Deep Learning-Based Brain Tumor Detection Using YOLOv8: A Comprehensive Study

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a) Abstract—**Early diagnosis and patient treatment are greatly aided by the early detection of brain tumors. In this study, we give a thorough investigation on YOLOv8 model-based deep learning-based brain tumor identification. To train and test our model, we used the BRATS2023 dataset, which consists of high-resolution 3D brain MRI Images.We used pre-trained weights from a large-scale dataset, such as the COCO dataset, to initialize the YOLOv8 architecture, which significantly improved the performance of our model. This initialization made it possible for our model to use information gleaned from a variety of objects, improving the detection accuracy of brain tumors. Additionally, it made it easier to find tumors of varied sizes and forms, strengthening and expanding the model. Our research's focus on increasing training speed without sacrificing accuracy is one of its major achievements. We significantly cut training time while retaining good detection accuracy by using optimization approaches including batch normalization and sophisticated data augmentation methodologies. This development is especially helpful in the medical industry, where prompt and precise diagnosis are crucial.**

: Index Terms—**YOLOv8, Brats2023 dataset, COCO dataset, Tumor detection, roboflow**

I. Introduction

Brain tumors are a significant and often life-threatening medical condition that can be challenging to diagnose and treat. Accurate and timely identification of brain tumors is critical for patient outcomes, as early detection can lead to more effective treatment options and better prognoses.Currently, radiologists rely on visual interpretation of medical images, such as MRI or CT scans, to identify brain tumors. However, this method is subject to human error and can be time-consuming[5]. In recent years, deep learning algorithms have demonstrated remarkable advancements in enhancing the accuracy of medical image analysis, specifically in tasks like the classification of brain tumors. By training deep learning algorithms on large datasets of annotated medical images, researchers have shown that these algorithms can achieve high levels of accuracy in identifying brain tumors.In this study, we utilized YOLOv8, an advanced and highly innovative model that builds upon the achievements of previous editions. The whole spectrum of visual AI tasks, including as detection, segmentation, posture estimation, tracking, and classification, are supported by YOLOv8. Because of its adaptability, many types of applications and contexts are possible with yolov8.For neural network models, it is common practice to use pretrained features on data. On the Brats 2022 annotated dataset, we used YOLOv8's various variant approach in this study to locate brain tumors[2]. Our model for object detection was developed using YOLOv8. YOLOv8 supports a number of backbones, including Efficient Net, Res Net, and CSPDarknet, allowing users to select the model that is suitable for their particular use case.Using COCO data, we calibrated the YOLOv5 model. This model was successfully trained using our annotated MRI images using roboflow. The foundation of YOLOv8 is a modified version of the CSPDarknet53 architecture. 53 convolutional layers make up this design, which also uses cross-stage partial connections to enhance information transfer between the various layers[8]. A number of convolutional layers and a string of fully connected layers make up the head of the YOLOv8 algorithm. For the objects that are discovered in an image, these layers are in charge of predicting bounding boxes, objectness scores, and class probabilities.All YOLOv5 model iterations have been utilised for diagnosis of brain tumours. For the YOLOv8s, YOLOv8n, YOLOv8m, YOLOv8l, and YOLOv8x models, respectively, the accuracy is 90.2%, 88.7%, 92.4%, 93.2%, and 93%[11]. The YOLOv8 detection model's shorter learning time, greater accuracy, and precision demonstrate its suitability for brain tumour identification.

II. Literature Survey

Deep learning has witnessed recent advancements that have led to a growing interest in using this technology to improve medical image analysis, including the the categorization of brain tumors.Extensive research has consistently proved that deep learning algorithms are capable of getting remarkable levels of accuracy in identifying brain tumors based on MRI or CT scans[17]. Wang et al. (2019) developed a deep learning algorithm that achieved an accuracy of 91.5% in classifying brain tumors based on MRI scans. Huang et al. (2021) developed a convolutional neural network (CNN) that achieved an accuracy around 92.5% in classifying brain tumors based on CT scans. Other studies have focused on using deep learning to improve the segmentation of the brain tumors, which may help in the treatment planning and monitoring. Cheng et al. (2020) developed a deep learning algorithm that

