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Detection of Brain tumors using integrated Mask-RCNN and spatial attention mechanism.

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***Abstract*—** The proposed novel deep learning methodology incorporating Mask-RCNN integrated with spatial attention mechanism precisely identifies three basic brain tumors types such as glioma, meningioma, and pituitary tumors by concentrating on pertinent spatial areas within an MRI scan, thereby enhancing the detection of tumor types from MRI images. The proposed leightweight approach attained a mAP of 98.96%, surpassing the baseline Mask RCNN model which achieved a mAP of 88.34%, in contrast to YOLOv8's 89.30% mAP for a custom dataset comprising 1322 annotated MRI scans. These scans were annotated utilizing the VGG annotator tool, and the model was trained for 40 epochs with a batch size of 35, making use of the computational capabilities of a T4 GPU. The integration of a spatial attention mechanism into Mask-RCNN demonstrates superior performance in comparison to both the Basic Mask-RCNN and YOLOv8 in terms of average loss, accuracy, and mean average precision (mAP) for the identification of glioma, meningioma, and pituitary brain tumor subtypes which can be the lightweight model for clinical integration to accurately detect early tumors.

Keywords: *Brain tumor type, Mask RCNN, Spatial attention mechanism, YOLOv8..*

1. INTRODUCTION

I. The importance of automated detection and classification techniques cannot be overstated as they play a crucial role in accurately evaluating the size and location of tumors, which is indispensable for effective treatment planning and ultimately enhancing patient outcomes. Brain tumor detection utilizing the Mask R-CNN with an integrated spatial attention mechanism signifies an innovative strategy that exploits advanced technologies for the precise and automated segmentation of brain tumors in MRI scans. Among various CNN-based methods like R-CNN, Fast R-CNN, and Faster R-CNN, the Mask R-CNN model is distinguished by its exceptional performance in the detection and localization of brain tumors [1],[2],[3]. Extensively evaluated, these models have displayed notable progress in segmentation precision and efficiency. Particularly, the Mask R-CNN framework excels in its capacity to produce high-quality segmentation masks in tandem with bounding box predictions, thereby offering a more detailed and precise delineation of tumor regions.

II. In order to bolster the resilience and precision of brain tumor detection, scholars have integrated transfer learning and a tailored Mask R-CNN architecture featuring a DenseNet-41 backbone has achieved mean classification accuracies of 96.49%, 97.31%, and 98.79%. for BRATS2018,19,& 20 dataset respectively [2]. This amalgamation capitalizes on pre-existing models, modifying them to cater specifically to brain tumor detection tasks, resulting in commendable performance metrics. Notably, the model attained an accuracy rate of 97.6% for segmentation and 98.34% for classification [3], underscoring its efficacy in precisely recognizing and demarcating tumor boundaries. Such a high level of precision is imperative for facilitating surgical blueprints and treatments, ensuring that healthcare professionals can depend on intricate and accurate imaging data.

MRI image techniques have always proved to detect benign and malignant growths for the treatment of the brain tumor patients [20]. The incorporation of Mask R-CNN for brain tumor detection upon medical imaging data from MRI scans, CT scans, and other modalities, automated segmentation techniques are imperative for meticulous tumor evaluation. Convolutional neural networks (CNN), a form of deep learning, have been adeptly employed to extract features and identify anomalies in MRI images with remarkable accuracy, thereby aiding in the discernment of abnormal brain scans and estimating tumor density for therapy guidance [11],[12]. The integration of an attention mechanism with CNN has yielded notable enhancements in mitigating the influence of extraneous background information on classification outcomes, thereby augmenting brain tumor recognition tasks. Moreover, the amalgamation of stacked CNN models including VGG16, VGG19, AlexNet, MobileNetV2, and InceptionResNetV2 into a unified model has showcased exceptional success rates in brain tumor detection, achieving nearly 99% accuracy in recall, precision, and mAP [13]. The successful deployment of Mask R-CNN in brain tumor detection highlights its potential to revolutionize neuro-oncology diagnostics. By furnishing automated, precise, and efficient detection of glioma, meningioma, and pituitary tumors, Mask R-CNN not only enhances diagnostic capabilities but also contributes to the formulation of more efficacious treatment strategies [14]. Deep learning offers the main benefit of requiring less photo preprocessing when processing MRIs [24] which is the major reason behind more widely use of the model.

Contribution of this paper

This article presents a novel approach by integrating the spatial attention mechanism with Mask R-CNN for the precise identification of all three categories of brain tumors from MRI scans. The primary contributions are listed below:

1.Precise Detection through Mask RCNN integrated with spatial attention mechanism: The suggested Mask R-CNN model with spatial attention mechanism attained an outstanding mean bounding box accuracy of 98.96% on a custom dataset of 1322 annotated MRI images.

