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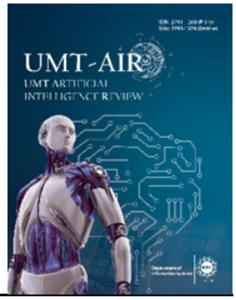

Title: **Multiclass Light Weight Brain Tumor Classification and Detection using Machine Learning Model Yolo 5**

Author (s): Asif Raza[1], Usman Amjad[2], Muhammad Abubakr[3], Dr. Humera[4], Asad Abbasi[5], Asher Ali[1]

Affiliation (s):
[1]Syed University of Engineering and Technology, Karachi, Pakistan
[2]NED University of Engineering and Technology, Karachi, Pakistan
[3]MNS-University of Agriculture, Multan, Pakistan.
[4]University of Karachi, Pakistan
[5]Benazir Bhutto Shaheed University Lyari, Karachi, Pakistan

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Multiclass Lightweight Brain Tumor Classification and Detection using Machine Learning Model Yolo v5

Asif Raza[1*], Usman Amjad[2], Muhammad Abubakr[3], Dr. Humera[4], Dr. Asad Abbasi[5], Asher Ali[1]

[1]Department of Computer Science and Information technology, Sir Syed University of Engineering and Technology, Pakistan
[2]Department of Computer Science and Information Technology NED University of Engineering and Technology, Pakistan
[3]Department of Computer Science, MNS-University of Agriculture, Multan, Pakistan
[4]Department of Computer Science, University of Karachi, Pakistan
[5]Benazir Bhutto Shaheed University Lyari, Karachi, Pakistan

***Abstract*- Early brain tumor identification is a critical challenge for neurologists and radiologists. Manually identifying brain tumors through magnetic resonance imaging (MRI) is difficult and prone to mistakes. The diagnosis of tumor is a complex job when performed in a traditional manner. Brain abnormalities can be fatal, lowering a patient's quality of life and adversely harming their overall health. Brain tumors vary in nature based on where they are situated and how rapidly they develop inside the skull. Tumors are a proliferation of abnormal nerve cells that form a mass. Some brain tumors begin in the cells that support the brain's nerve cells. This paper proposes a machine learning algorithm known as YOLO v5 SSD (single shot detection) to detect and classify such tumors namely meningioma, glioma, and pituitary gland with 88% accuracy. For this purpose, data augmentation was applied to the publically available dataset from Kaggle. MRI of different classes including 396 glioma images, 397 meningioma, 380 no tumor, and 399 images of pituitary tumors were employed. The current study presents false negative, true positive false positive, and true negative, which were used to test the YOLO v5 (You Only Look Once) classifier performance. It was determined that the YOLO v5 model is giving 88% accuracy.**

***Index Terms*- machine learning, magnetic resonance imaging (MRI), medical imaging, single shot detection (SSD), YOLO v5.**

[*] Corresponding Author: asif.raza@ssuet.edu.pk

I. Introduction

Brain tumors comprise the formation of abnormal tissues inside human brain. Brain tumors can be classified through MRI into different types based on their mutation, location, and genetic cell composition. The most common primary brain tumors are meningioma, glioma, and pituitary tumors [1], as shown in Figure 1.

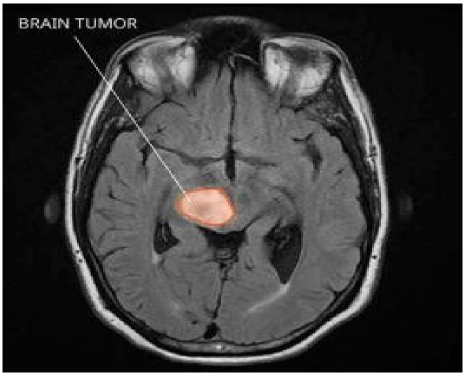

Fig. 1. Brain Tumor MRI image [2]

Brain illnesses, such as tumors, are a primary cause of mortality and disability because they damage the principal cells in the human brain. Brain abnormalities increase the risk of brain tumors which are the ninth leading cause of death across the world.

YOLO v5 was used to construct the object detection model. This model is managed by employing the dark net framework. It offers a single network used for classification and prediction by having bounding and labeled boxes possessing the same characteristics. It's significantly lighter and quicker. In the past, this model was trained on the "COCO" dataset. Its structure consists of 24 convolutional layers for feature extraction from images and two fully connected layers for bounding and labeled boxes prediction by using the dark net framework.