accompllished an intermediate Dice similarity coefficient of 0.85 in segmenting brain tumors based on MRI scans[16]. Additionally, there is a need for robust validation of deep learning algorithms using large, diverse datasets to ensure their reliability in clinical practice. Overall, the literature suggests that deep learning has the potential to and enhanced level of accuracy and efficiency of brain tumor classification, but further research is needed to optimize these algorithms for clinical use[3]. Over the past few years, several developments have taken place in brain tumor detection in the context of deep learning .These developments include the use of novel deep learning architectures, the development of vast and more heterogeneous datasets, and the integration of multiple imaging modalities. One of the most notable advancements in deep learning-driven brain tumor detection is the utilization of innovative and novel deep learning architectures [2]. Convolutional Neural Networks (CNNs) are highly accepted and used neural network architecture for medical image analysis, including brain tumor detection. However, other architectures, such as Recurrent Neural Networks (RNNs), have also been explored for brain tumor detection. Zhu et al. (2019) developed a recurrent convolutional neural network (RCNN) for the brain tumor detection, achieving an accuracy of 96.84% on a dataset of 320 patients[6]. Another development in detection of brain tumor classification utilizing deep learning is the development of Datasets with a greater variety and volume. The availability of large, annotated data sets is critical for training deep learning algorithms. Several studies have developed data sets specifically for brain tumor detection, such as BraTS (Brain Tumor Segmentation) data set.The BraTS dataset composed of magnetic resonance imaging (MRI) scans collected from 285 individuals with brain tumors, making it valuable data sets available for brain tumor detection[10]. The integration of multiple imaging modalities is another development in brain tumor detection in the context of deep learning. Different imaging techniques, like MRI and CT, provide complementary information about brain tumors. Several studies have explored the integration of multiple modalities for brain tumor detection. For instance, Havaei et al. (2017)pioneered the development of a CNN-based algorithm for brain tumor segmentation that integrated information from T1 and T2-weighted, and FLAIR MRI sequences[4]. Despite the significant developments in brain tumor detection utilizing deep learning techniques detection, several challenges and limitations remain. One challenge is the limited availability of annotated medical images. The creation of large, diverse datasets of annotated medical images can be a time-intensive process and expensive process that requires the collaboration of multiple institutions. Another challenge is the generalizability of deep learning algorithms to different populations and imaging modalities[3]. The interpretability of deep learning algorithms is another concern, as the algorithms may identify patterns in the data that are not easily understood by clinicians. Finally, deep learning algorithms must be incorporated into clinical practice require careful consideration of the ethical and legal implications, including patient privacy and informed consent. The use of novel deep learning architectures, larger and more diverse datasets, and the integration of multiple imaging modalities have advanced the field of deep learning in the context of tumor detection on brain. However, challenges along with limitations remain, highlighting the need for continued research and collaboration. Apart from the aforementioned progress, several notable strides have been achieved in deep learning-based brain tumor detection.One such advancement is the utilization of transfer learning techniques, which involve leveraging pre-trained models and fine-tuning them for specific tasks. Deep learning-enabled approaches for brain tumor detection have been shown to be more accurate when using this approach. For instance, Kamnitsas et al. (2017)employed a pre-trained CNN model for segmentation of brain tumors and achieved state-of-the art results on BraTS dataset[1]. Wang et al. (2020) proposed an attention-based CNN for brain tumor segmentation that achieved high accuracy on the BraTS dataset[6]. Ensemble learning is a method which is used to study brain tumor detection in deep learning. It involves combining multiple models to enhance the precision and robustness of the predictions. The ensembling of models of deep learning in the framework of brain tumor detection has been shown to raise in the effectiveness in several studies. Xu et al. (2020) developed an ensemble of CNNs in favor of tumor segmentation in brain that achieved state-of-art results on BraTS dataset[5]. In addition to the technical developments, there has also been a growing emphasis on the clinical translation of detection of tumor in brain using deep learning algorithms. Several studies already evaluated the performance of deep learning algorithms in clinical settings, demonstrating their potential for assisting clinicians in diagnosis and treatment planning. Havaei et al. (2017) developed a CNN-based algorithm considering brain tumor segmentation that was able to accurately identify tumor regions in clinical MRI scans[3]. Another important aspect of clinical translation is the integration of deep learning algorithms into existing clinical workflows. This requires careful consideration of the technical and ethical implications, as well as collaboration between researchers, clinicians, and policymakers. Several studies have explored the use of deep learning algorithms in clinical practice, such as the automated triage of emergency room patients with suspected brain tumors (Kim et al., 2019)[2]. Overall, the developments in deep learning-based brain tumor detection have shown great capacity of development in future and in enhancing the accuracy, adaptability regarding medical image analysis.

