Classification of Brain MRI Images and Cellular Localization Analysis

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Abstract— Brain Tumor is a type of disease in which brain cells get abnormal growth which causes harm to the person if not detected early. But even if it is detected it sometimes gets hard to identify the location of the cells. If it is found, then proper treatment can be provided to the patient to treat the disease. It is because the brain is the most important part of our organ system which if not treated properly can make a person in a coma or worse condition. Accurately identifying the location is the most important while diagnosis of brain tumor. To do it AI can assist in tumor detection while also helping in finding the location of the cell. The analysis first identified the tumor presence by training the model multiple image preprocessing such as enhancement and denoising, resizing and other were employed for better performance and learning. Next for the cell location identification, many images were manually annotated using Roboflow and then using YOLOv5 with few changes in parameter the model was trained for identifying the cell location. The process was followed such as if the image has classified into tumor class then further its location will be identified. For it TumorDetModel is created using several different layers and pre-trained model gives accuracy score as 94% and using the yolov5 object detection model is created which has an accuracy of 96.2% for the given validation dataset.

Keywords: *Brain Tumor Detection, Hybrid Model, Image Segmentation, Enhancement*

I. Introduction

A. Background

Brain Tumor is said to be the disease or the abnormal growth in the cells of the brain. As it grows in the brain it can be life-threatening if it grows in a vital part of the brain. There are many types of brain tumor that can be developed in the brain. So, there is a need to identify them so it can be cured or removed by the medical expert.

In recent years, AI, particularly DL has emerged as a powerful tool that can assist in medical image analysis. AI models can help in assisting the medical experts by automating the process for detecting if the patient has a tumor or not. Further, DL models like CNN have demonstrated their potential in learning complex features of medical images that help in assisting the identification of tumors in the images. This research explores the use of deep learning and transfer learning techniques for developing a robust system for detecting brain tumors.

B. Related Work

Various past studies have been explored for AI-based techniques for tumor detection. For instance, in a recent study by [1], a transfer learning-based active learning framework reduces annotation costs while maintaining model stability. The model achieved an AUC of 82.89% on an MRI dataset. This demonstrates the efficiency of transfer learning in medical image classification.

In another study, [2] proposed a CNN-based architecture designed to classify brain tumors, stating the strength of CNN in feature extraction. Similarly. [3] focuses on developing a neural network model, which shows the significant improvement in identifying the presence of a tumor based on the input image.

Studies of [4] and [5] conducted the experiments of using ResNet50, a popular transfer learning model, to classify different types of tumor present achieving the impressive results. These studies emphasize the role of transfer learning for overcoming challenges made by limited medical datasets.

Preprocessing the image is crucial for enhancing the quality of the input data. Work done by [6] explores various types of enhancement done on images and explains its impact on the images, while [7] stated how Histogram equalization can be important to doing on the image to make it more enhanced. Medical practitioners achieve better outcomes in brain tumor diagnosis through early recognition thanks to precise segmentation combined with classification methods despite structural differences among tumors and their positioning throughout the brain and their diverse sizes [8]. Deep Learning models along with Supervised, Unsupervised and Deep Learning protocols demonstrate effective MRI analysis potential yet technical difficulties including unbalanced data distribution and interpretation obstacles and model discrimination remain unresolved [9].

Deep learning systems based on CNNs and U-Net achieve 98.8% accuracy in their classification and segmentation responsibilities which outranks standard pre-trained models [10]. These advanced models need vast datasets accompanied by high-grade resources so they remain inadequate for clinical settings. The YOLO algorithm represents a major advancement in object detection technology which effectively strikes a balance between speed and accuracy according to [11]. The single-stage detection procedure of YOLO provides fast performance yet achieves inferior precision than two-stage detection systems [(12)]. The improvement of diagnostic potential through AI development stands parallel to ongoing efforts to tackle issues regarding limited available data as well as difficulties with data generalization and challenges posed by AI diagnostic systems.