Medical imaging is an important application of computer vision, where accurate segmentation of actual lesion symptoms is crucial for diagnosis and treatment. One effective technique for achieving accurate segmentation is the Grab Cut method, which is capable of segmenting out specific areas of interest. Moreover, the fine-tuning method Introduces to obtain image aspects along with the hand-crafted
(color, size) features. Feature optimization was achieved using entropy for accurate and rapid classification. The proposed model was verified using databases from prominent medical images and computing.MICCAI dataset was us ed along with BRATS for segmentation and Analysis [4].

This study presents a unique metaheuristic-based technique for tumor detection. The proposed technique contains classification, segmentation, and feature extraction by utilizing a deep neural network. Furthermore, this method is also compared with the existing matrix e.g. correct detection rate (CDR) an evaluation matrix, false acceptance rate (FAR), and False Rejection rate (FRR) indices, It was determined that the recommended strategy outperforms the other existing algorithms [5].

"Inception-v3" is associated with "DensNet201". Two alternative scenarios of brain tumor classification and detection were examined using these two models. The softmax classifier was further applied to categorize features. Secondly, features were extracted from multiple "DensNet" segments using the pre-trained "DensNet 201[6].

This research provides several Segmentation techniques e.g. Guide Segmentation and Semi-automatic Segmentation are introduced for cerebrum tumor diagnosis by using CAD. Using a GLCM matrix, texture-based features were retrieved. Correlation and homogeneity are some of the textural features of the images considered in particular. Multi-layer perceptron (MLP) and Naive Bayes algorithms were combined to get the highest accuracy of 98.6% and 91.6% respectively by analyzing approximately 212 MRI samples [7].

MRI analysis is yet again a common approach for detecting brain tumors. These images are trained of a new hybrid approach that combines Neural Autoregressive Distribution Estimation (NADE) with CNN, which was used to test 3064 T1-weighted contrast-enhanced scans of three different classes. The results revealed that when medical images are rarely available, then hybrid CNN-NADE can be employed with outstanding classification performance [8].

Brain tumors are difficult to detect. Recent literature suggests that more work needs to be done to improve detection rates. MRI scans, which are commonly used to detect brain tumors, are prone to acquiring noise during image acquisition. Removing this noise is a complex task that requires careful attention to detail. Despite advancements in imaging technology, there is still a need for further research and development to improve the accuracy of brain tumor detection. With continued effort and innovation, it is hoped that future methods will be more effective in detecting brain tumors and improving patient outcomes [9]–[11].

Segmentation is an important technique used in medical research to gain the full understanding of the structure and behavior of tumors. The current study focused on brain tumors and used YOLOv5, a state-of-the-art object detection, classification, and segmentation model. Four classes of images including normal brain images, as well as brain images with meningioma, glioma, and pituitary tumors were incorporated in this study. The main objective was to classify, detect, and segment the tumors more accurately. The results showed that YOLOv5 was able to effectively segment the tumors in brain images. In fact, the performance of YOLOv5 was faster and more accurate than the previous versions of YOLO.

This paper is organized as follows: Section I comprises Introduction, Section II presents the related work, Section III contains experimental results, and Section IV presents the conclusion and future directions.

II. Related Work

Precise epic localization algorithm in the YOLO v4 architecture for fetal brain MRI analysis represents a promising approach for detecting and classifying healthy and abnormal fetal brains. The algorithm's ability to detect the orientation of the fetal brain is particularly noteworthy, as this information can be crucial for accurate diagnosis and treatment planning. The use of a machine learning algorithm to evaluate the detection and classification of abnormalities, such as malformation, is also a promising approach. Machine learning algorithms can be trained on large datasets of labeled images to learn patterns and features that are indicative of specific abnormalities. Then, they can be used to accurately identify these abnormalities in new images [12].