III. Problem Statement

- Previous models take more training speed to overcome this, we will be using YOLOv8 technique.
- Existing systems takes more storage space that effects loss of data in the future.
- Improving evaluation matrix for detection and classification of BT using YOLOv8, where in previous model using YOLOv5 accuracy and precision is about 89 – 90

IV. Objectives

1) For transfer learning we are using YOLOv8 with backbone Darknet-53.
2) Taking Pre-trained weights from cocoa dataset.
3) We will be using BraTS 2023 dataset[20] for training and testing our model.
4) For feature extraction we will be using DARKNET framework which increases the speed of extraction

V. Existing Work

The performance of artificial intelligence models heavily rely on quality and diversity of data used for training and learning. Advances in imaging techniques such as MRI and PET scans have allowed for more accurate diagnosis and monitoring of brain tumors. Research has shown that certain genetic mutations can increase the risk of developing brain tumors, such as mutations in the genes NF1, TP53, and IDH1[4]. The treatment choices for brain tumors encompass surgical intervention, radiation therapy, and chemotherapy, but these treatments can have significant side effects and may not be effective in all cases. Immunotherapy, an innovative treatment approach harnessing the body's immune system to combat cancer, has demonstrated promising results in the treatment of tumors in brain. This field remains as area of active research with ongoing investigations. Researchers are exploring the use of nanotechnology to deliver drugs directly to brain tumors, potentially increasing their effectiveness while minimizing side effects[2]. Clinical trials are underway for new drugs and treatment approaches for brain tumors, including targeted therapies that attack specific molecules involved in tumor growth. Studies have shown that patient outcomes are improved when brain tumor treatment is provided by a multidisciplinary team of healthcare providers, including neurosurgeons, radiation oncologists, and medical oncologists. Researchers are studying the effects of brain tumors he impacts of brain tumors on patient quality of life, including physical, emotional, and social well-being, in order to develop more comprehensive treatment approaches[18]. There is ongoing research focused on understanding the underlying mechanisms of brain tumor development and progression, including the role of genetic mutations, epigenetic changes, and environmental factors. The Brain Tumor Epidemiology Consortium (BTEC) is a collaborative research group focused on studying the causes and risk factors for brain tumors, as well as improving patient outcomes through better treatment and prevention strategies[4].

