Identification and segmentation of tumor using deep learning and image segmentation algorithms

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ABSTRACT

Brain tumor is a typical mass of tissue that develops when cells proliferate and divide excessively. Brain tumor perception requires a great deal of work and experience from the medical professional in order to identify the tumor's precise location. If a brain tumor is not discovered in a timely manner, it affects a person's ability to function normally and raises the death rate. This study focuses on tumor segmentation and tumor detection using magnetic resonance imaging (MRI) images. This work helps the medical professional to precisely identify the tumor location and segmentation process provides cost effective data storage. The YOLOv8s model is utilized for tumor identification, while the image segmentation technique is employed for tumor segmentation. The images come from an open-source dataset used for research, and Roboflow 100 transforms them into .yaml files that are congenial with YOLOv8s. To train the model the dataset is split into training, validation and testing. Proposed model consists of dataset which comprises 639 images, of which 453 are utilized for training, 122 for validation, and 64 for testing, resulting in a ratio of 71:19:10. The dataset is subjected to preprocessing and augmentation. The suggested model performance is assessed depending on the parameters like precision, recall, mAP50 and mAP50-95.

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1. INTRODUCTION

Many diverse cognitive, sensory, and motor processes that are essential to human life and experience are done by human brain, an incredibly complicated and complex organ [1], [2]. The human anatomy consists of millions of cells, and as per our understanding of biology, cells have the natural ability to proliferate, grow, and divide to create new cells. However, certain extrinsic factors can disrupt this balance, leading to uncontrolled cell growth and the formation of tumors. The rising mortality rates in the infants and adults, and specifically in the elderly is due to the existence of tumor. As claimed by the GLOBOCON the brain tumor cases was 308,102 and 2.5% of people died with the tumor [3], [4]. Tumors can be assorted into two kinds: Benign tumors do not spread to other cells, making them non-cancerous and comparatively less dangerous. Malignant tumors, on the other hand, are made up of cancerous cells, are extremely dangerous, and are more likely to spread to nearby cells and tissue. Essentially, a tumor is an accumulation of cells that form a tissue, but unlike healthy cells, they lack regulation of growth and exhibit an uncontrolled proliferation rate [5]. The early exposure of the tumor is very important to decrease the mortality rate. Manual detection is very tedious, time consuming and requires expertise in it so automated methods is preferred.

The traditional method for the diagnoses of the brain tumor over the decades is ML based techniques like Supervised learning (ANN, SVM [6], DT, KNN and LVQ) and Unsupervised learning (FCM, K-Means, SOM, PCNN, FPCNN, Hierarchical Clustering) and deep learning (DL) based techniques like convolutional neural network (CNN) [7], deep convolutional neural network (DCNN), VGG19 [8], and auto-encoder techniques. Now-a-days, DL techniques are more explored by the researcher due to its fast and accurately detection rates. One of the various DL techniques, you only look once (YOLO), is utilized for real-time data recognition with excellent accuracy even in complicated settings, making it appropriate for magnetic resonance imaging (MRI) image analysis [9]. There are different versions of YOLO algorithm YOLOv2, YOLOv3, YOLOv4, YOLOv5, YOLOv6, YOLOv7 and recently YOLOv8. These entire algorithms can be used for detection of tumor but still there is a lacuna in systematic and fast detection. As YOLOv8 algorithm is a improvised version of remaining models it is used to achieve better results compared to others [10]. The core of the YOLOv8 model is the CSPDarknet53 feature extractor, which is followed by the C2f module in place of the conventional YOLO neck architecture. This helps with object recognition that is quicker and more precise [11], [12]. Hospitals store the patient's information in the cloud to maintain the patient medical history [13]. Continuous storage of all the medical data into the cloud may increase the storage cost [14]. Image segmentation might be used to effectively reduce the cloud storage space of medical images. Image segmentation is delineation of tumor region on medical images using any algorithm [15]. Thus, the scientific goal of this investigation is to explore the YOLOv8 model for brain cancer detection and segment the infected area using image segmentation algorithm. Further, segmented image will be saved in the cloud using patient id and location of image to save the cloud space and in turn cost of storage will be reduced. The pursuance of the prototype is evaluated based on dataset used, number of epochs it takes, precision, recall, mAP50, mAP50-95 and image size after segmentation.