II. Methodology

A. Data Information

The dataset for the following research is MRI images of Brain (BraTS 2019) obtained from kaggle is an open source. The dataset used is the same as the base paper but is large in size for the reason to solve the limitation seen in it. Table 1, tells the details of the dataset.

Table 1: Dataset Information

Folder	Yes Count	No Count
Train	1400	1400
Valid	100	100

B. Exploratory Data Analysis

While the data was in the form of an image there was not much need of exploration. As mentioned, the count of images was equal but to visually see it a pie chart is drawn where it is seen in fig 1, that both classes are equally present 50% each .

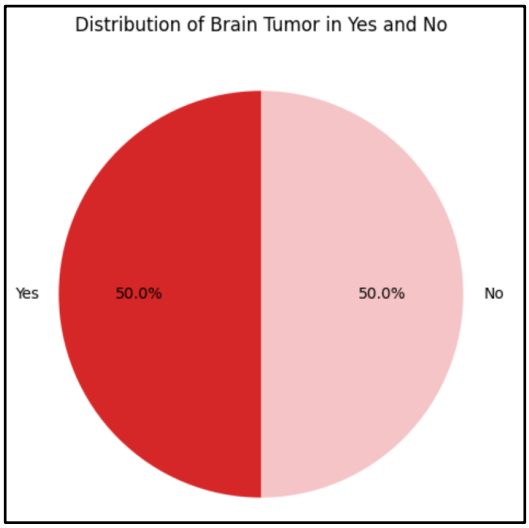

Fig 1: Distribution of Brain Tumor Classes

Further, the size of all the images were checked and it was found out that each image has a different size in form of height and width like (272, 277) or (630, 630). FIg 2, displays the images, tumor present in the brain. As seen the cells gradually increase (white area is the part tumor present). Depending on the area it can be hard to remove it.

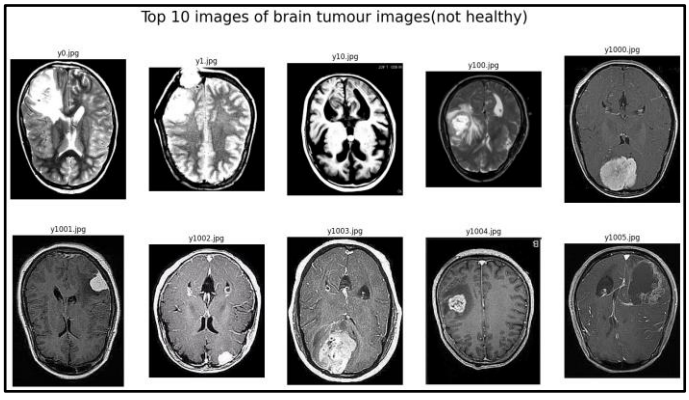

Fig 2: Top 10 images of Brain - Tumor

Fig 3, shows the images of normal brain and as seen there is no growth in the cell or white part. It indicates that there is no tumor present in the brain.

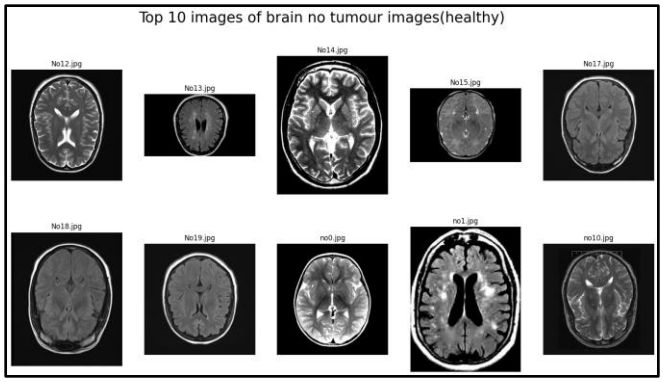

Fig 3: Top 10 images of Brain - Normal

C. Image Preprocessing

Many images with different types and sizes, image preprocessing was necessary to make it suitable and remove noise from it before passing to the model. Preprocessing done to all the images are as follows:

1. **Image Enhancement**: is the process of boosting an image's visual quality by making suitable changes to its levels. Here Clahe method is selected and was applied with dynamically adjusting it based on the image histogram distribution. This approach persevered fine details in the tumor region while enhancing overall contrast. Fig 4, displays the difference between original and image enhancement.