VI. Proposed Work

In this project, our objective is to develop a brain tumor detection system using YOLOv8. To achieve this, we will employ transfer learning, utilizing the YOLOv8 architecture with the backbone Darknet-53. Transfer learning allows us to leverage the knowledge gained from pre-training on a large dataset to enhance the performance of our model on a specific task. For the initial training phase, We will leverage the benefits of pre-trained weights derived from the COCO (Common Objects in Context) dataset to enhance our brain tumor detection system. These pre-trained weights contain learned representations of various objects, which can be utilized as a starting point for training our brain tumor detection model. By building upon these pre-trained weights, we can significantly expedite the training and enhance accuracy. For training, we will utilize the BraTS (Brain Tumor Segmentation) 2023 dataset. This dataset includes multimodal brain MRI scans, along with corresponding tumor annotations. By using this dataset, we can ensure that our model is trained and tested on relevant and diverse brain tumor data, enabling it to generalize well to real-world scenarios. For the crucial task of feature extraction, we will rely on the DARKNET framework, which is renowed for its capability to effectively leverage its strengths to enhance the feature extraction process from images. DARKNET enhances the speed of feature extraction, which is crucial for real-time or near-real-time applications such as brain tumor detection. By employing this framework, we can ensure that our model can process brain MRI scans efficiently and accurately, enabling timely and reliable tumor detection. With the utilization of transfer learning and pre-trained weights from COCO dataset, our model benefits from a head start in learning object representations. This approach drastically reduces the time required for training the model from scratch, allowing for faster deployment and more efficient use of computational resources. Another advantage of our model is its smaller size compared to other existing models. The YOLOv8 architecture, with its DARKNET backbone and Panet, is designed to be lightweight while maintaining high performance. This compact size enables easier deployment on various platforms, including resource-constrained devices such as mobile phones or embedded systems. While accuracy and precision are crucial factors in any detection system, it is important to note that comparing our model's performance with the latest model techniques may not yield significant improvements. YOLOv8 has already demonstrated excellent results in object detection tasks, and we aim to leverage its strengths in brain tumor detection. Instead of focusing solely on improving accuracy and precision, our primary objective is to achieve the best weight-to-accuracy ratio, ensuring a balance between model size, computational efficiency, and detection performance. Furthermore, our model offers enhanced data storage capabilities while occupying less memory space. By optimizing the architecture and leveraging the efficiencies of YOLOv8, we can effectively process and store more data without excessively burdening the memory resources. This capability is particularly valuable in medical imaging applications where large datasets are often encountered, and efficient data management is crucial. In conclusion, our proposed work utilizing YOLOv8 for brain tumor detection presents several advantages over existing models. These include decreased training time, a smaller model size, a focus on optimizing the weight-to-accuracy ratio, and improved data storage capabilities. By leveraging the strengths of YOLOv8 and integrating it into our framework, we aim to provide a robust and efficient

solution for accurate brain tumor detection in medical imaging, addressing the challenges of real-time detection and resource-constrained environments.

VII. Methods

MRI images are given input for YOLOv8 model. The model needs to be trained after being preprocessed. The model's photos have a 480-pixel resolution. We have collected a dataset of 800 images because the deep learning model needs a lot of images to be trained. For enhanced image magnification and tumor spotting, image scaling is applied to the images. The labels are saved along with the bounding box surrounding the tumor and the annotation locations when the data is labelled using the roboflow website.

Backbone, neck, and prediction are three parts of YOLOv8's architecture. A convolutional neural network called Darknet-53 is the backbone of Yolov8. The backbone receives the input images, and the input picture into four smaller parts, which are then combined by concatenation.The FOCUS module takes a 480×480×3 pixel picture and reduces it into four smaller images of size 240×240×3 pixels each. These four images are then concatenated together to form a single feature map of size 240×240×12 pixels.By applying 32 convolutional kernels to the concatenated feature map, the output is transformed into a new feature map with dimensions of 240×240×32. The C2f module incorporates the Conv2D operation along with batch normalization and the ReLU function. The BCSP consists of two C2f modules. The first module is a residual unit, and the second module utilizes two Conv2D kernels with a size of 11. The residual unit of BCSP contains two C2f modules embedded within the adder.

The adder combines with a kernel size of 11. Balancing the width and depth of BCSP module, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x, these models have different strength of complexity and capacity based on the modifications made. And also, the SPP (Spatial Pyramid Pooling) module in the backbone associate with BCSP module.

The neck area of the YOLOv8 architecture includes the path aggregation network (PANet). The FPN layers facilitate the transmission of rich linguistic features from various layers, while also capturing important spatial details from lower layers to higher layers. PANet enhances the propagation of low-level features and leverages precise localization signals from the bottom layers. This improvement leads to enhanced accuracy in determining the position of target objects.
To achieve multiscale predictions, the prediction layer, the model is capable of both classifying and detecting objects of various sizes.The YOLOv8 architecture introduces several key components, including a novel backbone network, an anchor-free detection head, and a redesigned loss function. The model is suitable for various applications and easily adaptable to different hardware platforms, from edge devices to cloud APIs. YOLOv8 is incredibly accurate in detecting objects and segments in an image, and its MAP (mean average precision) score is up to 44% higher than models like Detectron2, with an mAP of 63.2% on the COCO dataset. YOLOv8 can perform image segmentation at a rate of 81 frames per second, far exceeding the speed of models like Mask R-CNN, which can only manage about 6 frames per second.