2.Thorough Tumor Recognition: The Mask R-CNN model with spatial attention mechanism exhibited high precision in pinpointing and categorizing glioma, meningioma, and pituitary tumors.
3.Clinical Significance: The research highlights the capability of the Mask R-CNN model with spatial attention mechanism to significantly boost the effectiveness and precision of brain tumor diagnostics in clinical environments.

2. LITERATURE REVEIW

The method combining Mask R-CNN with DenseNet-41 [3] attained 96.3% accuracy in tumor segmentation and 98.34% in classification. A methodology utilizing convolutional neural networks (CNN) and data augmentation with VGG-16 [4] exhibited high efficacy on a limited MRI dataset.

An evaluation of a CNN model with Local Binary Pattern and a multi-layered SVM classifier [5] was conducted using metrics such as DSC, JSI, SE, ACC, SP, and PR. An integrated deep learning approach [6] that combines CNN and CNN-LSTM architectures achieved 98.8% classification precision.

Another investigation [7] utilizing an optimized neural network and CNN has shown significant efficacy in tumor identification from MRI scans. A study on cerebral hemorrhage recognition employing Mask R-CNN [8] obtained a diagnostic precision of 97.6% in segmenting brain tissue and identifying coagulation areas.

Another research endeavor [9] utilizing a transfer learning model with a deep convolutional neural network achieved close to 100% accuracy, specificity, and sensitivity on a small dataset. Mask-RCNN using transfer learning [16] achieved classification accuracy of 75% and 87%, respectively for the ResNet-50 and ResNet-101 for 1000 epochs. The KNN classification with Mask R-CNN training data handles overlapping objects with multiple classes [17]. The method using Mask-RCNN with transfer learning [18] improved the mAP to 93% for skull stripping by fully automated it to reduce its processing time and operational cost.

The proposed model [19] for classification of meningiomas, metastases, and high-grade glial tumors has achieved an impressive DICE score range of 94%–95% and an accuracy of 98% in pathology estimation. Eventhough a deep learning technique [21] has achieved an exceptional accuracy of 100% for dataset consisting of 7,023 images; it suffers with the resource exhaustion in real time clinical integration. On the other hand one more study using same dataset with 7,023 images has obtained an accuracy value of 84% [22].

The RESNET-152 model [23] obtained better results than other baseline approaches. The Extended Adaptive Global Treshold (eAGT) function in ATM algorithm for segmentation process produces 93.74% accuracy in detection [25].

3. PRAPOSED METHODOLOGY

3.1. CUSTOM CONFIGURATION DETAILS

System: T4 GPU
Images_Per_GPU = 2
Num_Classes = 1 + 3 # Background Glioma, Meningioma, Pituitary
Epoch: 40
Steps_Per_Epoch = 35

Detection_Min_Confidence = 0.95

3.2. IMAGE DATA DESCRIPTION.

We have considered the dataset present in the repository https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset and obtained 1,322 images after manual inspection for the training purpose. Figure 1,2, and 3 shows the sample images and Table 1 shows the split of dataset.

Table 1. Image data description

Sl. No	Tumor type	Total MRI images
01	Glioma	544
02	Maningioma	475
03	Pituitary	303
	Total	**1,322**

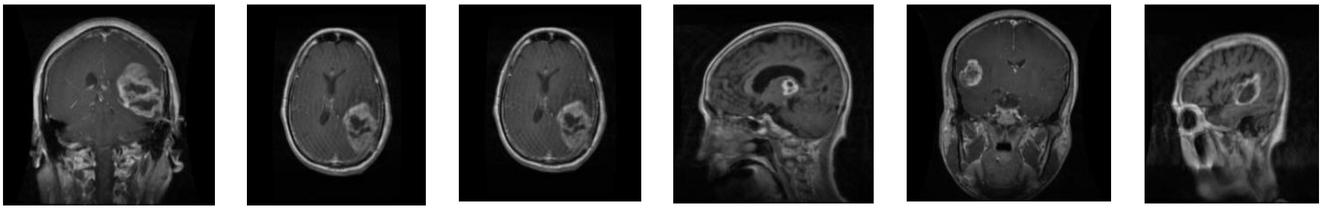

Figure 1: Sample glioma type tumor.

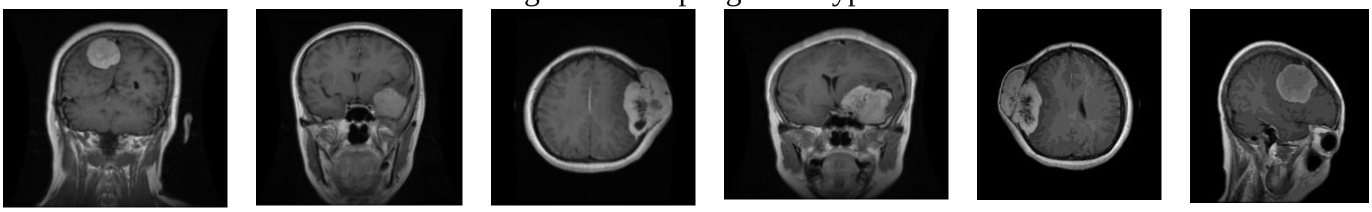

Figure 2: Sample meningioma type tumor.