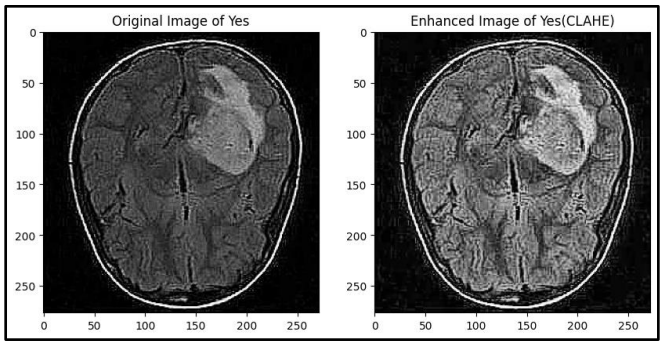

Fig 4: Top Original Vs Enhanced Image

2. **Denoising**: it means the process of removing the noise present and making the image clearer [8]. A custom Non-Local denoising was implemented with targeting nois-prone areas while keeping in mind of preserving critical edges. Fig 5, showing how the image changes.

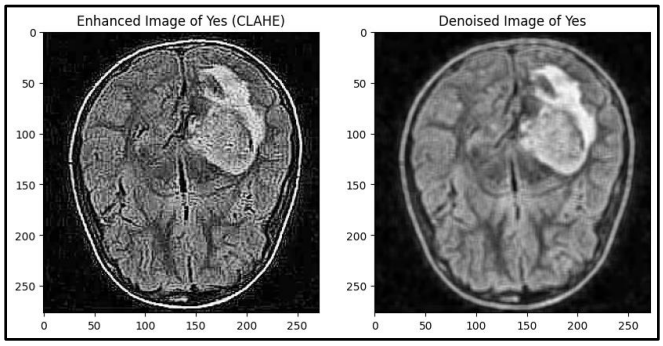

Fig 5: Denoised Image

3. **Affine Transformation**: is used for maintaining planes and points along with the straight line [9]. The function used for this applies scaling, rotation and transformation to the image. Fig 6, shows the result after applying the function.

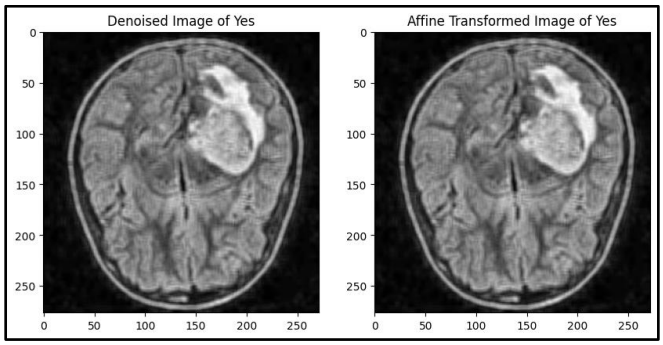

Fig 6: Affine Transformation Image

4. **Segmentation and Masking**: is the method of utilizing binary masks to isolated areas and dividing an image into multiple sub regions [10]. A hybrid segmentation method approaches combined binary thresholding with pre-trained edge detection algorithms. This technique helped in isolating the tumor region while minimizing false positives. Fig 7, shows the result after applying the function.