Muhammad Irfan Sharif *et al.* [16] used lesion enhancement, feature extraction and selection for classification, localization, and segmentation. It comprises the four stages of the proposed model. To reduce noise, a homomorphic wavelet filter is employed. The YOLOv2-inceptionv3 model is intended to serve in tumor localization. In terms of brain lesion location, segmentation, and classification, the model produced prediction values higher than 0.90. Oksuz and Gullu [17] used YOLOv2 single stage DL model for the brain tumor tissue detection. Ali *et al.* [18] proposed two-stage paradigm for medical image analysis. Classification using the GoogleNet model is the first step. Tumor localization using YOLOv3 is the second step. The DICOM dataset was utilized in this instance. A total of 1000 pictures were utilized, of which 700 showed tumors and 300 showed normals. 97% object classification perfection was attained using the GoogleNet model. 81.9% accuracy on training dataset and 94.3% accuracy on the testing dataset is obtained using YOLOv3 for tumor localization. The YOLOv4 small model is used by the researcher in [19] to train tumor identification. The tagged images in the dataset were retrieved from the figshare data repository. 80:10:10 ratio of the dataset is set aside for testing, validation, and training, correspondingly. Preprocessing methods were applied to refine the image's attributes. For raw data, the model yielded an average mean precision (mAP) of 0.8074, whereas for processed data, it was 0.8324. Using YOLOv5, Paul *et al.* [20] investigates brain tumor segmentation. The BRATS 2018 dataset, which incorporate 1992 photos, was the dataset utilized for the study. The prototype was trained on 720 photos, and it was validated on 180 images. With an precision of 85.95%, the model demonstrated good performance. Shelatkar *et al.* [21], YOLOv5 was used to detect and categorize brain tumors. The BRATS 2021 dataset from the RSNA-MICCAI brain tumor radio genomic categorization is used. The model offers an accuracy of 88%. Abdusalomov *et al.* [22] for the precise identification of pituitary gland tumors, gliomas, and meningiomas, uses YOLOv7. For training, the model uses a publically accessible dataset that includes 2500 photos of non-tumorous cases, 2658 images of pituitary tumors, 2,582 images of meningiomas, and 2548 images of gliomas. To enhance YOLOv7's feature extraction capabilities, the convolutional block attention module (CBAM) is incorporated, focusing on salient regions associated with brain cancer. Additionally, the model integrates the spatial pyramid pooling fast+ (SPPF+) layer into its fundamental architecture to enhance sensitivity. Furthermore, the bidirectional feature pyramid network (BiFPN) is employed for multi-scale feature fusion, efficiently capturing tumor-relevant information. With these enhancements, the proposed model achieves notable overall precision compared to existing models".

Passa *et al.* [23] proposed YOLOv8 algorithm along with data augmentation can detect the brain tumor (meningioma, glioma and pituitary) efficiently. There are three categories of brain tumors in the dataset, which consists of 3061 T1-weighted contrast-enhanced images. Testing, validation, and training sets of data are separated apart. 496 training, 141 validation, and 71 testing pictures are available for meningioma.

There are 143 testing, 285 validating, and 998 training images for gliomas. 186 validating images, 83 testing images, and 651 training images are accessible for Pituitary. The data preprocessing is done like data normalization, removing the redundant data and data conversion is done in Roboflow. Data augmentation like flip, 90^0 rotate, crop, rotation, shear, grayscale, brightness, exposure, blur and noise is applied. Yolov8s of hyperparameter configuration with the input size of 640×640, 100 epochs and batch size of 8 is the utilized for training the data. Researcher analyzed pursuance of the model for both condition with data augmentation and without data augmentation. The model performs better with augmentation yielding a precision as 0.942, recall as 0.908, mAP50 as 0.952 and mAP50-95 as 0.733. Mercaldo *et al.* [24] also used YOLOv8s algorithm for the disclosure of the brain cancer. The real-world data utilized in this study came from a source that is openly accessible for academic usage. There are 300 brain MRIs in total, of which 210 are used for training, 60 for validation, and 30 for testing. The dataset includes a variety of tumor forms, including pituitary, glioma, and meningioma. The images were resized to 512×512 pixels, the number of epochs used is 50 and batch size is 16. The data augmentation methods like 90^0 clockwise, 90^0 counterclockwise and upside down is applied. The models performance is evaluated based on the precision (0.943), recall (0.932), mAP50 (0.941), specificity (0.938) and mAP50-95 (0.421). Vineela *et al.* [25] used YOLOv8 algorithm to detect the brain tumor. They have used freely available dataset which consist of 1923 images out of that 87.5% of images are meant for training, 8.3% are meant for validation and 4.2% for testing. The pursuance of the model is evaluated using the parameter precision, recall, mAP50, mAP50-95,box loss, class loss and dfl loss. Predicted the tumor with a accuracy of 96.4%. According to Hashemi *et al.* [26] the data efficient image transformer model (DeiT) and vision transformer models from a fine-tuned ResNet152 as a teacher in the classification phase can improve YOLOv8n performance. They made advantage of the national brain mapping lab (NBML), which has 81 patients, 30 of whom have tumors and 51 of whom are healthy. Chen *et al.* [27] photoacoustic imaging (PAI) is used instead of MRI images and to classify-detect benign tumor and malignant tumor YOLOv8-MedSAM model is used. Ren *et al.* [28] multiscale dilated attention and multi-head self attention are integrated inside the YOLOv8 network in the proposed enhanced lesion detection model DHC-YOLO. For improved features, it also incorporates the feature pyramid network. The datasets for esophageal cancer, colonic polyps, and brain tumors are used to evaluate this approach. The accuracy of the brain tumor dataset was 88.3%.

