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Brain MRI Image Classification and Cells Localization Analysis

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Abstract— Brain Tumor is the type of ailment in which the brain cell attains irregular growth and, unless diagnosed at an early stage, it will cause an individual to get injured. But once it is diagnosed, one does not know where the cells are at times. Should it be diagnosed with, then the patient may be advised with a suitable cure to eradicate the ailment. This is so because the brain is the most significant organ in our system of organs whose failure to treat well can leave an individual in a coma or even worse. The most important aspect of the diagnosis of brain tumor is to be capable of identifying the correct location. AI can be used to detect tumors and here, it would assist in locating cell as well. The initial analysis involved training the model to identify the presence of a tumor therein with a combination of several image preprocessing techniques such as enhancement, denoising, and resizing among others were implemented so as to provide adequate performance and learning. To find the location of the cell, many images were annotated manually both using Roboflow as well as using YoloV5 with the parameters and a few adjustments only and then the model was trained to determine the location of the cell. They followed the process in the sense that when the image is suspected to be classified as tumor class, the location will be subsequently identified. Into it BrainDetModel1 is made with the aid of several distinct layers and pre-trained model give the accuracy score of 94% and yolov5 model object detection is made which has the accuracy score of 96.2% on the given validation dataset.

Keywords: *Brain Tumor Detection, Hybrid Model, Image Segmentation, CNN, ResNet, YoloV5, Enhancement,*

I. Introduction

A. Background

Brain Tumor can be termed as the disease or the disorder of abnormality in the brain cells of the brain. It becomes fatal when it grows in the brain, especially in case it grows on some vital part of the brain. There are many types of brain tumors which can be acquired in the brain. Thus, the medical professional has a need to be able to diagnose them in order to treat the condition or remove it.

In the recent years, AI and DL in particular has emerged as an effective tool which could assist with medical image analysis. It is at this point that the AI models will be used to help the medical experts by automating the procedure of identifying whether the patient has a tumor or not. In addition, the DL architectures like CNN have also demonstrated how they can be useful in learning of complex attributes in medical images that can be deployed to facilitate the tumor detection process in the images. The research offers the study of feasibility of using the deep learning and transfer learning models to develop a strong brain tumor detection system.

B. Related Work

Other past studies have been reviewed in the consideration of AI-based solutions in the detection of tumors. To illustrate, an active learning framework that applies transfer learning suggested in a recent study conducted by [1] achieves a minimal cost of annotations without reducing the stability of the model. With the model on an MRI data set, an AUC of 82.89 percent was achieved. This demonstrates the effectiveness of transfer learning when classifying medical images.

In the same manner, [2] invented the architectural structure of CNN which was established in the classification of the brain tumors based on the strength of CNN in feature extraction. Similarly. The [3] is focused on developing the model of the neural network which illustrates the overwhelming improvement in the detection of the presence of a tumor based on the image input.

In their work, [4] and [5] conducted the experiments by utilizing one of the most helpful transfer learning models, ResNet50, to classify the different types of tumor present and obtain the stunning results. These studies are based on the significance of transfer learning to solve the issue of medical information being insufficient.

Preprocessing of the images is quite critical in enhancing the input data. The enhancement that was carried out on the images by [6] describes the type of enhancement carried out and the impacts which are given to the images whereas [7] described how Histogram equalization can be important to carry out on an image in order to enhance it to be more improved. An improved outcome is achieved in the diagnosis of brain tumor because of its early diagnosis through the accurate segmentation and classification techniques although tumors of various shapes and locations differ in size and location within the brain region [8]. The Deep Learning models and the Supervised, Unsupervised and Deep Learning schemes demonstrate the power of effective MRI analysis, however, the technical obstacles like uneven proportions in the data sets, the barriers of interpretation and discrimination of models remain open to be solved [9].

The accuracy of CNNs and U-Nets based deep learning systems is 98.8 because of the classification and segmentation tasks that exceed the popular models of pre-training [10]. Since it involves such sophisticated models, they need substantial volumes of data to be backed by the best resources hence can not be applied in clinical practices. Among the major technological advances to object identification is the yolo algorithm which is time sensitive and takes preciseness into consideration as it is explained in [11]. As compared to the two-stage detection algorithms, the one-stage detection algorithm of the YOLO system is fast yet of lower precision [(12)]. The dramatic increase in diagnostic potential as a result of the creation of AI can also be linked to a further solution to the issue of the lack of available data, as well as the actualization of data generalization and the problem of AI diagnosis 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

When data used was in the form of image then there was not much of exploring. As stated the number of images was the same but visually one can draw a pie chart where it is visible as fig 1 that both the classes are equally present 50% each.

