determine the dimensions of the objects. The width and height of the bounding boxes are computed as offsets from cluster centroids, while the center coordinates are predicted relative to the filter's application location. A sigmoid function is used to constrain the center coordinates, ensuring that the predictions remain within the appropriate range.

It enhances performance and effectively deals with objects at various scales. The model excels in the capture of contextual information from multiple scales by incorporating multi-scale feature fusion that increases the accuracy of object detection. Spatial pyramid pooling also aids in extracting information in multiple scales and effectively deals with various sizes of objects. Lastly, up sampling layers are integrated to enable the model to enlarge its feature maps for better detection of smaller objects. In the approach, it has used concatenation operations along with multiple convolutional layers that iteratively improve the object representation and increase the precision of the bounding box predictions.

Below is the implementation of a brain tumor segmentation model using YOLOv10, hosted using Gradio on Google Colab. The project implemented a structured workflow that was guaranteed to be both accurate and accessible to the user in medical imaging. Key steps and technical specifications of the process are given below.

E. Model training on google colab

Platform:

Google Colab was used to leverage the free cloud environment and free access to GPUs and TPUs, which aids in training the deep learning model, YOLOv10. With such environments, training could be done very efficiently without requiring expensive computation resources.

Dataset:

The BraTS (Brain Tumor Segmentation) dataset used was of a publicly available form-their collection of brain MRI scans-developed as such to develop the models. This dataset was both trainable and for validation, owing to its variety of images to ensure non-varying robustness of the models.

Preprocessing:

Several preprocessing steps were performed, including:

- Resizing all images to meet YOLOv10's input requirements.
- Normalizing pixel values to maintain consistency across the dataset.

  Data augmentation techniques, including random rotations and flips, were employed to diversify the training dataset and improve the model's ability to generalize to new, unseen data.

YOLOv10 Configuration:

YOLOv10 was configured with optimized parameters, including:

- Input size and anchor boxes, fine-tuned to detect tumors of various sizes.
- Hyperparameters like the learning rate, batch size, and the number of epochs were meticulously chosen to ensure optimal performance of the model. These parameters were fine-tuned to strike a balance between training speed and accuracy.

Training:

The YOLOv10 model was trained using Google Colab's GPU, significantly reducing training time. During training, key performance metrics, such as Intersection over Union (IoU) and cross-entropy loss, were monitored to ensure precise segmentation of tumor regions. Regular validation helped track model convergence and detect overfitting.

2.6: MODEL DEPLOYMENT WITH GRADIO

After training and validation, the deployment process utilized Gradio, creating an interactive web interface for user engagement.

Integration:

The trained YOLOv10 model was integrated with Gradio, enabling end-users to upload MRI scans and receive real-time tumor segmentation results.

Interface Design:

An intuitive interface was designed, allowing users to:

- Upload their MRI scans.
- View both the original MRI image and the segmented tumor areas.
- Access confidence scores, providing insights into the model's certainty regarding the detected regions.

Real-time Inference:

The inference ability of the model was leveraged to integrate its inference capability into the system, where it could process uploaded MRI images in real-time. It provided real-time accuracy to the segmentation, which makes the model more practical for clinical use.

Visualization:

Built-in tools of Gradio have been used to depict directly on MRI images the tumor regions segmented with distinct overlays on tumor regions and the corresponding confidence scores to ensure clear interpretation by clinicians.

F. Implementatuon details

Dependencies:

All necessary dependencies were installed, including:

- TensorFlow and PyTorch for implementing the YOLOv10 model.
- OpenCV for image processing tasks.
- Gradio for deploying the web interface.

Code Structure:

The project was organized into distinct modules:

- A preprocessing module to manage data augmentation and preparation.
- A training module to handle model training, validation, and evaluation.
- A deployment module for integrating the model with Gradio and managing user interactions. This modular approach facilitated easier maintenance and debugging.

Testing and Validation:

Testing Phase: The system was subjected to rigorous testing with various MRI images such that the performance in terms of segmentation was quite accurate. The correctness of the proposed model has been ensured by using various metrics such as precision, recall, and F1-score.

This all-inclusive approach designed a feasible, intuitive, and reliable solution for the segmentation of brain tumors by relying on deep learning and on the use of an interactive interface with real-world medical imaging applications.

III. RESULTS

This section presents all the essential details for deploying YOLO-based models for brain tumor segmentation and classification. Additionally, it offers a thorough evaluation and analysis of the results, providing insights into the findings and conclusions drawn from this study.

A. Preliminary study

The models used for brain tumor detection were trained and evaluated using the Google Colab Pro environment, which is powered by the A100-SXM4-40GB GPU. The YOLOv10GitHub repositories were cloned to Google Drive for easy access. For evaluation, a dataset containing over 2000 brain tumor images was utilized. Both models were trained with hyperparameters, applying the stochastic gradient descent algorithm with a learning rate of 0.001 across 100 epochs.

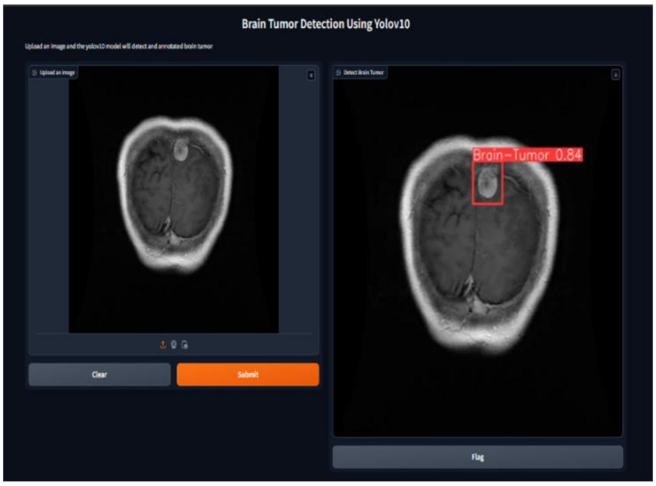

Figure 4.1: Final Result

IV. CONCLUSION

The critical enhanced step in medical imaging analysis is represented by YOLOv10 for the segmentation of brain tumors from MRI images. Enhanced feature extraction, efficient architectures, and sophisticated loss functions are given to YOLOv10 to achieve fast and accurate detection in brain tumors, which are crucial for the early stages of diagnosis and treatment planning. The appeal of the model to clinical environments has been made through real-time processing. However, difficulties in using such models arise concerning the quality of the data involved, computational cost, and generalization of the model. In a nutshell, YOLOv10 seems to be an acceptable solution toward the better detection and segmentation of brain tumors in MRI that would lead to a host of better patient outcomes.

Such findings validate the potential of YOLO models and can be used for the accurate detection of brain tumors, especially in meningioma cases. Beyond these findings into performance characteristics and limitations, there's definitely an open path for further development in computer vision as well as further medical research.

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