This study offers a method for automatically recognizing and segmenting brain tumors. Seven light weight versions of Yolo are used for detections are segmentation. The use of neural networks for detection and segmentation is a common approach in computer vision. This article proposed, seven different neural networks perform effective segmentation task. Each of the seven neural networks likely has a specific architecture and is optimized for a particular aspect of the detection and segmentation process. The use of multiple algorithms provides a comprehensive evaluation of the effectiveness of different approaches, which can help to identify the most promising method for their further development and refinement. The use of popular and widely used frameworks, such as YOLO v3, YOLO v4, Scaled YOLO v4, YOLO v4 Tiny, YOLO v5, Faster-RCNN ensured that the results remained relevant and comparable to other studies in the field. After training and evaluating the models on 641 MRI scan images from the dataset, the YOLO v5 model was determined to provide the best performance. This suggests that the YOLO v5 algorithm may be particularly effective in brain tumor detection and segmentation. Furthermore, it could be a promising area for future research and development [13].

Overall, the proposed algorithm holds a significant potential for processing large sets of brain tumor images and providing quick and accurate outcomes for medical diagnosis and treatment planning. The faster convergence rate and the higher accuracy achieved by the proposed model makes it a promising approach for improving the efficiency and effectiveness of brain tumor detection and classification [14]

Given the potentially life-threatening nature of brain tumors, their accurate and efficient detection is crucial for improving patient outcomes. The proposed model's superior performance in detecting brain tumors from MRI images demonstrates its potential for improving medical image analysis, while aiding in more precise diagnosis and treatment planning for patients with brain tumors. Compared to other CNN-based models, such as AFP-Net, Mask RCNN, YOLOv5, and FCNN, the proposed model demonstrated better performance in detecting brain tumors.

Deep learning architecture was developed for brain tumor classification using MRI images. The framework consists of three main stages: data set pre-processing, deep learning feature extraction, and classification. The data set pre-processing stage involves image normalization, resizing, and data augmentation to improve the quality and quantity of the dataset. The deep learning feature extraction stage uses the VGG19 model as feature extractor, followed by either a CNN, GRU, or Bi-GRU model for further feature extraction. The classification stage employs the extracted features to classify brain tumors into three types. The three models used for classification are VGG19 + CNN, VGG19 + GRU, and VGG19 + Bi-GRU [16].

The U-Net architecture has been

widely used and has achieved state-of-the-art results in brain MRI segmentation tasks. Several improved versions of U-Net have been proposed to further improve the segmentation performance. For this purpose, data comprising lower-grade glioma collections with minimal FLAIR can be particularly useful, as this is a challenging task due to the subtle nature of these tumors. This paper proposes a better U-Net Architecture for brain tumors using VGG16. In this regard, it upgraded the U-Net Architecture with VGG-16 by using k-fold cross validation on the TCGA-LGG dataset to segment MRI images and identify tumor cell regions [17].

Tumor detection and segmentation using MRI images remains difficult and error-prone. As a result, for the early identification of the disease, a tumor detection system is necessary. This study proposes two deep learning methods for tumor classification diagnosis using the cutting-edge object framework and the DL library FastAi. The BRATS 2018 dataset was used in particular, which includes 1,992 MRI scans [18].

DCNN model for brain tumor segmentation differs from the existing CNN models in the sense that it employs a trial-and-error approach. Furthermore, It employs ensemble learning for enhanced efficiency, resulting in the highest possible accuracy in tumor detection [19]. In this paper, a method for tumor segmentation using FLAIR MRI and FCNNs is suggested. In a previous study, FCNN produced tumor-containing sub-regions in the original picture and provided segmented full-size FLAIR to help radiologists to enhance their diagnosis [20].

The ability to accurately distinguish between firm and soft meningiomas is critical in determining the appropriate treatment strategy for patients. The proposed deep learning approach that uses YOLO v4 can aid in improving the accuracy of diagnosis, leading to more appropriate patient counseling and operative procedures. Furthermore, the superior performance of the YOLO v4 model over the traditional classification methods, such as SVM and RF, highlights the potential of deep learning-based approaches for a more accurate and efficient medical image analysis [21].

Based on an encoder-decoder architecture, a semantic segmentation network for tumor sub-region segmentation from 3D MRIs was established. A variational auto-encoder branch was included to recreate the input images, owing to a restricted training dataset size, in order to regularize the shared decoder and to place extra limitations on its layers [22]. The current study proposes feature recombination for semantic segmentation which uses linear expansion and compression to build more complex features, as well as a segmentation SE (SegSE) block for feature recalibration that captures contextual data while preserving spatial meaning. Furthermore, it evaluates the proposed approaches for brain tumor segmentation using publicly available data [23].