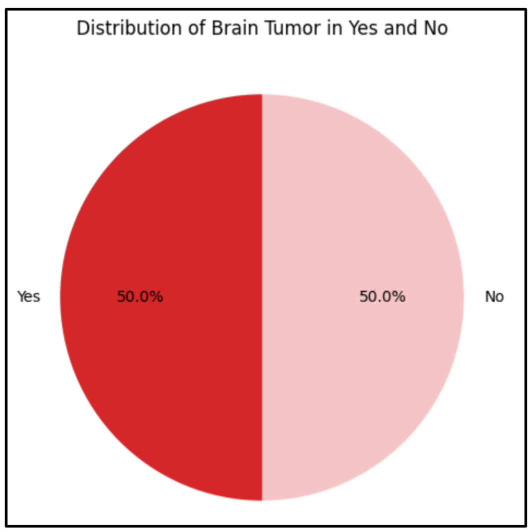

Fig 1: The classes Distribution of Brain Tumors

More so, the size of all the images were verified and it has been discovered that all the images had various size in terms of height and width such as (272, 277) or (630, 630). FIg 2, shows the pictures, tumor in brain. As can be observed the cells grow in numbers (white area represents part tumor that is present). It may be difficult to get rid of it depending on the area.

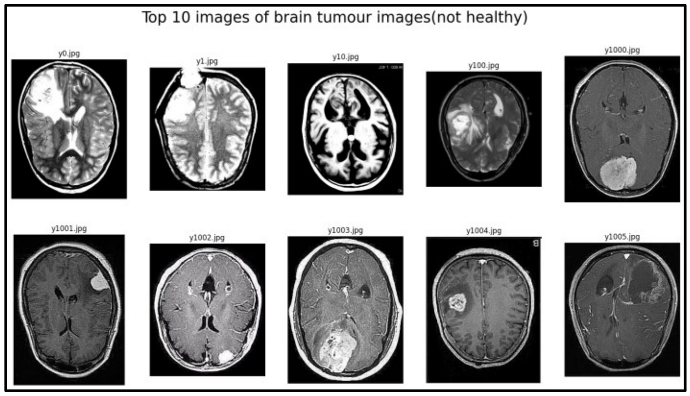

Fig 2: The top 10 pictures of Brain - Tumor

Fig 3, depicts images of normal brain and as it can be observed there is no growth in the cell or white part. It shows no tumor in the brain.

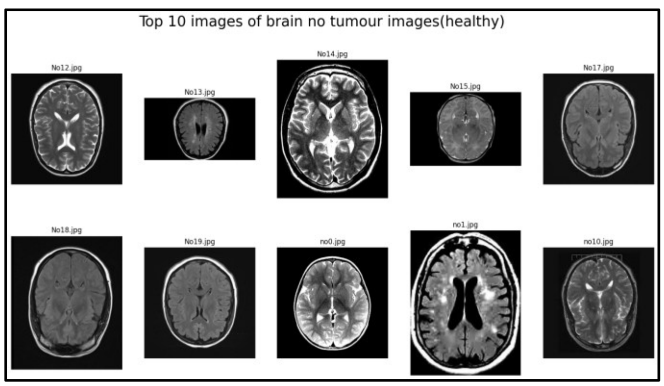

Fig 3: Top 10 images of Brain - Normal

C. Image Preprocessing

Many images of diverse types and sizes were processed, and it was required to preprocess the image to make it compatible and remove noise in the image before sending it into the model. All the preprocessing performed on the images include:

Image enhancement: the problem of augmenting the visual quality of an image through suitable manipulation of its levels. A selection between Clahe method is made and this method was applied as dynamic parameter adjustment in accordance with histogram distribution of the image. This method assisted in the preservation of details in the tumor region, and at the same time enhanced global contrast. The representation of the image enhancement and original is as shown in the Fig 4, below.