However, after a thorough review of the literature, we can conclude that YOLOv8 model may provide a higher level of perfectness in tumor detection then YOLOv2, YOLOv3, YOLOv4, YOLOv5 and YOLOv7 without any additional enhancer and feature extractor model, which might slow down performance. In all the above articles, the researcher has only concentrated on the localization, detection and classification of brain tumor but storing images in cloud with the compressed format is not discussed. In proposed research, YOLOv8 is used for precise detection of tumor and image segmentation is done to reduce the data storage in cloud. This research paper is formulated as: section 1 contains introduction and survey of the existing work, section 2 contains methods and implementation, section 3 contains result and discussions and section 4 contains conclusion and future scope.

2. METHODS AND IMPLEMENTATION

The tumor's size, form, and proper location can all fluctuate, making manual analysis quite challenging from the MRI image. To aid the medical community in accurately and conveniently diagnose tumor and segment the tumor region the proposed method might be used. The suggested approach utilizes the most recent version YOLOv8s model to identify tumor, which are segmented using image segmentation techniques and the segmented image is stored in the cloud using the patient id and position of the tumor for the future reference. Before applying YOLOv8s model image preprocessing is done which includes conversion of MRI image into the .yaml file which is appropriate for the model, resizing the image, removing repeated images, auto orientation and data augmentation. The effective evaluation of the prototype is done by using the metrics like precision, recall, mAP50, mAP50-95. Figure 1 depicts the block diagram for the brain tumor identification using YOLOv8s.

2.1. Magnetic resonance image

A non-invasive imaging technology capable of generating detailed three-dimensional anatomical images is commonly employed for disease detection, diagnosis, treatment and monitoring. This technology relies on advanced mechanisms to stimulate and detect alterations in the rotational axis of protons within the water constituting living tissues. This is best suited to detect tumor because they create image with high resolution that clearly show the brain structure, size and location. So here we are using MRI images to detect tumors.

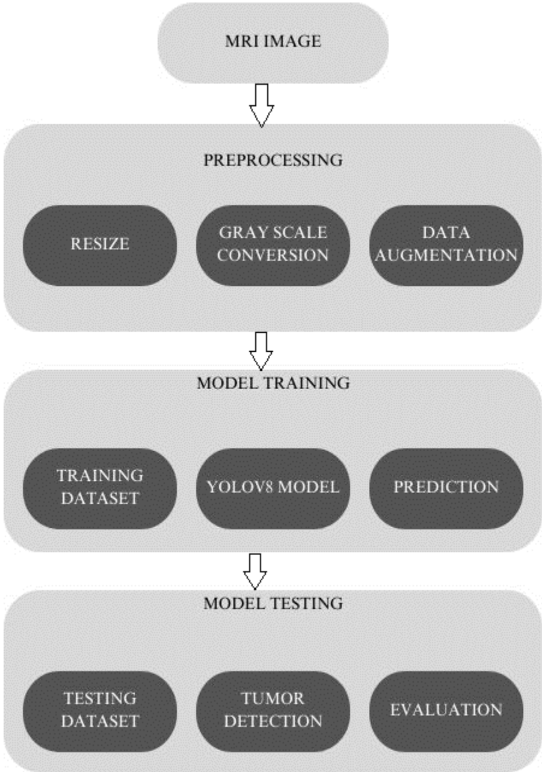


Figure 1. Brain tumor detection using YOLOv8s model

2.2. Dataset

The dataset used in proposed method is freely available open-source dataset which is their for-research purpose, the link of the dataset is given here [29]. The dataset consists of 639 images which consist of tumorous, non-tumorous, and also various tumor types like meningioma, glioma and pituitary. For training the model the data is split into training, validation and testing. In our dataset we have taken 453 images for training, 122 for validation and 64 for testing in a ratio of 71:19:10. The image size is taken as 640×640. On the dataset, image preprocessing like data conversion to the suit the format of YOLOv8s, removing repeated images, resizing the image and grey scale conversion is applied using Roboflow application. The next step is data augmentation.