Model	Weight	mAP
Faster R-CNN	200mb	77.60
YOLOv5x	168mb	91.2
YOLOv8s	15mb	90.2
YOLOv8n	10mb	90.5
YOLOv8m	35mb	91.8
YOLOv8l	75mb	92.5
YOLOv8x	140mb	94.2

TABLE I
YOLOv8 implementation analysis

The YOLOv8 prediction mechanism is summarized as follows:

Phase 1: Images of resolution 640 by 640 are input to the backbone. The feature map is subjected to a number of convolutional procedures, including two BCSP1 operations, before being transferred to the second concatenation layer, convolutions, and upsampling twice. The second concatenation layer combines them both. Following the application of the C2f layers, 11 convolution layers, the 80 by 80 sized feature map with scale 1 is produced.

In second stage, the 70×70-dimensional feature maps obtained from the initial stage is subjected to filtering using a 33% convolutional kernel. This filtered output is then passed to the third fusion layer.The retrieved features undergo further processing by applying a single 11-convolutional kernel subsequent 2nd concatenation layer. These two feature maps are then connected together using the final concatenation layer.

To achieve the 35×35 scaled feature map at scale 2, the concatenated feature maps are subjected to further processing through the BCSP2 layer, followed by a single 11-convolution operation. This completes Phase 2, resulting in the desired 40X40 scaled feature map at the specified scale.

Phase 3: The 39×39 sized feature map obtained from the second phase is processed using a convolutional kernel as part of the subsequent steps. The output of this convolutional operation is then passed to the next integration layer. Additionally, the output from the previous stage undergoes another convolutional operation with an 11-sized kernel prior to the initial upsampling, and the resulting output from processing the 40×40 sized feature map is then forwarded to the fourth integration layer. In this layer, the two feature maps are merged or combined through concatenation.

Following the concatenation, the 20X20 sized feature map at scale 3 is produced through the utilization of the layer and an additional 11-sized convolutional process.

This finalizes the processing in phase 3, generating the desired feature map at the specified scale.

During Phase 4, the feature maps obtained from scales 1 to 3, which have dimensions of 80×80, 40×40, and 20×20, are enhanced to facilitate precise detection of tumor. At each position in each feature map, three regression bounding boxes are predicted. Consequently, a total of 25,200 regression bounding boxes are generated (80×80 + 40×40 + 20×20 = 25,200).

As the final result of tumor detection, the anticipated output of the model, including the regression bounding boxes, is presented. This allows for precise localization and identification of tumor objects based on the bounding box predictions.