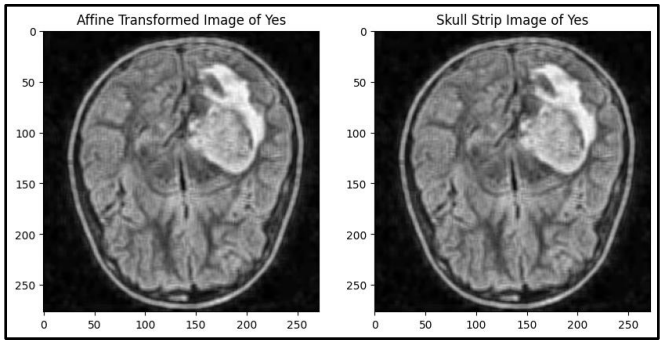

Fig 7: Segmentation and Masking Image

5. **Spatial And Frequency Domain Filtering**: The function used applies Gaussian blur to the image with the use of kernel size of (5,5) and std. Fig 8, shows the result after applying the function.

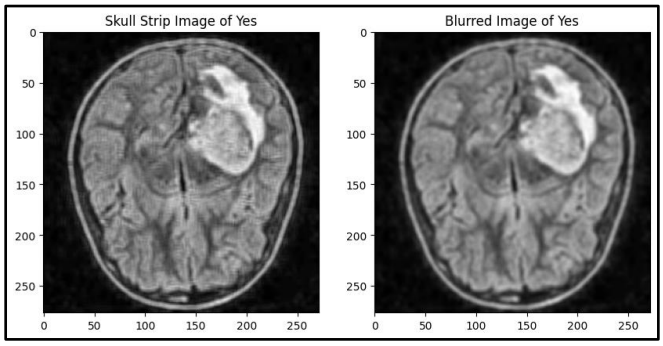

Fig 8: Spatial And Frequency Domain Image

All these preprocessing methods ensure high-quality and standardized input that can enable models with better feature extraction and accuracy.

D. Data Augmentation

Data Augmentation is known as the method that creates new images from the present one, making it modified and creating new ones to train the model with varieties of images so it can learn well and efficiently [11].

The data augmentation strategy adopted in this study was both innovative and comprehensive, and was designed to enhance the robustness of the model by providing a more diverse training dataset with a lot of varieties. For this, a custom GAN was employed to generate synthetic MRI images that would mimic the real-world tumor and non-tumor cases, helping in expanding the data without introducing redundancy in it.

For further investigation, context-aware augmentation was implemented to create more realistics variation of the image, it was done by scaling tumor regions, altering the brightness level along with simulating tumores in normal brian scan to make the training more challenging. These methods were implemented. These methods were supplemented with traditional augmentation techniques which included flipping, rotating and zooming to further add diversity in the training data.

By combining all these methods, this approach helped in generating a rich and varied dataset, improving the model's ability to generalize and perform well on unseen data.

E. Image Labelling

To increase the novelty of present work, some of the specific features are introduced at early stages of the pipeline. When assigning images during the labeling step, we use RoboFlow for manual annotations; however, to continue to these steps, consider active learning and weak supervision methods. These approaches scale down the calibration work and enhance the annotation quality in a number of cycles.

Figure 5: Image Labeling using RoboFlow

Further, the presented dataset is a domain-specific dataset with 1,400 selected tumor images with associated labels, and the images were preprocessed using several augmentation techniques to further enhance the variability of the low sample variation. These subcategories are added in the labeling process because the standard labels, such as malignant and benign, do not reveal much information about the tumor; therefore subcategories, such as early-stage tumor and advanced-stage tumor, are included in the labeling process to provide more information.

F. Model Architecture

In model building, the proposed **BrainDetModel1** employs Vision Transformers (ViT), which has been established in the literature as providing excellent generalization for modeling global dependencies and relationships in images. In contrast to convolutional networks, ViT takes images in the form of sequences of patches, consequently, the model takes into account both spatial and contextual features. In this work, more layers are developed to complement the ViT architecture, especially attention-based layers designed to produce richer features based on the input tokens and dense layers for classification purposes. To render interpretability, saliency maps and Grad-CAM diagrams are integrated to give measures on where the model identifies tumor features. To properly handle the severity of false negatives that missed objects imply, the authors present a custom loss function. Thus, this work follows this approach to incorporate the strengths of pre-trained ViT models from the specified domains, preserve robust feature extraction and accurate predictions from those domains' challenges.