2.3. Data augmentation

A ML or DL model's efficacy is heavily relying on quality, quantity, and relevance of training data. The major challenge in implementing machine learning application is the cost and time taken to collect the data. Augmentation methods were developed to answer this problem. To enlarge the size of data artificially and to create a new dataset within existing one the augmentation method is used. The motive of this rapid and effective approach is to enhance a model's capacity to induce, novel, unseen samples by diversifying the training data. In various areas of research, including signal processing, computer vision, speech processing, and natural language processing, augmentation is becoming more popular.

Approaches such as noise addition, data rotation and scaling intentionally augment the dataset size. Additionally, modifications such as zooming, horizontal or vertical flipping, and brightness adjustments contribute to enlarging pictures. By employing these methods, data augmentation effectively increases the dimensionality of the training data, thereby increasing the performance and flexibility of ML and DL models. Operations like rotation -15^0 to $+15^0$, gray scale upto 15% and noise addition is used on this dataset.

2.4. YOLOv8

YOLOv8, the latest and most sophisticated YOLO model, may be used for applications including object detection, instance segmentation, and image classification. YOLOv8 was created by Ultralytics, the same firm that created the popular and industry-defining YOLOv2, YOLOv3, YOLOv4, YOLOv5, YOLOv6, and YOLOv7 models. Keeping the general structure as YOLOv5, YOLOv8 makes modifications to CSP Layer, which is also called as C2f module. "Cross-stage partial bottleneck with two convolutions," as this module is short called, efficiently combines contextual information with high-level characteristics to increase detection accuracy. The anchor-free model of YOLOv8, which has a decoupled head and allows each branch to focus on its own job, improves overall accuracy by addressing objectness, classification, and regression tasks individually.

YOLOv8 computes objectness score, or probability of an object being present within a bounding box, using the sigmoid function. For class probabilities, indicating the likelihood of an item to be owned by each class, the "softmax function" is utilized. YOLOv8 enhances detection efficiency, especially for small objects, by integrating distance feature level (DFL) and complete intersection over union (CIoU) loss functions for bounding box loss. Additionally, "binary cross-entropy" is enforced to mitigate classification loss.Furthermore, YOLOv8 presents YOLOv8-Seg, a semantic segmentation model. This model departs from the conventional YOLO neck design by having a C2f module and a CSPDarknet53 backbone. For the sake of anticipate semantic segmentation masks, YOLOv8-Seg combines two segmentation heads. YOLOv8's detection heads have the same five modules and prediction layer as the identification heads in YOLOv8. On several object identification and semantic segmentation benchmarks, YOLOv8-Seg regularly delivers state-of-the-art performance while retaining exceptional speed and economy [11], [12]. YOLOv8 simplifies installation through a PIP package and provides a command-line interface (CLI) for execution. It offers various integrations for deployment, training, and labeling tasks. Figure 2 shows the generalized architecture of the YOLOv8. From object detection to more complicated tasks like instance segmentation, pose/keypoints identification, oriented object recognition, and classification, these models are made to meet a variety of needs. There are five versions of YOLOv8: In terms of parameter count and floating operations, YOLOv8n (nano) is the smallest model. YOLOv8s (small) is the next smallest model, followed by YOLOv8n, YOLOv8m (medium), YOLOv8l (large), and YOLOv8x (extra large) [23], [24]. The suggested approach makes use of YOLOv8s as it strikes a compromise between having more parameters and FLOPs than YOLOv8n while remaining comparatively quick in comparison to the bigger models.