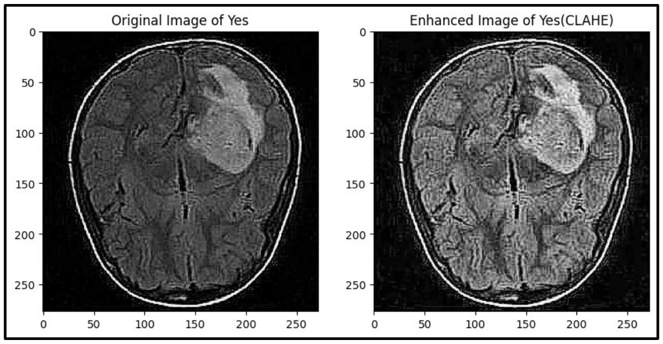

Fig 4: Top Original Vs Enhanced Image

Denoising: this means removal of the noise present and making the picture to be clear [8]. Custom Non-Local denoising was also introduced whereby the nois-prone areas were targeted and precaution was taken over preserving important edges. The Fig 5 is an image transformation.

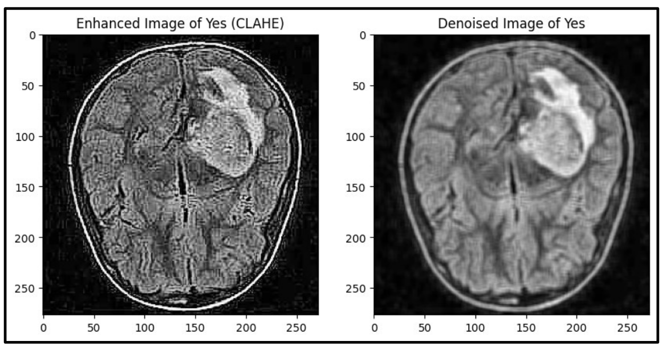

Fig 5: Denoised Image

Affine Transformation: it is concerned with plane and point survival and straight line [9]. This is done by subjecting the image to scaling, rotation and transformation using the assistance of the employed function. The Fig 6, shows the result of the applying of the function.

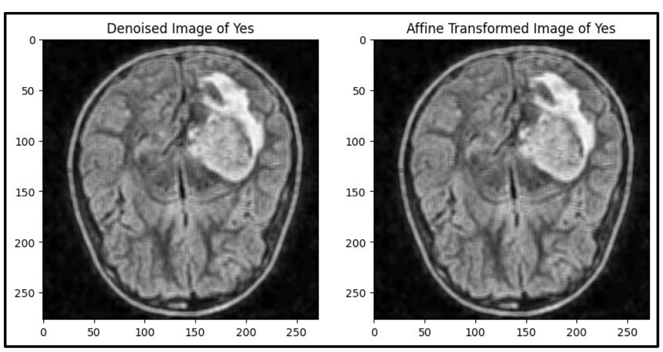

Fig 6: Affine Transformation Image

Segmentation and Masking: It is the process that involves the isolation of regions using binary masks and the division of an image into other regions [10]. A combination of combined binary thresholding and the learning edge detection algorithms are being attempted to create the hybrid segmentation method. This process was helpful in the localization of the tumor region with little false positive. Fig 7, shows the results of the implementation of the function.

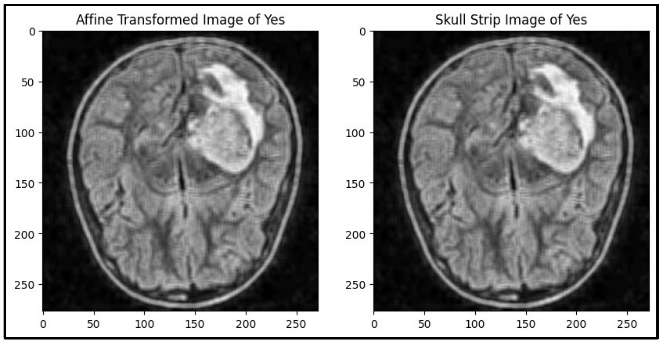

Fig 7: Segmentation and Masking Image

Spatial And Frequency Domain Filtering: In carrying out this operation, the Gaussian blur is applied on the image with the application of the kernel size of (5,5) and std. As shown in Fig 8, the result of carrying out the function is presented.