When applied to tumor detection, YOLOv5 comes with defaults anchors as well as feature pyramids tuned to detect small objects which includes tumor cells in this case. Some of the techniques that have been incorporated through preprocessing include adaptive contrast enhancing which enhance the Medical image detection accuracy. Other specific non-post-processing variations applied for specifically minimizing false positives include customized non-maximum suppression. To achieve good results, a mixed solution is introduced to integrate TumorDetModel with the fast detection of YOLOv5 while maintaining good classification performance.

The work's application potential is illustrated by a discussion of a real-time deployment system for professional utilization in clinical practice where surgeons or radiologists would be able to identify tumors immediately. To further demonstrate the versatility of the model, it is expanded to infrequent tumor types and multiple modalities; such as fusing histopathological images with other modalities like MRI and CT scan images.These enhancements as a whole

create the basis for considering the work novel and contribute useful additions to the existing methods for tumor identification and classification.

G. Model Training

The training process adopted curriculum learning, Further Hard example mining was integrated to ensure that the model focuses on challenging samples improving the robustness.

H. Model Evaluation Metrics

The model is evaluated on various metrics such as: Accuracy, Recall, Precision and other.

1. Accuracy: predicts the total right results and is calculated as

$$Accuray = \frac{no\ of\ right\ answer}{Total\ right\ answer}$$

2. G-Mean: It measures the balancing of the classes.

$$G - mean = \sqrt{sensitivity * specificity}$$

3. Hamming Loss: is the ratio of incorrect labels to the total no. of labels.

$$Hamming\ Loss = \frac{no.of\ different\ element}{n}$$

4. Cohen's Kappa Score: calculates to measure the level of convergence between two raters who classify items into division.

$$Cohen's\ Kappa\ (k) = \frac{p_0 - p_e}{1 - p_e}$$

III. Results and Discussion

Table 2 shows the results of both the build models, BrainDetModel1 performs well in all the metrics. There is only a large difference between both the models in accuracy. The result proved to beat the base model [14] which had accuracy score 84.1%.

Table 2: Tabular Comparison of the Base Model

Model	Accuracy	G-Mean	Cohen Kappa	Hamming Loss
BrainDet Model1	0.94	0.94	0.88	0.06
BrainDet Model2	0.74	0.74	0.47	0.27

The result shows that BrainDetModel1 has outperformed the second model of it. The less Hamming Loss means the model is good to classify the correct label. And as seen in fig 9, it shows the visual comparison of

the model accuracy. There is around a 9% gap between base paper and the proposed model indicating the good sign.

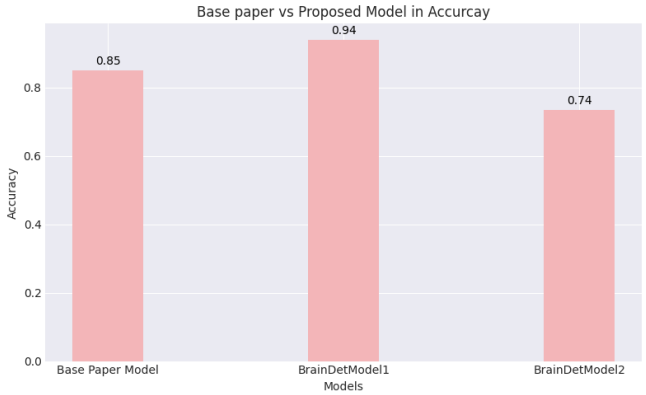

Fig 9: Accuracy Comparison

Below Figure 10, shows the ROC curve for both the models where it is said that BrainDetModel1 has the best AUC Score as 0.95 and BrainDetModel2 has 0.72 AUC Score.