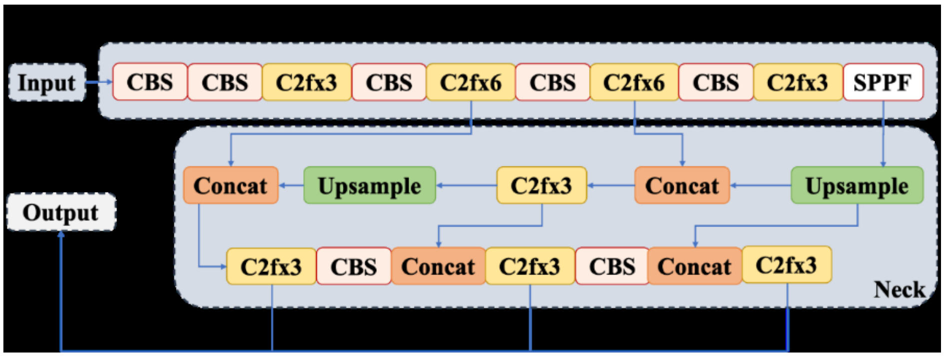


Figure 2. YOLOv8 architecture

2.5. Performance evaluation

The pursuance of the prototype is intent on using parameter like dataset used, number of epochs to train the data, precision, recall, mAP50 and mAP50-95. After training the model validation of the prototype is performed using the confusion matrix. It contains true positives in which the model precisely predicts a label that is consistent with reality. False positive events indicate that prototype has predicted a label that wasn't in the ground truth. When a model predicts a negative label, it is true negative since it is compatible with the ground truth not having that label. When a model predicts a label that is really a element of the ground truth, it is apparently producing false negative occurrences [23].

Precision is a measure that expresses the percentage of correct predictions within the total number of predictions and is utilized to assess how accurately the system responds to user requests. Correctness of the model is assessed by this metrics. Conversely, recall is the amount of genuine positives to all items. For instance, if an image had 100 trees and the model properly recognized 75 of them, then recall is 75%. The subsequent (1) and (2) shows the formula for precision and recall.

$$Precision\ = True\ Positive/True\ Positive\ +\ False\ Positive \quad (1)$$

$$Recall/Sensitivity\ = True\ Positive/True\ Positive\ +\ False\ Negative \quad (2)$$

The mean average precision (mAP) is the average of the average precision (AP) for each class. Recall values between 0 and 1 are used to calculate average accuracy. A number of parameters influence the mean average precision calculation, including the intersection over union (IOU), precision, recall, precision-recall curve, and average precision (AP). The amount of overlap between two bounding boxes is measured using the IOU metric. A number between 0 and 1 represents the IOU value, where 0 indicates no overlap and 1 indicates a perfect match or complete overlap [24]. The metrics mAP50 assess accuracy at the 0.5 or 50% IOU threshold. All that matters is that if there is more than 50% overlap between the anticipated and ground truth bounding boxes, the process is deemed successful. In a similar way, mAP50-95 denotes IOU between 50 and 95. In (3) and (4) which is shown below is intended for the calculation of the IOU and mAP.

$$IOU = Area\ of\ Intersection\ /\ Area\ of\ Union \quad (3)$$

$$mAP = 1/N\ \Sigma\ Ni = 1\ APi \quad (4)$$

2.6. Implementation

The work is implemented on Google Colab using Python language. The system specification for training the model are Ultralytics YOLOv8.0.196, Python 3.10.12, torch- 2.3.0+cu121 and CPU (Intel Xeon 2.20GHz). The dataset considered for evaluation consist of the 639 images out of which 453 images were for training, 122 images were meant for validation and 64 images were meant for testing in a ratio of 71:19:10. The Table 1 specifies the engine or the trainer specification in detail. The images utilized for training purpose has following specification.

Table 1. Trainer specification

Configuration	Value
Algorithm used	YOLOv8s
Image size	640×640
Batch size	16
Patience	50
epochs	20