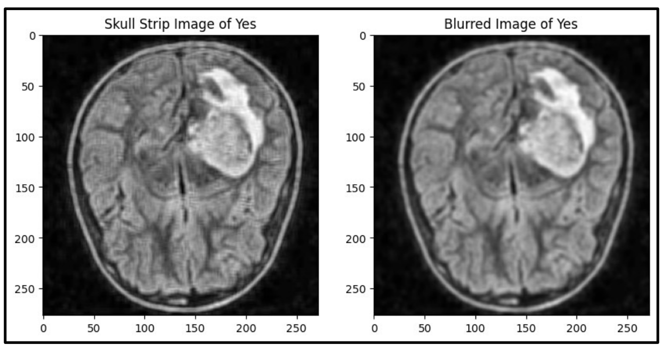

Fig 8: Spatial And Frequency Domain Image

All these preprocessing techniques guarantee quality input and a standardized input that can support the models with better feature extraction and accuracy.

D. Data Augmentation

Data Augmentation approach can be termed the one that creates new images from the existing one thereby altering it thereby creating new ones to use in training the model with different images thereby being trained well and effectively [11].

The nature of the data augmentation strategy employed in this paper was new and quite comprehensive and would enhance and make the model in question much stronger because it has more diverse training data and many variations. In this regard, synthetic GAN was applied to generate synthetic MRIs that will be capable of replicating the real-life tumor and non-tumor cases that would be employed in the expansion of the information without necessarily being redundant in the available information.

To further explore, Augmentation was done in context-aware manner to generate more real-life variation of image by scaling areas containing tumor, changing level of brightness and simulating tumores on normal brian scan was achieved in order to make the training harder. Such strategies were implemented. This was augmented with standard augmentation techniques, which included flipping, rotation and zooming to provide further distribution of the training data.

All of these means were mixed with each other that, simultaneously, helped to build a deep and diverse set of data and led to improved generalizability of the model and its results on the unseen data.

E. Image Labelling

To increase the level of novelty of the existing work, some of the particular features are introduced within the first sections of the pipeline. When providing images during the labeling step, we will be using RoboFlow in manual labels, yet in moving forward to the next steps, consider active learning and weak supervision. The operations reduce the size of the calibration task and make the annotation of a high quality in a few iterations.

Figure 9: Image Labeling using RoboFlow

The proposed set is a domain-specific one in which 1,400 tumor images were selected along with their labels, and its images were also preprocessed using a wide array of augmentation techniques in order to further enlarge the territory of low sample variance. The labeling process introduces such sub categories because the common names such as malignant and benign do not reveal very much about what is happening in the tumor and as such, the sub categories early stage tumor and advanced stage tumor are introduced in the labeling process to provide more information.

F. Model Architecture

In the context of the building of the model, the proposed BrainDetModel1 makes use of the Vision Transformers (ViT) that have been identified in previous literature to do exceptionally well in generalization of modeling global patterns and global relationships in images. As opposed to the convolutional network, ViT takes into account both the spatial and the contextual information, but instead of the images being presented as the maps, the sequences of patches appear, which makes the model capture the contextual features. In this case, more layers will be designed to complement the ViT architecture, especially the attention-based layers that would produce more features with the input tokens and dense layers that would aid in classifications. Grad-CAM diagrams and saliency maps are mixed to allow measurements of points where the model detects tumor characteristics so that they can be interpretable. The authors add a personalized loss to ensure that they sufficiently address the extent of false negative brought about by misplaced objects. Through this process, the identified proposal work will be informed by this practice with the aim of ensuring the feature extraction and predictions success of the established domains obstacles.

In tumor detection, YOLOv5 incorporates the default anchors and feature-pyramids that are fine-tuned to detect small items, in this situation, the tumor cells. The integration of some of the techniques that happened to be a result of the preprocessing techniques include adaptive contrast enhancing which increases the level of the Medical image detection accuracy. Other customized non-maximum suppression are particular variations of non-post-processing that need to be applied in those cases where false positives must be minimized. In order to achieve good results, the idea of bringing a mixed solution into integration with TumorDetModel and the rapid detection method of YOLOv5 is proposed with good classification.

The pragmatism of the work is proved with the assistance of the discussion of the possible implementation of a real-time deployment system that might be applied by the professionals in the clinical environment when surgeons or radiologists might realize the presence of the tumor on the side. To further demonstrate the versatility of the model it is generalized to rare tumor types and multiple modalities; fusion of histopathological images with other modalities including MRI and CT scan image.Overall these extensions can be exploited to define the premise in making the work novel and can be used as useful extension to the existing methods of 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 conclusion shows that BrainDetModel1 has been superior to the second model of the same. The fact that Hamming Loss less is an indication of a good model to predict the right label. And as it is shown in fig 9, it portrays the visual contrast of the model accuracy. The positive indication is that there is a nearly 9 per cent variance between base paper and the proposed model.