III. Methodology

YOLO v5 is a newer version of YOLO, designed for segmentation. This model provides highly competitive results due to being lightweight in nature. The YOLO algorithm takes a dataset in the form of pictures and corresponding text files. The dataset is divided into different folders for training and validation. The .yaml extension file is used to define paths and classes and is mandatory in the newer YOLO versions. After proper processing and segmentation, results can be obtained. YOLO v5 is a highly efficient model that can accurately perform segmentation tasks, making it a valuable tool for various medical industries.

IV. Results and Findings

A typical strategy in machine learning uses 80% of the images for training and 20% for validation. This split is designed to train the model on several images, while still reserving a group of images separate for validation to make absolutely sure that the result is conclusive to avoid over fitting. Having 4 different classes, this particular model shows a relatively better average accuracy of around 88.4%.

A. YOLO

The current object identification model was built with YOLO v5. It was managed by the dark net framework that offers a single network for both item classification and prediction through bounding boxes. This particular version is now substantially faster and lighter. This model was rapidly trained on the unique annotated MRI images. It featured fully connected layers for bounding box prediction. This network was built more efficiently using the dark net framework [24]. This model offers particular benefits in its design.

i. Comprehensive object identification, tumor placement, as well as fast detection speed and accuracy.

ii. Recognizing microscopic tumor objects in murky, noisy, and hazy pictures.

B. Use of Simulation Software

In the current study, Google-Colab was used to run and train classification techniques. The accuracy rate was initially quite low for all models, as shown in Figure 5. Although, it rose as epochs increased up to 142. Epoch was executed with a batch size 16.

The current study used a confusion matrix to classify the relationship between distributions and data in order to examine the performance of the classification process. The precision rate was above 88%. Classification may be evaluated in a broad spectrum by analyzing different confusion matrices. The study includes four basic keys: “true positive”, “true negative”, “false positive”, and “false negative”. Model performance was computed in terms of specificity, accuracy, sensitivity, negative predictive precision, values, and the F1-scores Mentioned in Figures 3, 4, 5, and 6, respectively.

C. Performance Metrics

The four major parameters used to evaluate the efficacy of the system are true positives (TP), false positives(FP), true negatives (TN), and false negatives (FN). The following matrices stand to calculate the performance. The ability to accurately distinguish between different forms of brain tumors is measured by accuracy [25].

To evaluate a test's accuracy, the percentage of true positive and true negative occurrences in all examined instances was determined using the formula given below. A true positive (TP) arises when the model accurately predicts the positive class. An outcome where the model properly predicted the positive class is referred to as a true positive. Similar to a True positive, a true negative is a result for which the model accurately expects the negative class. When the model forecasts the positive class inaccurately, it is called a false positive as shown in Figure 2 shows the confusion matrix Yolo v5 model. Confusion matrix visualizes and summarizes the performance of classification algorithm. It shows the relevance of various classes, for instance, 0.42% accuracy for glioma, 0.92% accuracy for meningioma, 0.77% accuracy for pituitary cancer, and 0.99% accuracy for no tumor class.

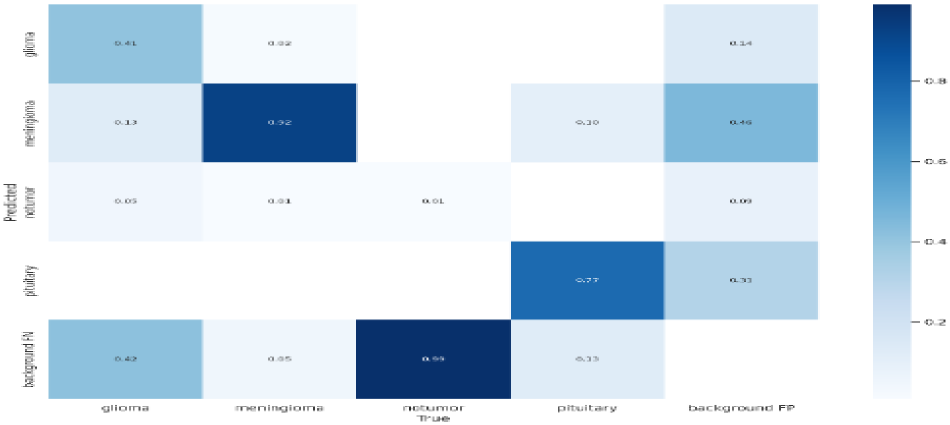

Fig. 2. Confusion Matrix of 4 Classes

Figure 3 shows the accuracy of a model tested on Kaggle (augmented dataset) based on F1. Figure 4 displays the number of positive results, correctly classified out of the total number of tests that conclude as positive. It is important to note that a few wrongly classified positive results can decrease the accuracy slightly. In Figure 5, the precision/recall curve is used to show the performance of parallel classification algorithms in situations where classes are heavily imbalanced. Similar to ROC curves, precision-recall curves provide a graphical representation of the classifier's performance over multiple thresholds, rather than a single value. Finally, in Figure 6, the number of positive tests accurately classified as positive is compared to the total number of positive tests.