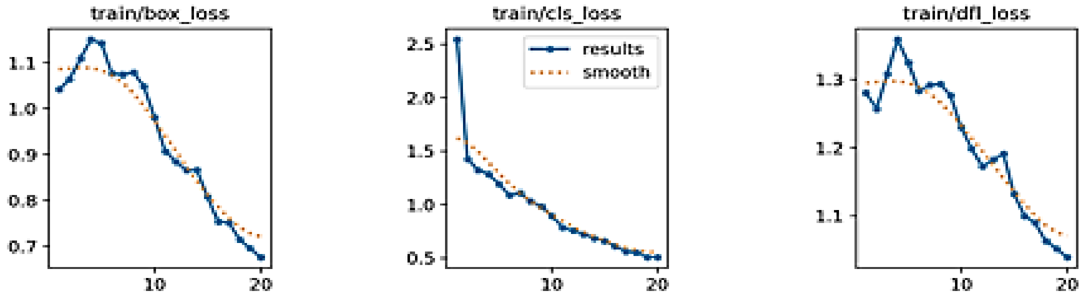
3. RESULT AND DISCUSSION

Tumor detection capability of the YOLOv8 is evaluated using parameter such as precision, recall and mAP50 and mAP50-95. The prototype detection findings are examined to evaluate how well it detects tumor. The prototype was trained for 20 epochs, taking instance of 5,10,15 and 20 and evaluating values of precision, recall, mAP50 and mAP50-95 for each instance. The model has 168 layers, 11125971 parameters, 0 gradients and 28.4 GFLOPS. We started training for 5,10,15,20 epochs respectively and noted the values of the precision, recall, mAP50 and mAP50-95. The epochs were stopped for 20 because after 20 epochs there was not much change in the values of precision, recall and mAP. The following Table 2 shows the outcome of distinct epochs.

Table 2. Output of distinct epochs

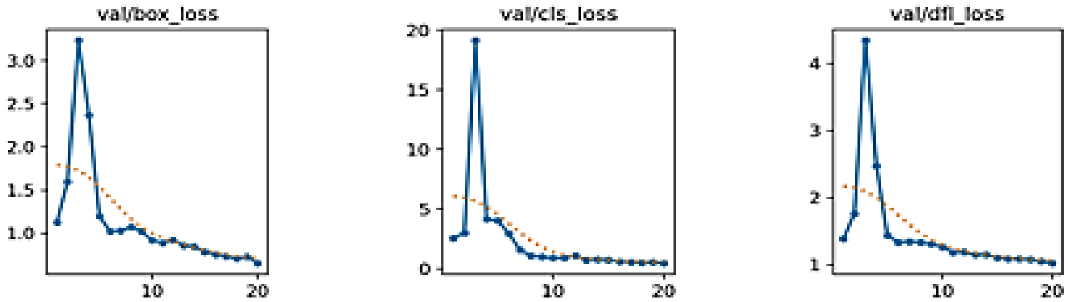
Epochs	Precision	Recall	mAP50	mAP50-95
5	0.759	0.733	0.802	0.595
10	0.933	0.915	0.947	0.756
15	0.939	0.915	0.961	0.78
20	0.944	0.921	0.969	0.811

The Figure 3 shows the training losses and Figures 3(a)-(c) shows the box_loss, cls_loss, dfl_loss respectively. The use of bounding boxes to detect several items in a image is shown in Figure 3(a). Finding the error between the expected and ground truth bounding boxes is the main goal of the box loss function. The model's ability to forecast the bounding boxes with accuracy will increase as these losses diminish across epochs. The objectness loss, or how the objectness and class scores behave in the model, is shown in Figure 3(b). Class score indicates the conditional probability of a certain class, whereas objectness relates to the model's confidence in the presence of an object inside the bounding box. The objectness and class score are multiplied to get the overall confidence curve. As the graph illustrates, objectness should ideally fall towards zero as the number of epochs increases. In relation to categorization, Figure 3(c). Determining if an object is in a picture and identifying its class are the two components of categorization. The prototype's ability to categorize inside the anticipated boundary boxes is depicted in the graph. The validation losses are shown in Figure 4, and the validation box_loss, cls_loss, and dfl_loss are shown in Figures 4(a)-(c), respectively. The performance matrix of algorithm is shown in Figure 5, where precision, recall, mAP50, and mAP50-95 of the training dataset are shown on the graph's y-axis in Figures 5(a)-(d), while the number of epochs is shown on the x-axis. At the conclusion of 20 epochs, the suggested model's losses are reported as box_loss of 0.6765, cls_loss of 0.507, and dfl_loss of 1.039.



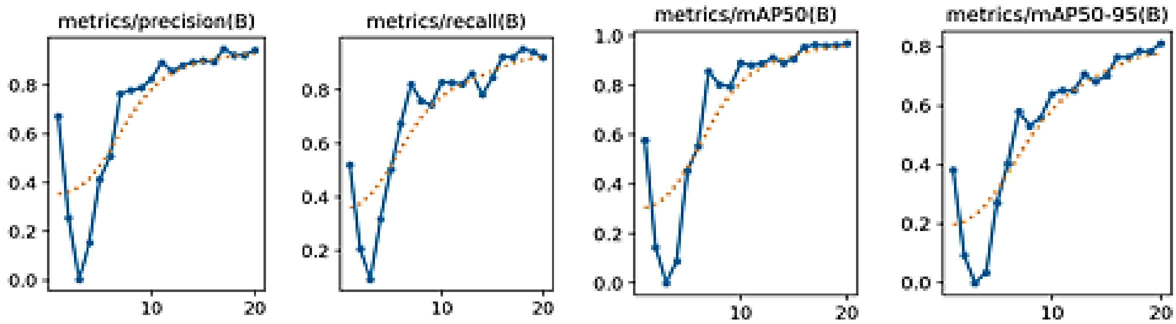
(a) (b) (c)