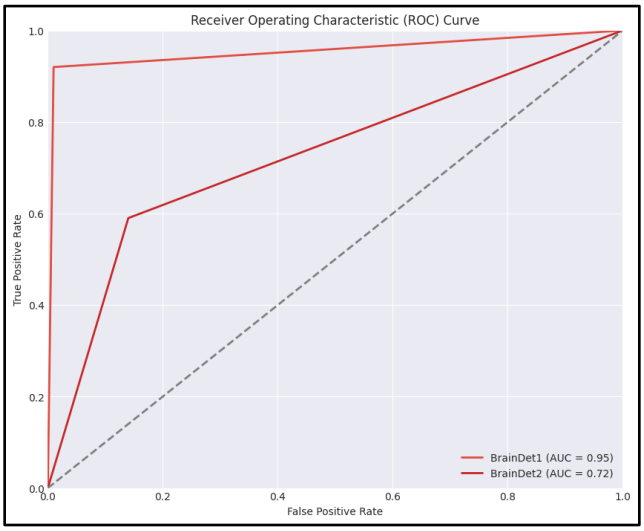

Fig 10: ROC Curve of Both Models

In fig 11, Confusion Matrix Plot is drawn to see how much correct prediction is done by the model. Where for test data the First Model has made only 12 wrong predictions. Second Models have made many wrong predictions and show a room of improvement.

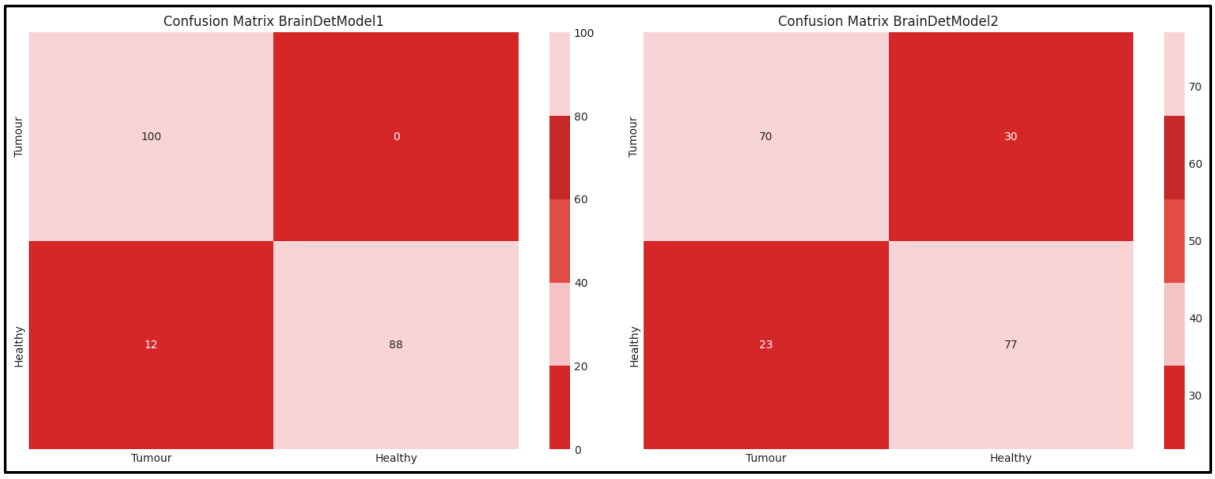

Fig 11: Confusion Matrix Plot

To compare the image shape different types of input shape were used to train on the same proposed model to which highest results are achieved by the (224, 224). Additionally, on both grayscale and rgb color were kept as the image channel and rgb and from this it was known that for MRI images, image channel as rgb provides significantly greater results.

Similar to this, different model optimizers were initially used and compared. From these experiments it was discovered that 'Adam' which is an advanced optimizer, proves to give better results than the previous optimizers.