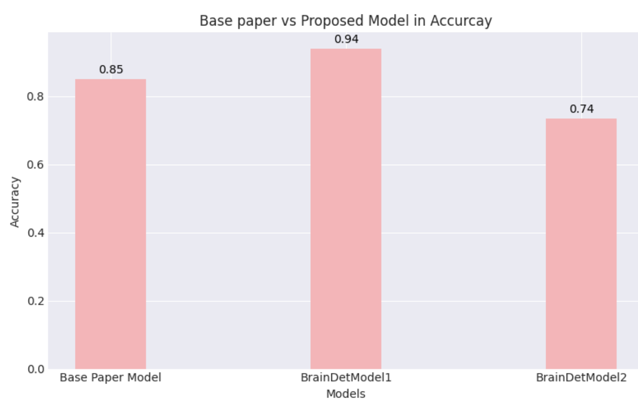

Fig 9: Accuracy Comparison

Below Figure 10 is the ROC curve of both models whereby it is indicated that BrainDetModel1 possesses greater AUC Score of 0.95 and BrainDetModel2 possesses AUC Score of 0.72.

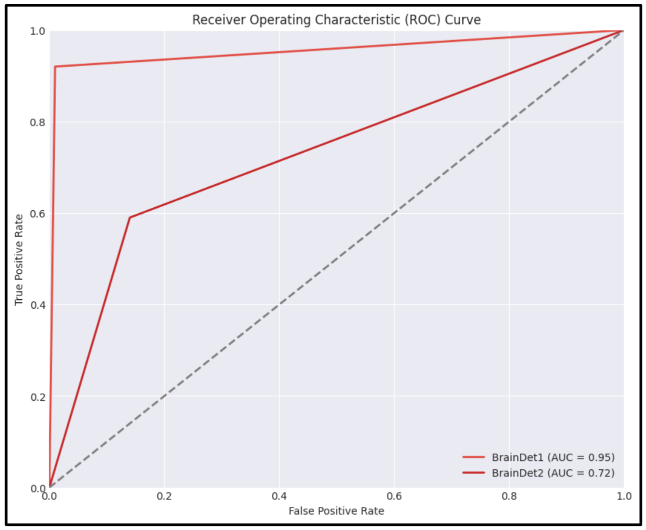

Fig 10: ROC Curve of Both Models

Confusion Matrix Plot is plotted in fig 11 to note how well the model has predicted. Where, in the case of test data, the First Model has only been wrong in predicting 12 occasions. Second Models have many wrong predictions and they give a space to be improved.