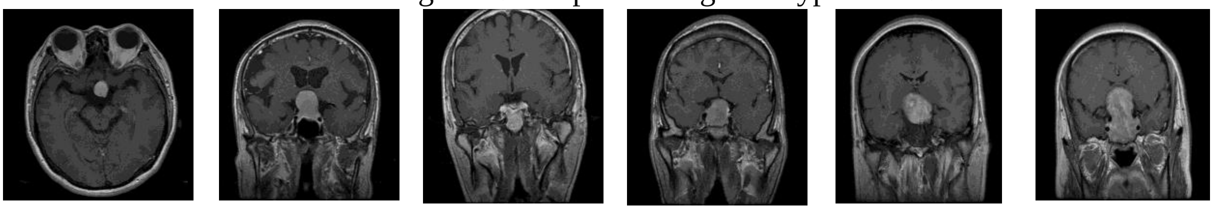

Figure 3: Sample pituitary type tumor

3.3. PROPSOSED ARCHITECTURE.

The figure 4 represents the architecture and workflow of a Mask R-CNN model with spatial attention mechanism designed for detecting glioma, meningioma, and pituitary Tumors. Mask R-CNN is an extension of Faster R-CNN that adds a branch for predicting segmentation masks on each Region of Interest (RoI), in parallel with the existing branch for classification and bounding box regression. This flowchart outlines the end-to-end pipeline of using Mask R-CNN for detecting glioma, meningioma, and pituitary tumors, from data preparation and model training to making predictions and generating segmentation masks.Here is a detailed explanation of each component in the flowchart:

1. **Data Generator (B1):** The component generates batchsize of 40 for the comlete dataset containing 1,322 images.

2. **Data Preprocessing:** The dataset images are resized to 640 * 640 pixels.

3. **Backbone Network (C1 with spatial attention mechanism) - ResNet Graph:** The ResNet is used as a backbone network for extracting feature maps from input images which is coupled with a spatial attention mechanism. High-level feature capture is aided by the deep convolutional neural network ResNet. Figure 5 below illustrates how the spatial attention mechanism is integrated. An outline of the steps involved in creating and integrating a spatial attention mechanism with Mask R-CNN for brain tumor detection is shown in figure 5. The procedure comprises feature extraction, region proposal generation, classification, segmentation, training, and inference in addition to defining the spatial attention function and combining it with convolutional layers. The goal of this strategy is to improve the model's capacity to concentrate on pertinent spatial regions, which will increase the precision of brain tumor identification and segmentation.
4. **Region Proposal Network (C2):** The Region Proposal Network (RPN) generates candidate object proposals. These proposals are regions in the image that are likely to contain objects of interest (i.e., tumors).
5. **ROI Align (C3):** This component checks for the regions of interest proposed by the RPN are accurately aligned and extracts features from the feature map for each proposed region