YOLOv5 Performance in Tumor Localization:

Following the build of the successful BrainDetModel1, the study further employed the Fine Tuned YOLOv5 model for tumor cell localization within the images that are identified as tumor images. The model performance is summarized in table 2. With the high accuracy score of 0.962 the model demonstrated effective finding of tumor cell locations. Additionally with the Precision of 0.971, it states a low false rate and its recall value shows the capacity to identify the location in majority within the dataset, making it a reliable tool for locating relevant areas in tumor images. The MAP50 score is 0.504 which is lower than the other metrics score, suggesting that there may be limitations in refining the bounding box to precisely surround the tumor cell.

Table 2: YOLOv5 Model Result

Model	Accuracy	Precision	Recall	mAP50
YOLOv5	0.962	0.971	0.929	0.504

Figure 7, shows the output of the model on the unseen data, stating the model prediction towards identifying the tumor cell location is 83% in confidence level. This result demonstrates the ability of the model to generalize well to new data, with a good prediction score at the identified tumor cell location.

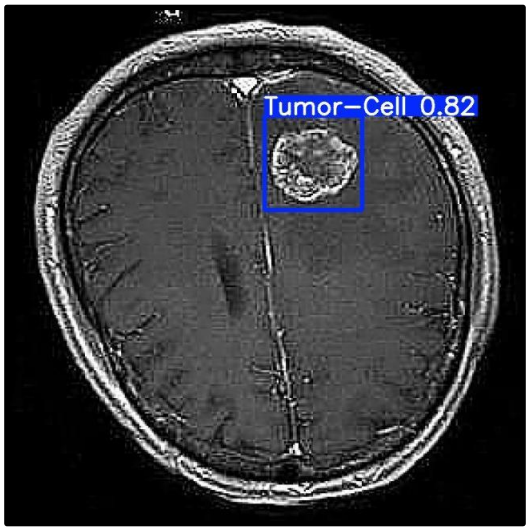

Figure 7: YOLOv5 model result on unseen data

Integrated Approach for Tumor Detection and Localization

The combined approach utilizes both BrainDetModel1 and YOLOv5 for effectively detecting and localizing tumors. The process was structured such that if the image is detected as a tumor it will further apply the YOLOv5 model for locating the cell in the given image. This helped in minimizing the unnecessary analysis that will be done by localization model, making it efficient and resource-saving when working with a lot of data. A custom module/function was developed to handle this dual analysis, ensuring a streamlined operation when testing the new image.