Figure 3. Graphical representation of training loss: (a) box loss, (b) cls loss, and (c) dfl loss



(a) (b) (c)

Figure 4. Graphical representation of validation loss: (a) box loss, (b) cls loss, and (c) dfl loss



(a) (b) (c) (d)

Figure 5. Graphical representation of: (a) precision, (b) recall, (c) mAP50, and (d) mAP50-95 w.r.t number of epochs

Figure 6 shows the precision-recall values obtained from each epochs are plotted in the form of precision-recall curve. This graph specifies how efficiently the model is going to predict the tumor. According to this graph our model's prediction rate is 0.969.

The normalized confusion matrix for the suggested YOLO model is shown in Figure 7. The best-performing and worst-performing models are identified by using the confusion matrix, which provides a more thorough view of the model's performance across several classes. In addition, the confusion matrix offers perception into the misclassification trends and assists in pinpointing the precise instances that have been erroneously categorized. One may see the distribution of actual labels for each class and forecasts for each class by looking at the confusion matrix. It makes it possible to assess the correctness of the model thoroughly, emphasizing regions where misclassifications are more common and pinpointing possible mistake causes. The model's performance in object identification tasks may be improved and refined with the use of this information.

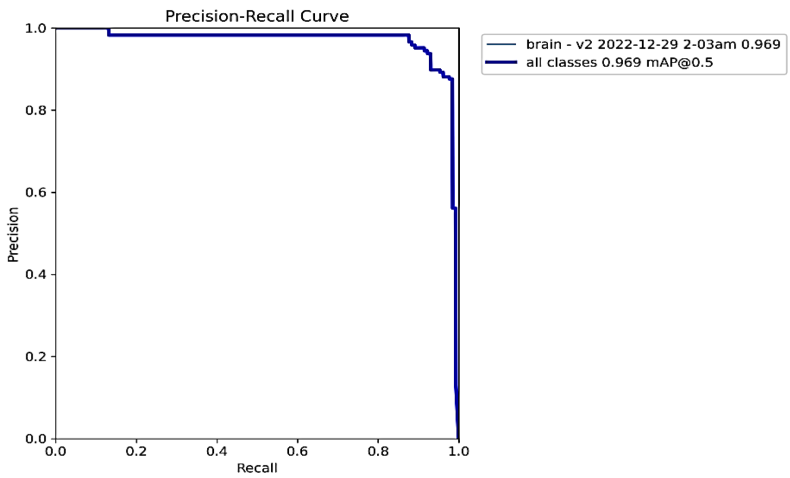
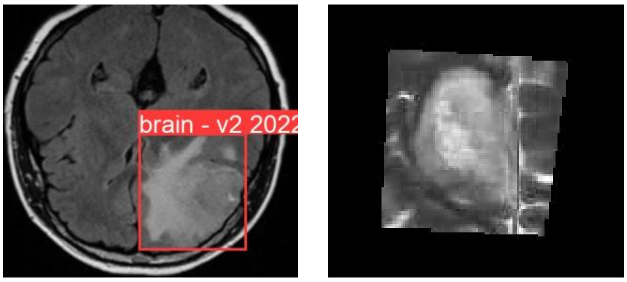


Figure 6. Precision-recall curve

Output	Tumor	Background
Tumor	0.969	1.00
Background	0.04	0

Figure 7. Normalized confusion matrix

After detecting, the tumor segmentation is done using image segmentation algorithm. The segmented image is placed on the cloud for future reference. The benefit of saving the image in the cloud might include maintaining the patient medical history, research purpose etc. The segmentation process may reduce the storage space in the cloud in turn cost of storage is reduced. The Figure 8 shows process of segmentation. The tumor predicted using YOLOv8s algorithm is depicted in Figures 8(a) and 8(b) shows segmented image.