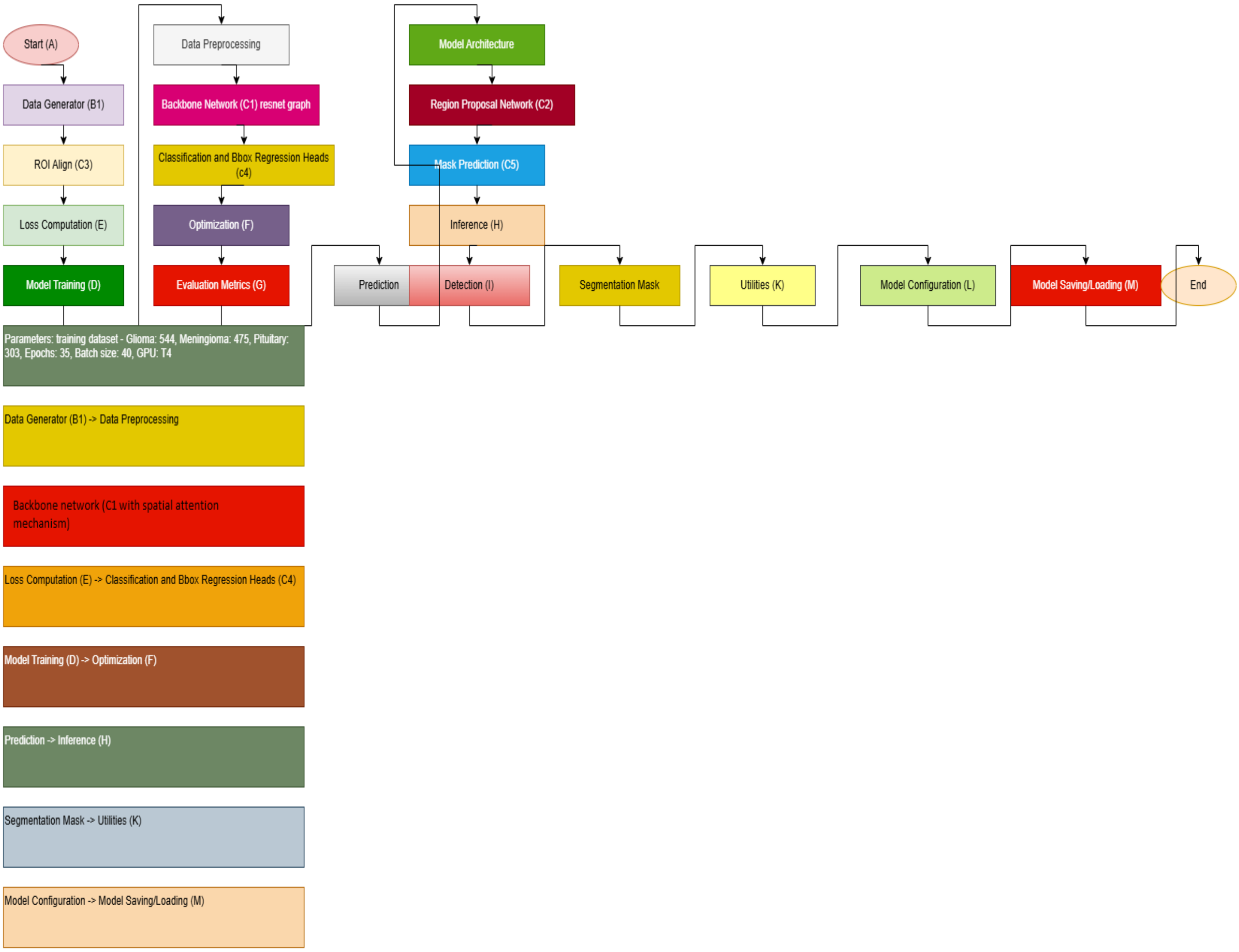

Figure 4: Mask-RCNN with spatial attention mechanism for brain tumor detection

6.Classification and Bbox Regression Heads (C4): This phase has two components.

(a) Classification Head: To predict the class of the object within the proposed region.

(b) Bounding Box Regression Head: To refine the coordinates of the bounding boxes.

7.Mask Prediction (C5): This branch predicts the segmentation masks for each region of interest, providing pixel-level delineation of the detected objects (tumors).

8.Loss Computation (E): The phase calculates the loss for each task including Classification loss, Bounding box regression loss, Mask prediction loss.

9.Optimization (F): Use of SGD optimizer has updated the model weights to minimize the loss.

10.Model Training (D): This component iterates over multiple epochs, repeatedly performing loss computation and optimization to train the model.

11.Evaluation Metrics (G): Performance is evaluated using metrics such as precision, recall, and means Average Precision (mAP

12.Prediction/ 13. Inference (H)/ 14. Detection (I)

Using the trained model(recent .h5 file), predictions are made on new, unseen data to detect and classify tumors.