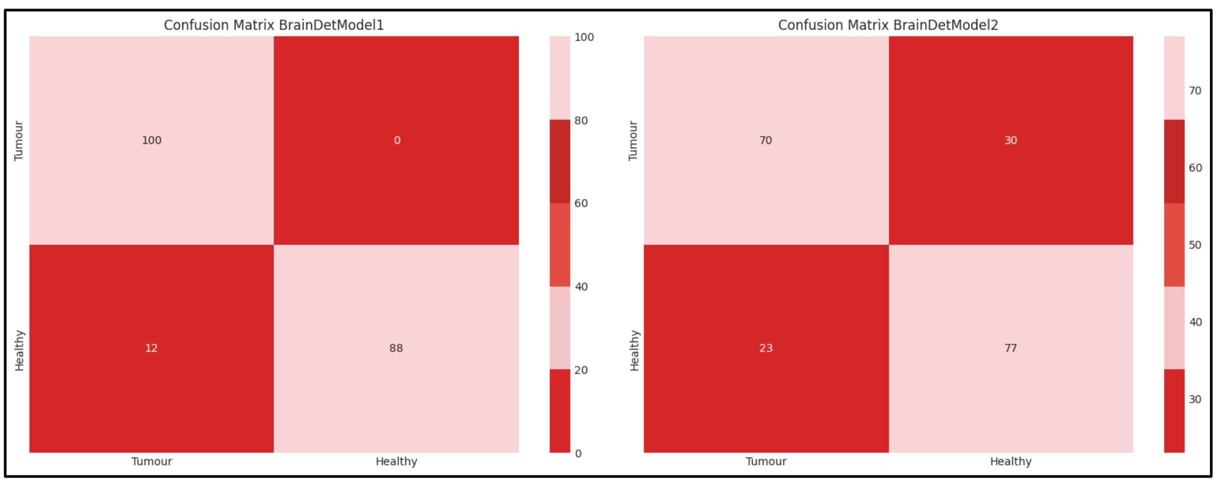

Fig 11: Confusion Matrix Plot

To make the comparison of the shape of the image, different types of input shape were used in the same proposed model where the (224, 224) has had the most results. Also on grey scale and rgb color were retained as image channel and as rgb and on the basis of this, it was made clear that in an MRI image, when the image channel is given as rgb, the results can be seen to be far better. Similarly, different model optimizers were applied and contrasted in the first place. It was determined depending on these experiments that Adam, an advanced optimizer, is observed to be superior to the previous optimizers.

YOLOv5 Performance in Tumor Localization:

After creating a successful BrainDetModel1, the research has also applied the fine Tuned YOLOv5 model in identifying the location of the tumor cells in the images classified as tumor images. The results of the model performance have been summarized in Table 2. The model had also obtained a high level of accuracy score of 0.962 which suggested that it was effective in its capacity to locate the position of tumor cells. The same precision of 0.971 also yields a small false level and the recall of the same also shows the capability to identify the location in most instances in the data set and thus a useful tool in identifying areas of interest in images of tumor. The score of MAP50 is 0.504 lower than its corresponding score of the other metric which suggests that it may have limitations of confining the bounding box closely around the tumor cell.

Table 2: YOLOv5 Model Result

Model	Accuracy	Precision	Recall	mAP50
YOLOv5	0.962	0.971	0.929	0.504

In Figure 7, the output of the model on the unseen data is presented, and it says that the expectation of the model to identify the location of tumor cell is 83 percent as its confidence level. This outcome shows that the model could generalize well to new cases, with an acceptable score of predicting the data at the detected tumor cell position.

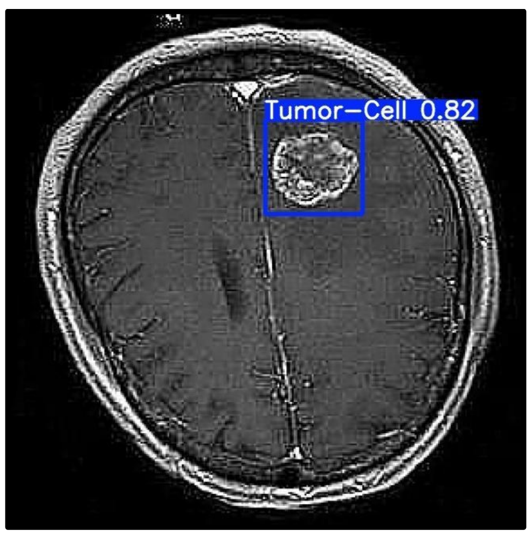

Figure 7: YOLOv5 model result on unseen data

Integrated Approach for Tumor Detection and Localization

The conjunction of the strategy applied is the use of BrainDetModel1 and YOLOv5 that can be applicable in tumor detection and localization. It has been programmed such that when it comes to an event where the image has been labeled as tumor it would also exploit the use of the YOLOv5 model that would be applied in determining the location of the cell within the respective provided image. This helped reduce unwarranted analysis that will be performed by localization model which will be resourceful and economical on resources where the amount of data to be analyzed is significant. To perform this dual analysis a custom module/function has been developed that would make this an easy process of testing the new image.