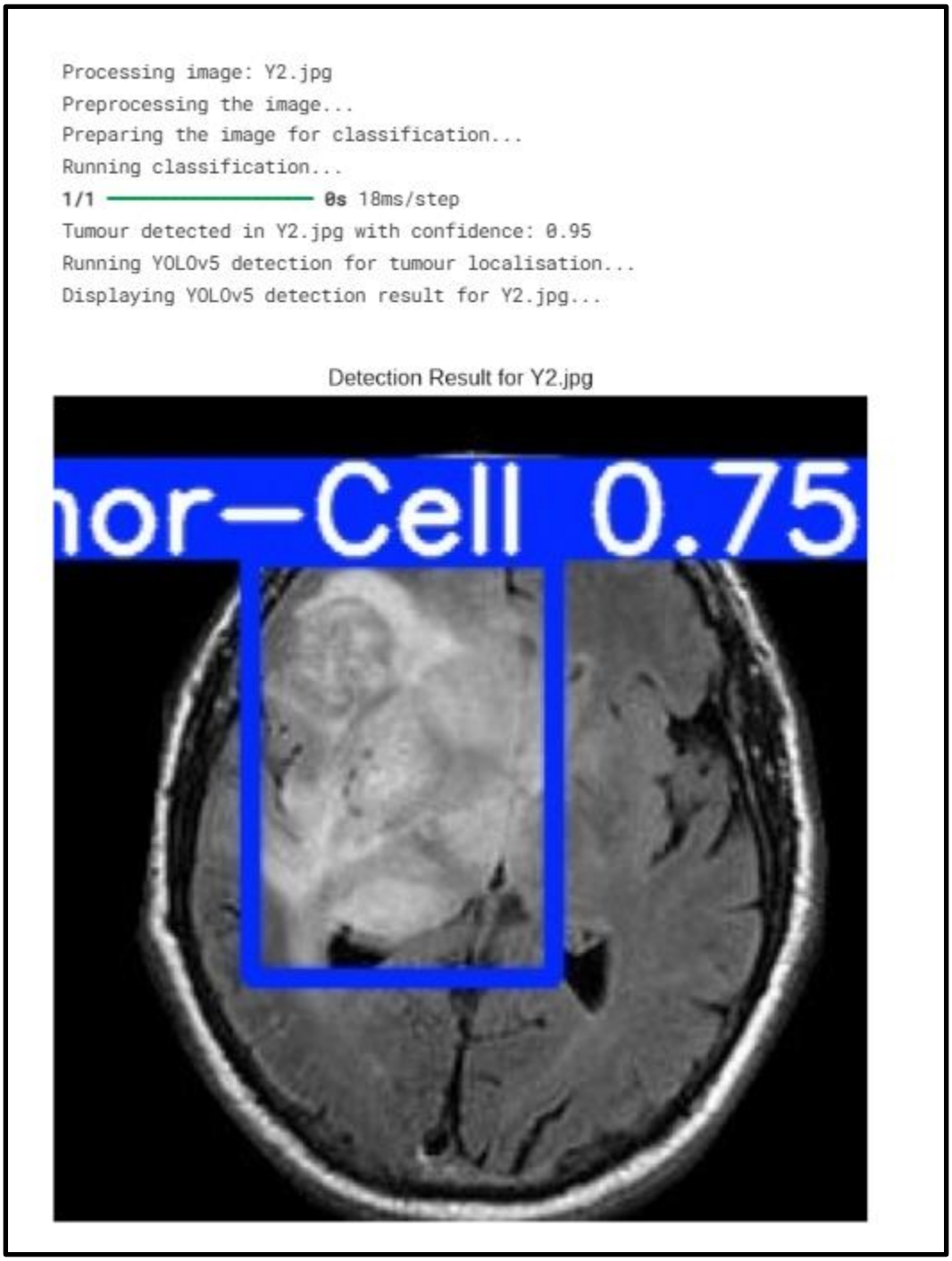

Figure 8: Result of the Integrated System

Overall, both the models achieved high performance in their given respective task that helps in detecting and identifying the tumor presence and location with a greater confidence score, improving early detection and supporting treatment planning.

IV. Conclusion and Future Work

Concluding the work, it is said that both the models are built well and work well on unseen data. For classifying the tumor, image preprocessing like enhancement and segmentation has helped in many ways to improve the model training by enhancing the images. Because of which, the Proposed model has robust performance and a score of 94% accuracy. For object detection, manual annotation was done using roboflow and was labeled as tumor-label. Which was later used for the YOLOv5 model for object detection which has an accuracy of 96.2%. Overall, both the models work well for their respective task and show a great learning that helps for testing new data. The module successfully first detects the tumor and identifies its location.

While working in future for the following research, shall be using advanced methods and making a new type of model with custom layers with the help of a pytorch. Along with it more images shall be annotated for more precision object detection using advanced software. Also, an advanced model for detecting the cell location shall be used to make it more robust in detecting the location of tumor.

V. Declarations

A. Availability of Supporting Data:

The datasets analyzed during the current study are available in the Kaggle repository, accessible at https://www.kaggle.com/datasets/aryanfelix/brats-2019-traintestvalid/data.

B. Competing Interests:

The author declares that they have no competing interests.

C. Funding:

This research has not received any grant from any funding agency.

D. Authors' Contributions:

Ashwin Chavan developed the BrainDetModel, conducted the experiments, and wrote the manuscript. Prof. Sandeep Vanjale supervised the research and provided critical revisions to the manuscript.

E. Acknowledgements:

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