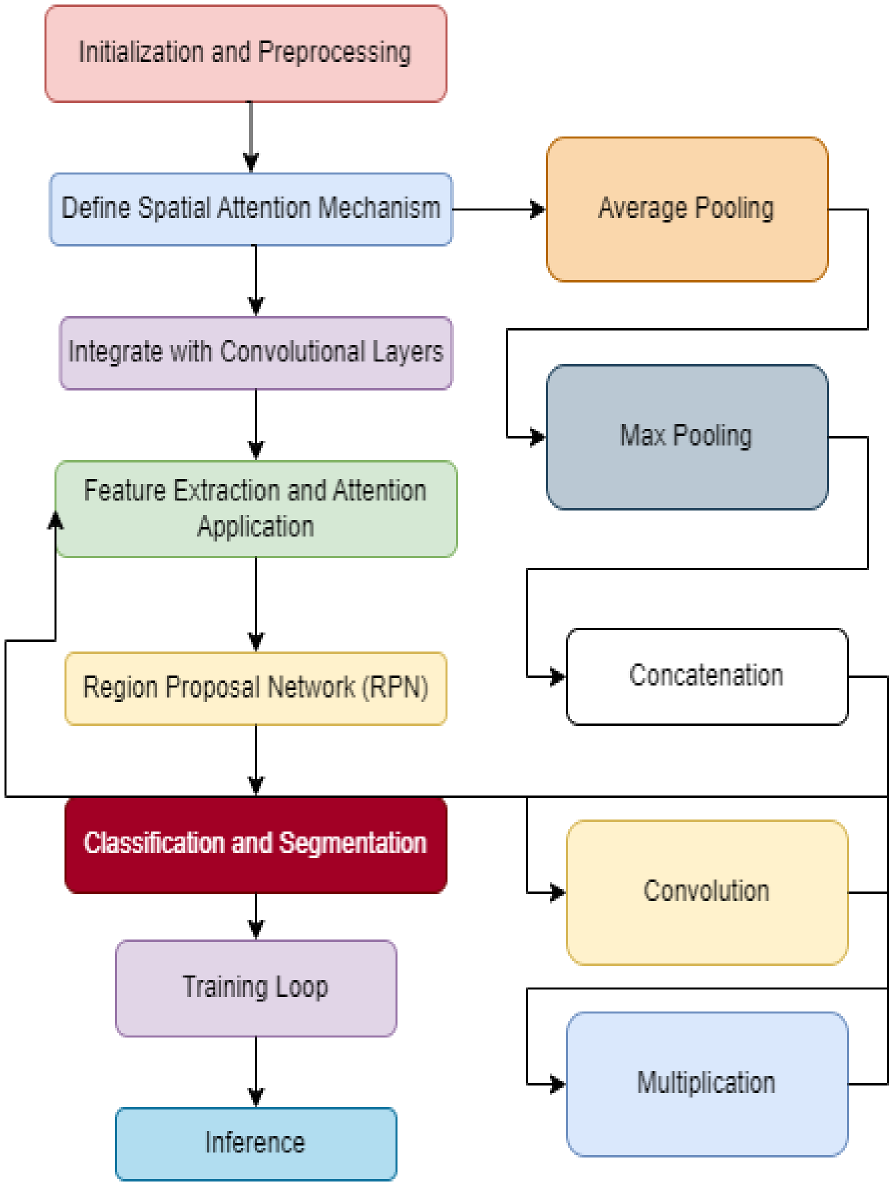

Figure 5: Define and integrate the spatial attention mechanism

4. Results and Discussion

Figure 6 shows the detection of glioma, meningioma, and pituitary tumors using basic Mask RCNN model with the mean average accuracy of 88.34% and Figure 7 shows the detection of tumors using proposed model with the mean average accuracy of 98.96% for the custom dataset configuration mentioned in the section 3.1.

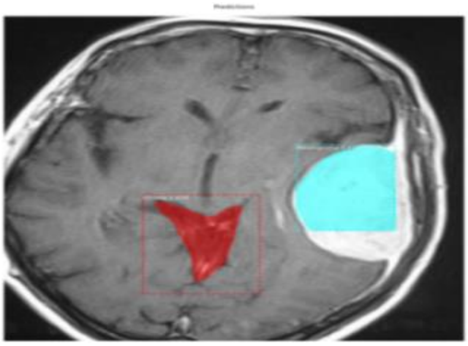

Figure 6: Glioma and meningioma detection with bounding box values 82.9% and 83.33 % respectively.

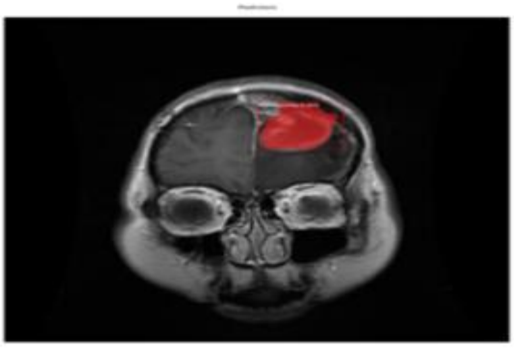

Figure 7: Meningioma detection with bounding box value 90.05%.

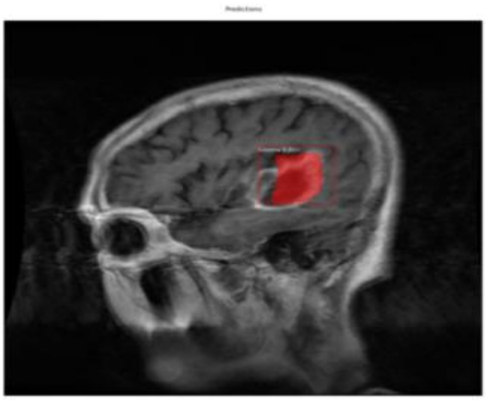

Figure 8: Detection of glioma type with bounding box accuracy 91%

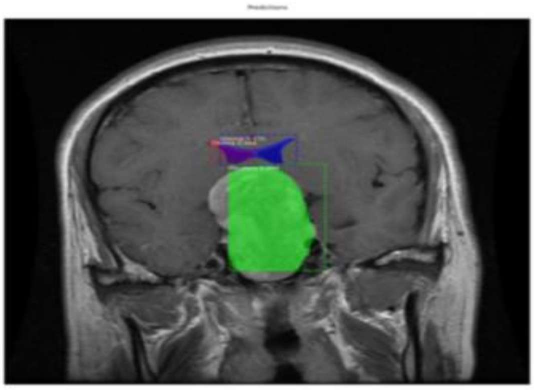

Figure 9: Detection of pituitary type with bounding box accuracy 89.4% and glioma type with 94.4%