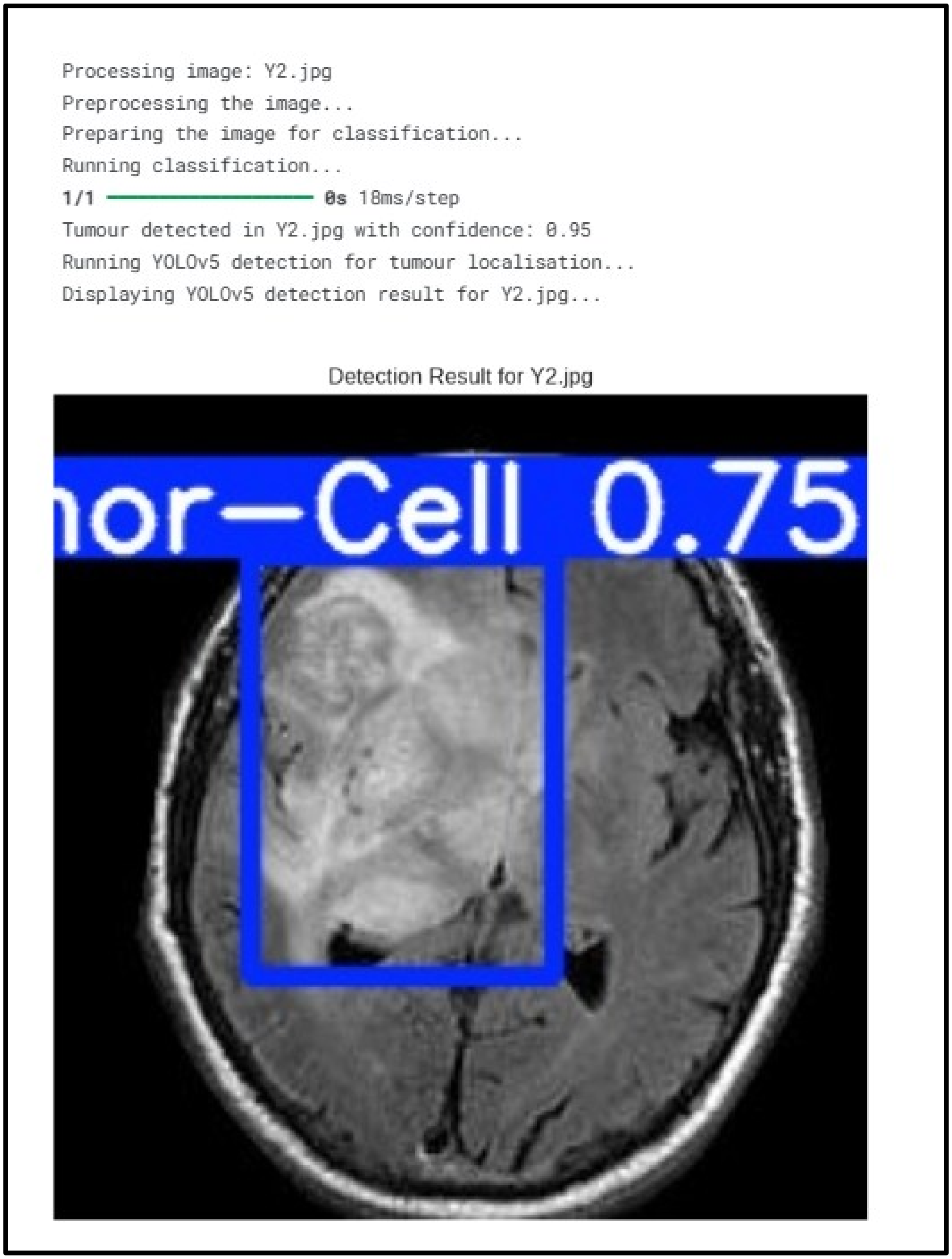

Figure 8: Result of the Integrated System

On the whole, the models were performing well within the assigned respective task that contributed to the early detection of the tumor presence and localization with a higher confidence index that would assist in treatment planning.

IV. Conclusion and Future Work

In the conclusion of the work it is mentioned that both models are properly made and they perform well on unseen data. Image processing which comprises image enhancement and image segmentation in one way or the other has played a role in training the model by enhancing the images used so as to classify the tumor. Owing to this, the Proposed model works effectively and obtains the accuracy of 94%. The task of manual annotation using roboflow (tumor-label) was conducted in order to detect the objects. It was subsequently used on the object detection model YOLOv5 with an accuracy of 96.2%. Overall, the models are not only effective in accomplishing the stated task, but also have excellent learning which is applicable during an attempt to test new information. The module can first find out the tumor and identify its location first.

In the future when carrying out work on the next study, I will be using advanced methods and developing a model of a different type with special layers with the help of a pytorch. Besides it, additional images will be annotated so that objects could be identified more accurately under the assistance of more sophisticated software. Moreover, a new model of locating the cell location will be adopted to further improve it such that it can become very sensitive in locating the location of the 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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