(a) (b)

Figure 8. Segmentation process (a) prediction of tumor in original image using YOLOv8s model and (b) tumor segmentation

The main objective of this study is to locate the tumor precisely and further segment the infected area to save in cloud to maintain the patient medical history. The proposed model yields (0.944) Precision, (0.921) Recall, (0.969) mAP50 and (0.811) mAP50-95 for 20 epochs on the open-source dataset which is used for research. The dataset consists of 639 images which is split in the ratio of 71:19:10. In [16] YOLOv2 along with inceptionv3 is used to enhance the prediction and they achieved accuracy upto 0.90. According to Ali *et al.* [18] YOLOv3 is used for tumor localization which gave accuracy of 83% after fine tuning the pre-trained YOLOv3 model. According to [19] YOLOv4 is used for tumor identification which gave an accuracy of 0.8324 on the processed data. In Shelatkar *et al.* [21] YOLOv5 is used for tumor detection and classification on BRATS2021 dataset and model gave an accuracy of 88%. According to Abdusalomov *et al.* [22] YOLOv7 is used for tumor detection and classification along with the feature extractor, sensitivity enhancer and multistage feature fusion to get the relevant information. Passa *et al.* [23] proposed YOLOv8 along with data augmentation can detect brain tumor efficiently and it gave accuracy around 0.95. The researchers [24] also used YOLOv8s model for the detecting tumor on the open-source dataset and it contains only 300 images, data augmentation was also applied and they got accuracy of 0.941. According to Hashemi *et al.* [26] to enhance the performance of YOLOv8n, DeiT model is used. In Chen *et al.* [27] photoacoutic imaging is used instead of MRI images to get better results from YOLOv8. Compared to all the above work, proposed model is giving better results with open-source dataset. Data preprocessing is used in model for noise reduction and data augmentation is used to enhance the data. The researchers in [23], [24], [26], [27] uses YOLOv8 algorithm but for different dataset and parameters compared to our study. The dataset used in proposed model was tested on the YOLOv5 model keeping all the parameters same as used in the YOLOv8 and results were noted. Table 3 shows the comparison of YOLOv5 and YOLOv8 algorithm used for the same dataset, from the table it is clearly noted that YOLOv8 algorithm is giving better accuracy compared to the YOLOv5. As well as in all the above paper researcher has only concentrated on the classification and detection of tumor but in suggested model image segmentation is done to reduce the image storage space in cloud. Reduction in image storage space is depicted in Table 4 for the sample image used for segmentation, from the table it is clear that by the image segmentation technique we can substantially reduce the cloud storage space.

Table 3. Comparison of YOLOv5 and YOLOv8 on the same dataset

Algorithm	Epochs	Precision	Recall	mAP50	mAP50-95
YOLOv5	20	0.861	0.783	0.855	0.587
Proposed model (YOLOv8s)	20	0.944	0.921	0.969	0.811

Table 4. Image storage space before and after segmentation

Memory storage required before segmentation	Memory storage required after segmentation
28kB	16kB

4. CONCLUSION

The automated method for accurate detection of tumor with less complexity and cost-effective storage of patient's medical history was needed. Our proposed model answered this issue by using YOLOv8s model for tumor detection and image segmentation is done to save the storage space in cloud. The effectiveness of the YOLOv8s model in detecting brain tumors and segmenting the tumor using an image segmentation method is presented in this study. One of the DL models, YOLOv8s, is accustomed to detect the tumor. The dataset that is being used here is an open-source dataset that is utilized to support scientific research. 639 tumor images make up the dataset, which is split in a ratio of 71:19:10 across training, validation, and testing. Preprocessing and Data augmentation is carried out prior to training. 20 epochs are utilized to train the model. In comparison to previous researchers who have used the same approach for tumor detection but have different dataset and parameters, the proposed model results after 20 epochs show that it is able to detect the tumor more precisely with a precision value of 0.944, recall of 0.921, mAP50 of 0.969, and mAP50-95 of 0.811. Thus, we may say that the YOLOv8s model has fast and good tumor detection rate. Furthermore, the tumor is segmented using the image segmentation approach and only the region of interest is saved in cloud which in turn reduce the cloud storage space which leads to low-cost storage. Future scope of this work is to enhance the perfectness of brain tumor detection using YOLOv8s models by training model with a various kind of dataset. Rebuilding the segmented images and reducing the image reconstruction losses. YOLOv8s model can also be used for prediction of diseases in X-ray, CT scan, ultrasound, PET scan. Our research might make it easier and more precise for medical professionals to locate tumor and segmentation process may help in cost effective data storage in cloud.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Shilpa Chippalakatti	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	
Renu Madhavi Chodavarapu		✓		✓		✓		✓		✓	✓	✓		
Andhe Pallavi	✓			✓		✓		✓		✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Roboflow Universe at https://app.roboflow.com/shilpa1/brtumor/browse?queryText=&pageSize=50&startingIndex=0&browseQuery=true, reference [29].

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