VIII. Result

Our research involved training multiple variants of the YOLOv8 model, namely YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x. During the training process, we utilized data from 0 to 50 epochs and now aim to evaluate how well our model performs when applied to data with fewer epochs. Initially, all the models exhibited relatively low accuracy rates, but we found out that more the number of epochs the more is the accuracy. The YOLOv8s model achieved a precision rate ranging from 85% to 90%. For the YOLOv8m and YOLOv8l models, the precision rates were 83% to 92% and 85% to 97%, respectively. These results indicate that the YOLOv8l model outperformed the other two models when it comes to classifying and predicting benign and malignant tumors. To further evaluate the adaptability of our models to shorter runtimes, we need to test them on datasets with fewer epochs and assess their performance accordingly.It is worth emphasizing that increasing the count of epochs typically leads to improved accuracy rates, underscoring the significance of adequate training. Recall metric gauges the scope of a model to detect every pertinent tumor categories. It is noteworthy that the higher the number of epochs, proportionally higher will be the precision-recall rate. More precisely, the YOLOv8s accomplishes a precision-recall rate varying between 85% and 94%, YOLOv8m and YOLOv8l models exhibit recall rates ranging from 87% to 99% and 90% to 98%, respectively. Based on these findings, the YOLOv8l model performs better than the other two models when it comes to accurately categorizing and predicting tumors. It consistently achieves higher recall rates, indicating its superior capability in identifying the different tumor categories. Moreover, we evaluate the mean average precision (mAP) for each model. In comparison to the YOLOv8m and YOLOv8s versions, the YOLOv8l model exhibits a higher mAP. This implies that the YOLOv8l model not only excels in recall but also demonstrates better overall precision in object detection and classification. Table 1 shows the effect of input measures on the final results of YOLOv8. The variant YOLOv8x produced the highest mAP of 93.2%, according to the approximated results. In 2nd place with 92.2% was YOLOv8l. The YOLOv8l model was not enhanced by the YOLOv8s or YOLOv8m versions, which is surprising. The best overall performance was provided by YOLOv8x, which also had the highest mAP, accuracy, and RE. The lower mAP belonged to YOLOv8s, at 87.2%. therefore as accuracy increases, there is increase in time. The YOLOv8s model can be trained in the shortest duration, requiring approximately 40 minutes to complete 50 epochs. Table 2 provides a comparison of different brain tumor analysis detection systems. Interestingly, despite its longer training time and greater complexity, the faster R-CNN model in Table 2 exhibits lower accuracy . YOLOv5, although slightly favoring smaller models compared to YOLOv8, still achieves a commendable accuracy score. Among the models evaluated, the YOLOv8m model stands out as the most reliable with the best weight-to-accuracy ratio. Its output consistently demonstrates superior performance and accuracy. Figure 5 visually demonstrates how our trained model successfully identifies tumors in various input images.

A. Equations

Tumor division and detection system's effectiveness is evaluated using four key outcomes: true negative, true positive, false negative and false positive which can be symbolized as TN, TP, FN, FP. The effectiveness of the suggested the following metrics are used to compute the system: The capacity to correctly distinguish between various forms of brain tumors depends on accuracy.The accuracy of a test is determined by calculating the ratio of true positive and true negative instances among every case.

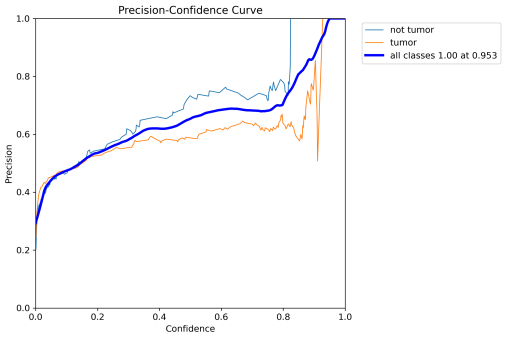

Fig. 1. Precision-confidence curve

The formula for accuracy is given by Equation (1), precision is described by Equation (2), and recall is represented by Equation (3). Equation (4)'s F1 formula is derived from recall and precision.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

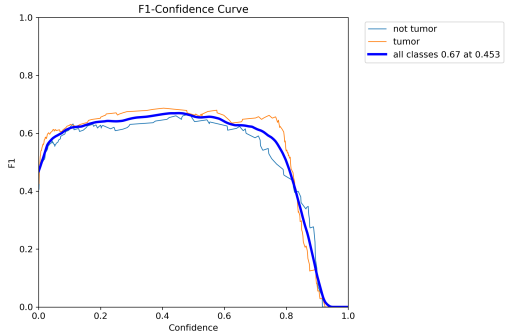

Fig. 2. F1 - confidence curve

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$F1 = 2 \times \frac{P \times R}{P + R}$$