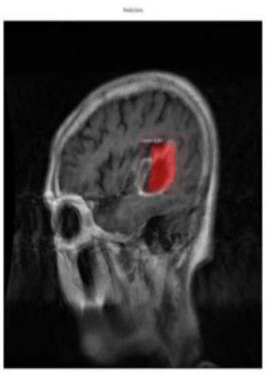

Figure8:Glioma type

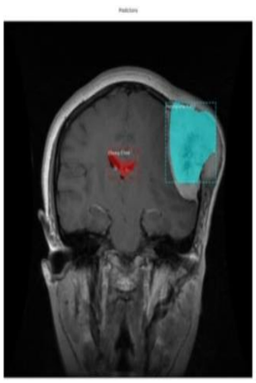

Figure 9: Glioma & Meningioma type

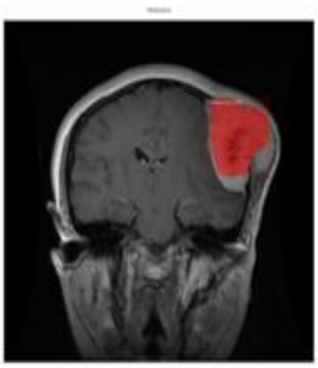

Figure10:Meningioma type

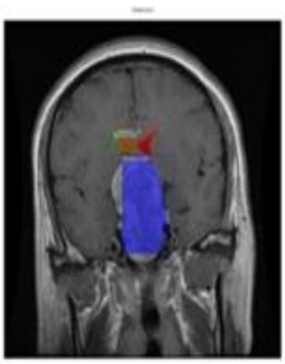

Figure 11: Glioma & Meningioma type

4.1. TRAINING AND VALIDATION LOSS

Training Loss: The dataset containing 1322 MRI images shown in the table 2, takes 3.45 hours for the custom configuration details shown in the section 3.1. The below table 2 shows the performance metrics for the Mask RCNN standard model for every epoch.

Table 2: Base Maskrcnn training and validation loss values for initial 10 epoch.

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Performance metrics	Epoch 1	Epoch 2	Epoch3	Epoch4	Epoch5	Epoch6	Epoch7	Epoch8	Epoch9	Epoch10
rpn_class_loss	2.4301	2.3271	2.0741	2.0743	2.0047	1.9534	1.7331	1.0131	1.0012	0.9900
rpn_bbox_loss	2.3378	2.0122	1.9800	1.9856	1.6800	1.5808	1.4352	1.2348	1.1243	1.0033
mrcnn_class_loss	3.1378	2.9131	2.3201	2.3754	2.5342	2.3451	2.2234	2.0007	1.9901	1.8999
mrcnn_bbox_loss	3.4762	3.0014	2.6511	2.6512	2.4352	2.4751	2.3702	2.1101	2.0001	1.9987
mrcnn_mask_loss	2.8811	2.1167	1.9325	1.9334	1.7905	1.7800	1.5854	1.2114	1.1114	1.0034

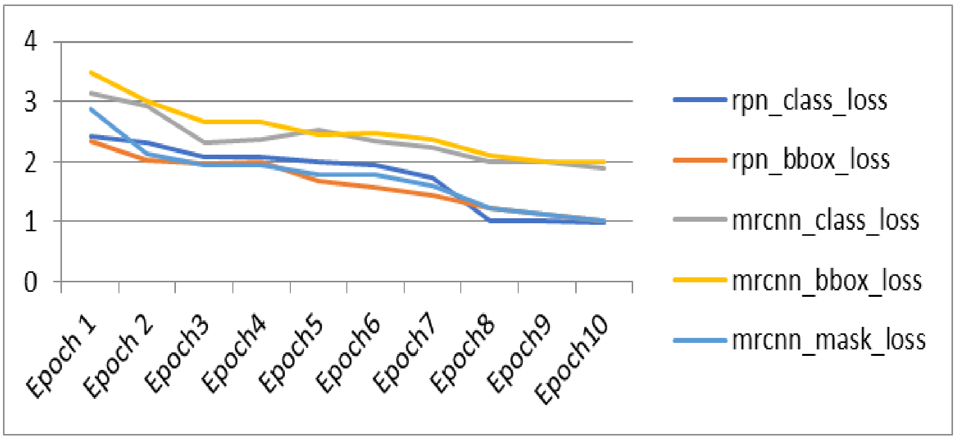

Figure 12. Graphical representation of Mask RCNN performance metrics for the epoch: 1 to 10

Training Loss: The dataset containing 1322 MRI images shown in the table 2, takes 3.45 hours for the custom configuration details shown in the section 3.1. The below table 2 shows the performance metrics for the Mask RCNN standard model for every epoch.