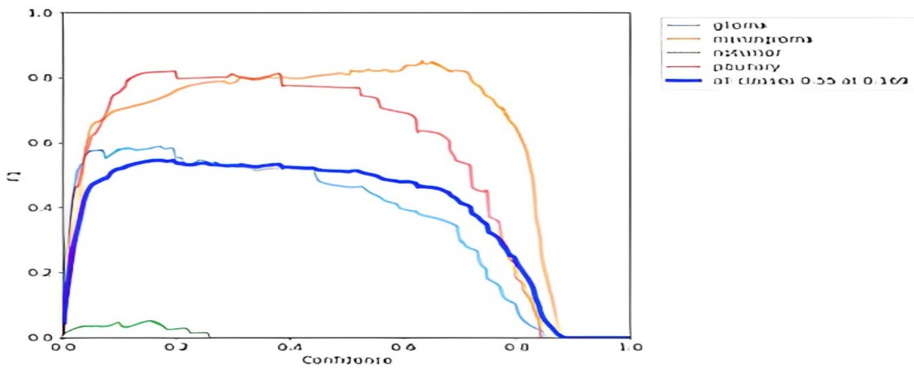

Fig. 3. F1 Score

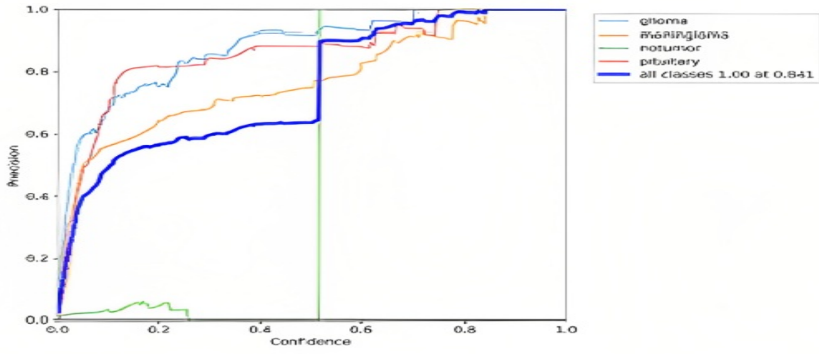

Fig. 4. Precision

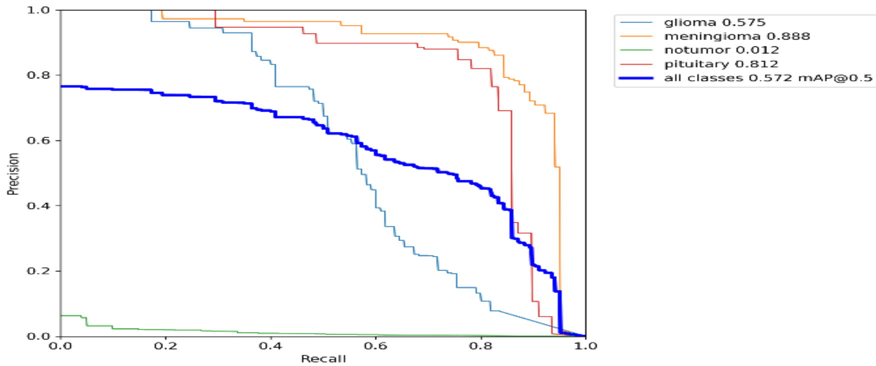

Fig. 5. Precision

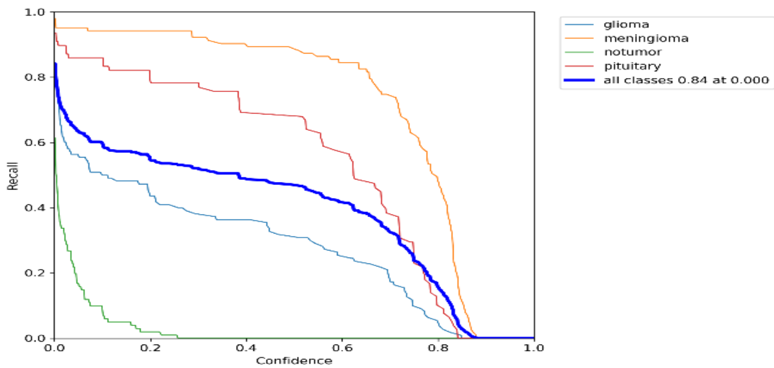

Fig. 6. Recall

Figure 7 describes the number of images provided into the dataset of brain tumors, containing 4 classes in the graph format. Fig 8 describes the pair plot and Labels Correlogram of the provided dataset. Figure 9 shows the prediction of validation batch, while Fig 10 contains labels, instances, and image intensity coordinates levels. Fig 11 shows the results and Fig 12 represents Training Batch 1.