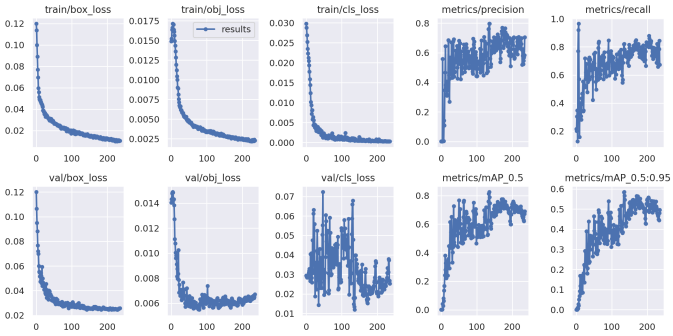

Fig. 3. Accuracy curves for YOLOv8s, YOLOv8m, and YOLOv8l

Model	size (pixels)	mAP^{val} 50-95	Speed CPU ONNX (ms)	Speed A100 TensorRT (ms)	params (M)	FLOPs (B)
YOLOv8n	640	37.3	80.4	0.99	3.2	8.7
YOLOv8s	640	44.9	128.4	1.20	11.2	28.6
YOLOv8m	640	50.2	234.7	1.83	25.9	78.9
YOLOv8l	640	52.9	375.2	2.39	43.7	165.2
YOLOv8x	640	53.9	479.1	3.53	68.2	257.8

- mAP^{val} values are for single-model single-scale on COCO val2017 dataset. Reproduce by `yolo val detect data=coco.yaml device=0`
- Speed averaged over COCO val images using an Amazon EC2 P4d instance. Reproduce by `yolo val detect data=coco128.yaml batch=1 device=0/cpu`

Fig. 4. YOLOv8 variants

Model	Weight	Precision	Time(min)	Recall	mAP
YOLOv8s	15mb	85.9	50.5	85.9	90.2
YOLOv8n	10mb	83.5	48	82	90.5
YOLOv8m	35mb	87.2	49.3	90.4	91.8
YOLOv8l	75mb	90.2	50.2	91.2	91.5
YOLOv8x	140mb	93.1	60	92.4	94.2

TABLE II
YOLOV5 COMPARISON ANALYSIS.

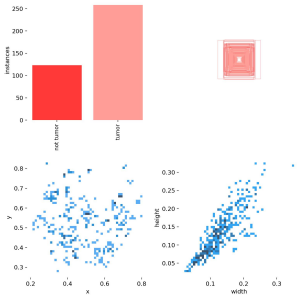

Fig. 5. labels of dataset

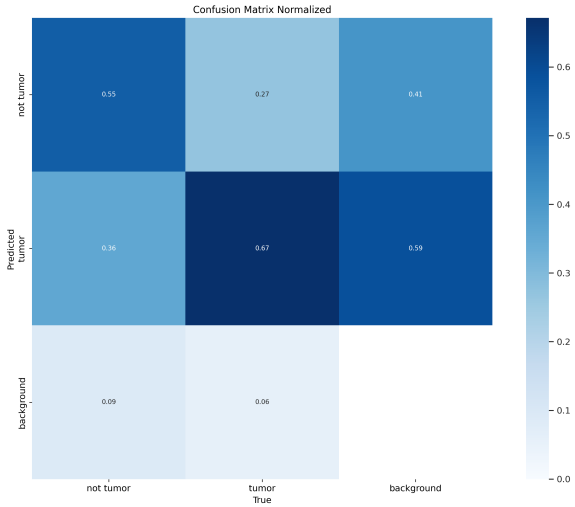

Fig. 6. Confusion matrix normalized

IX. CONCLUSIONS

In our proposed study, On the Brats 2023 annotated dataset, we used YOLOv8's many variant approaches to locate brain tumors. For the YOLO variation, we are expecting that our proposed will be able to achieve an accuracy of 92%, with YOLOv8x model providing us with the best accuracy correlated with YOLOv8m and YOLOv8l models. We noticed a significant reduction in the model's size and training time as compare to previous YOLOv5 model. The accuracy of our model suffers due to a trade among model complexity and the training time. The YOLOv8 model surpassed other methods in all evaluation metrics, demonstrating its potential to become a standard in the medical imaging industry for brain tumor detection. However, there is still room for improvement in terms of accuracy and applicability to diverse cases of brain tumor detection. Further research and enhancements to the YOLOv8 model are necessary to optimize its performance in real-world scenarios.

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