Table 3: Maskrcnn training and validation loss values for initial 10 epoch

Performance metrics	Epoch1	Epoch2	Epoch3	Epoch4	Epoch5	Epoch6	Epoch7	Epoch8	Epoch9	Epoch10
rpn_class_loss	0.0108	0.0101	0.0090	0.0079	0.0056	0.0062	0.0037	0.0034	0.0021	0.0017
rpn_bbox_loss	0.2567	0.2482	0.2379	0.2363	0.2147	0.2213	0.2104	0.2101	0.2112	0.2002
mrcnn_class_loss	1.7033	0.2136	0.2128	0.2119	0.2057	0.2043	0.2001	0.1902	0.1808	0.1673
mrcnn_bbox_loss	1.0720	0.0937	0.0926	0.0912	0.0782	0.0543	0.0542	0.0537	0.0532	0.0447
mrcnn_mask_loss	1.1580	0.1032	0.1001	0.0980	0.0908	0.0784	0.0713	0.0711	0.0701	0.0668

The graph depicted in figure 8, which is constructed based on the data provided in table 2, presents a comprehensive overview of the training performance exhibited by a Mask R-CNN model across 10 epochs utilizing a batch size of 35. The evaluation of performance encompasses various metrics such as:

1. **RPN Class Loss:** This metric signifies the loss incurred by the region proposal network (RPN) during the classification process. The values demonstrate a consistent decrease from 0.0108 to 0.0017 from the first to the tenth epoch, indicating enhancements in region proposal classification throughout the training procedure.

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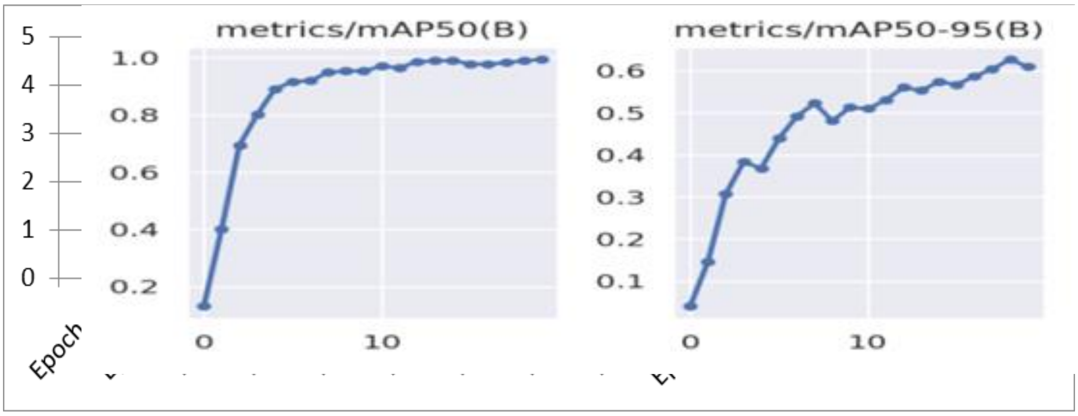


Figure 13. Graphical representation of maskrcnn with spatial attention performance metrics for the epoch: 1 to 10

2. **RPN BBox Loss:** This parameter gauges the precision of bounding box predictions generated by the RPN. The gradual reduction observed from 0.2567 to 0.2002 across the initial to the tenth epochs suggests an enhancement in the RPN's ability to predict bounding boxes for potential objects.
3. **MRCNN Class Loss:** This measure is associated with the classification of identified objects. A notable decrease in this loss from 1.7033 to 0.1673 from the first to the tenth epochs signifies an improvement in accurately classifying detected objects as specific tumor types (e.g., glioma, meningioma, pituitary).
4. **MRCNN BBox Loss:** This metric evaluates the accuracy of bounding box regression for objects detected by the Mask R-CNN. The substantial decrease from 1.0720 to 0.0447 from the initial to the tenth epochs indicates an increased precision in localizing objects within the images.
5. **MRCNN Mask Loss:** This parameter reflects the precision of predicted masks for the detected objects. The consistent decrease in this loss from 1.1580 to 0.0668 indicates an enhancement in accurately segmenting tumor regions.