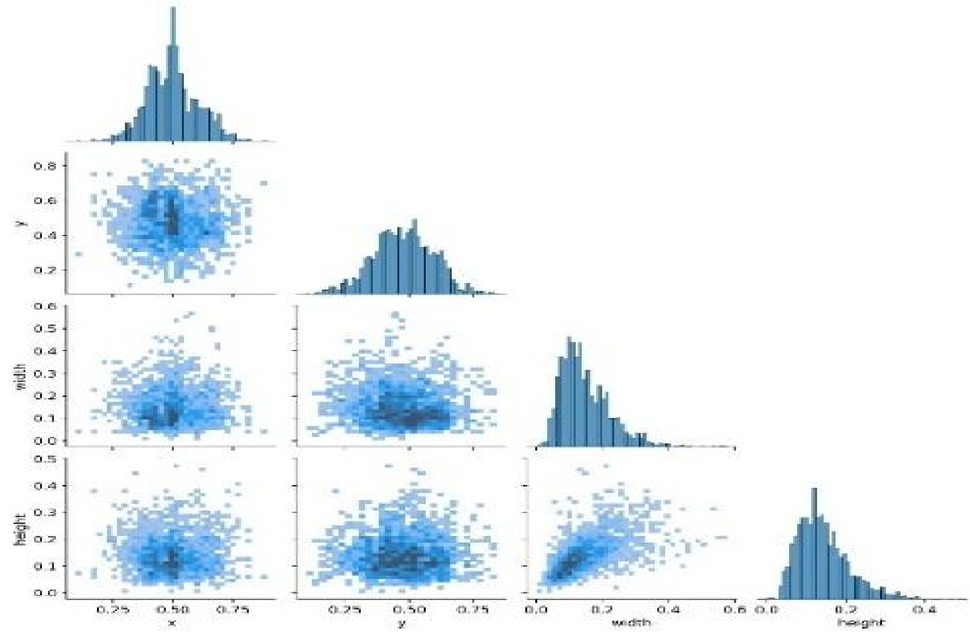

Fig. 7. Number of Images

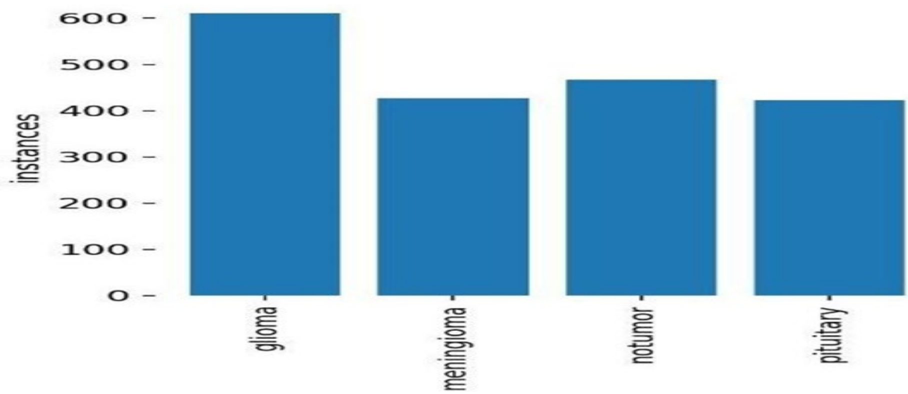

Fig. 8. Labels Correlogram

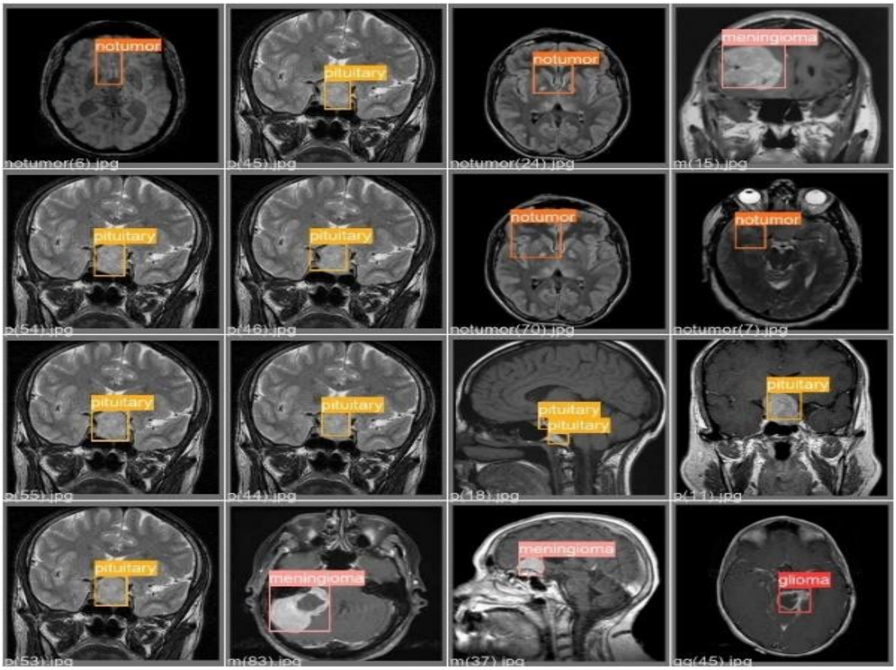

Fig. 9. Validation Batch Prediction

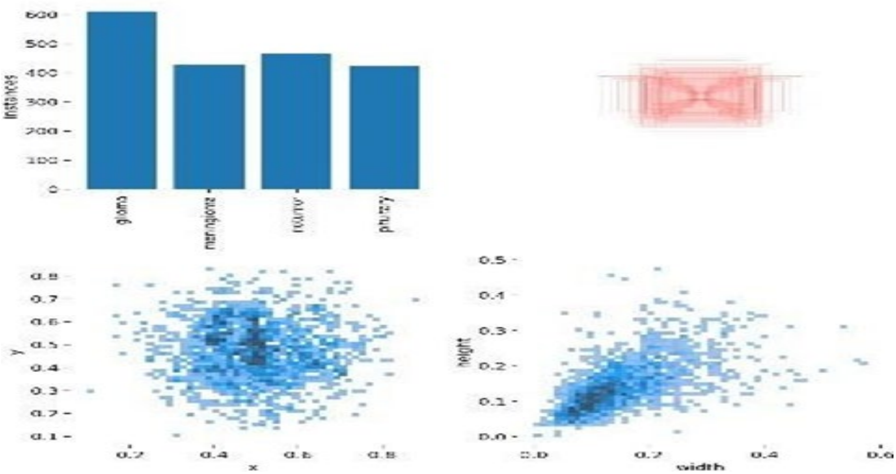

Fig. 10. Labels

Yolo v5 performs well in terms of validation loss and precision accuracy. A validation loss of less than 0.5 is considered a good standard in machine learning. It is good to see that the algorithm meets this standard.