Key observations on the training losses

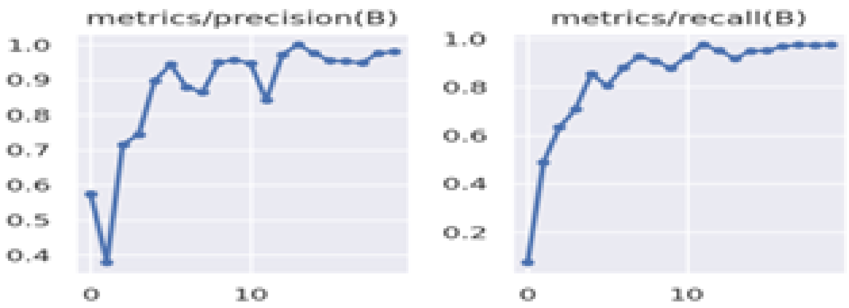
Trends in Losses: When employing Mask RCNN in figure 8, all types of losses (rpn_class_loss, rpn_bbox_loss, mrcnn_class_loss, mrcnn_bbox_loss, and mrcnn_mask_loss) exhibit a continuous decline over the epochs.

In figure 9, utilizing Mask RCNN with spatial attention integration, mrcnn_mask_loss experiences a sharp decline from the first to the second epoch, followed by a relatively stable trend in the subsequent epochs. The remaining four losses initiate from lower values and maintain consistency throughout all epochs, indicating an improvement in training and validation losses compared to the basic Mask RCNN model.

- ❖ **Early Learning Impact:** The notable early reduction in mrcnn_mask_loss indicated in figure 12 suggests rapid learning in mask generation by the model. Conversely, the other losses (rpn_class_loss, rpn_bbox_loss, mrcnn_class_loss, and mrcnn_bbox_loss) display minimal variation, implying limited improvements following the initial epochs

(a) Precision for training (b) Recall for training

2. **Validation loss:** The figure 13 depict the performance of maskrcnn training and validation across training epochs for a machine learning model, likely a deep learning model used for object detection. Below is the detailed explanation of the obtained performance.



(c) Mean average precision IoU=0.50 (d) Mean average precision IoU=0.50-0.95

Figure 14. Precision and recall of training and validation loss for proposed method.

Performance Metrics

1.Metrics/precision (B): This plot shows the precision metric, which measures the proportion of true positive detections out of all positive detections made by the model. The precision starts around 0.1 and increases to about 1.0, indicating high precision in predictions.

2.Metrics/recall (B): This plot represents the recall metric, which measures the proportion of true positive detections out of all actual positives. Recall increases from 0.2 to nearly 1.0, indicating the model is successfully detecting most of the actual positives.

3.Metrics/mAP50 (B): This plot shows the mean Average Precision at IoU=0.50, a common metric for object detection. The mAP50 starts around 0.1 and increases steadily to about 0.9, indicating a high level of performance.

4.Metrics/mAP50-95(B): This plot shows the mean Average Precision across multiple IoU thresholds from 0.50 to 0.95. The mAP50-95 starts around 0.1 and increases to about 0.6, indicating good overall detection performance across various levels of overlap. The table 3 provides the performance comparison with average metrics.

Table 3. Comparison of brain tumor detection results of Mask-RCNN with the YOLOv8.

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Sl. No	Evaluation Metrics	Proposed Mask-RCNN with spatial attention method value (0 to 1)	Mask-RCNN basic model	YOLOv8	Remarks
1	Average data loss	0.0104	0.197	0.242	This suggests that the model is fitting the training data well without noticeable discrepancies in its predictions.
2	mAP	0.9896	0.870	0.893	Model has an outstanding ability to correctly identify positive cases out of all predicted positive cases. This suggests minimal false positives in the predictions.

Key observation of training and validation results of proposed model

1. Spatial attention model shows sharp loss decline in first two epochs.
2. By epoch 10, spatial attention model has significantly lower loss values and stabilizes rapidly.
3. Model achieves over 98.96% mAP, effectively classifying tumors and building accurate masks.

CONLUSION

This paper presents a novel utilization of Mask R-CNN combined with a deep learning spatial attention mechanism for the precise identification of three categories of brain tumors (pituitary, meningioma, and glioma) from MRI images. The training of the model spanned 40 epochs with a batch size of 35 on a T4 GPU, yielding an impressive average bounding box accuracy of 98.96% on a specialized dataset of 1,322 annotated MRI scans. The results underscore the enhanced performance of the Mask R-CNN model integrated with spatial attention over the conventional Mask R-CNN model in terms of speed of convergence and final loss metrics.

Upon comparison of the Mask R-CNN with spatial attention to the standard Mask R-CNN (0.197) and YOLOv8 (0.242), it becomes apparent that the former demonstrates the lowest average loss (0.0104), signifying superior adaptation to the training data. Demonstrating a mean Average Precision (mAP) of 0.9896, the Mask R-CNN with spatial attention excels in the precise identification of positive instances, leading to a reduced false positive rate. Conversely, YOLOv8 (0.893) and basic Mask R-CNN (0.870) exhibit lower mAP values, suggesting that the spatial attention mechanism boosts the model's learning efficacy and efficiency during initial training phases. This enhancement bears substantial potential in refining the accuracy and precision of brain tumor diagnosis, particularly concerning precise tumor localization and classification.

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