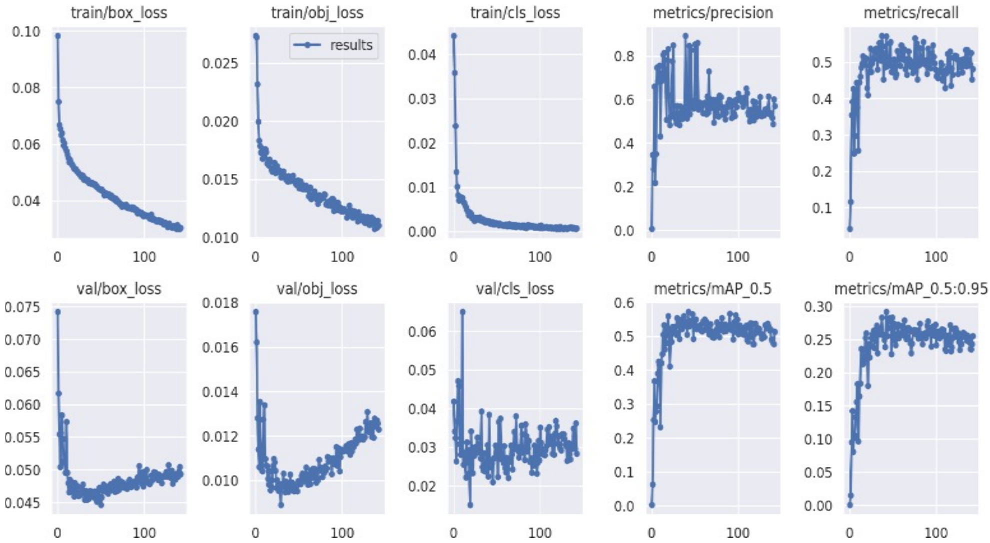

Figure 11. Results

The precision accuracy of more than 88.41% indicates that the algorithm makes accurate predictions. The efficacy of YOLO v5 model is also evident in the validation and prediction batch shown in Figure 9, where the bounding boxes are detected sufficiently during the validation process. Overall, these results are a testament to the effectiveness of the algorithm and the YOLO v5 model being used.

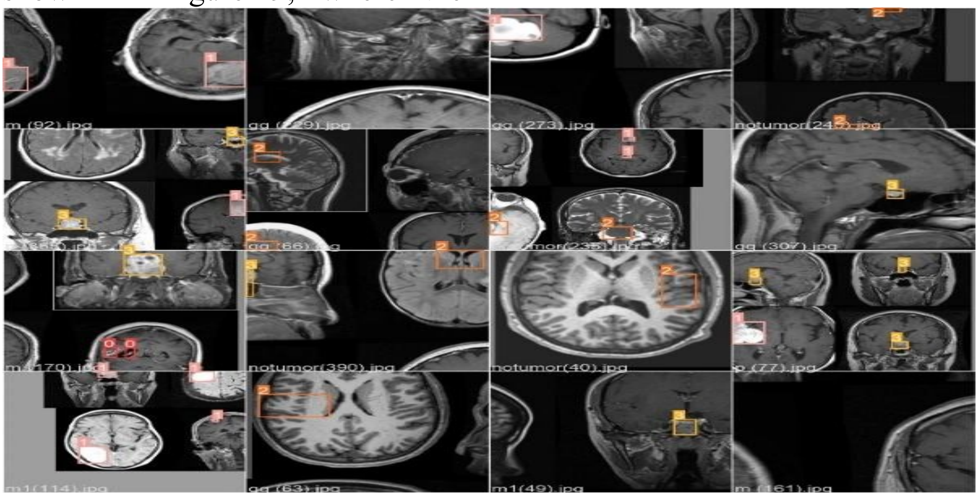

Fig. 12. Training Batch 1

D. Comparison of Results

The results of YOLO v5 model with other existing results were compared on the basis of the following parameters:

- Training loss
- Validation per object loss
- Training Loss / Class
- Metric / Precision Accuracy
- Metric / Recall Accuracy

Considering the above parameters, the model performed well in terms of the reduction of training loss, validation per object loss, metric/precision accuracy, and training / class loss.

Table I

Please provide caption here

Ref	Training loss	Validation /Object Loss	Training / Class loss	Metric/Precision	Metric/Recall	Tool
[26]	0.13-0.04	0.004	0.15	87 %	0.8	NVIDIA
[12]	0.10-0.01	0.0050	0.01	84.30 %	0.8	Tesla/Google Colab
Proposed	0.10-0.01	0.012	0.01	88.41	0.6	Google Colab

V. Conclusion and Future Work

The current study proposed a method for the detection and classification of MRI in 4 different classes. Tumor progression, position, and region were extracted by using YOLO v5 SSD algorithm. Tumor class such as glioma, meningioma, pituitary tumor, and no tumor were determined from the dataset. The study yielded relatively better accuracy with this algorithm. The proposed work is divided into two phases, namely (i) classification and (ii) feature extraction. Furthermore, the aim is to develop a new method in the future along with a larger dataset with different size and resolutions to improve algorithm accuracy.

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