MRI Based Brain Tumor Detection Using Deep Learning Methods – YOLOv5

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This Project report has been submitted in fulfillment of the requirements for the Degree of Bachelor of Science in Software Engineering.

Declaration

I hereby declare that the work which is presented in this thesis paper which titled, "**MRI – Based Brain Tumor Detection Using Deep Learning Method – YOLOv5**", is the outcome of the research done by **Md. Shahriar Parvez** under the guidance of **Mr. Bikash Kumar Paul**, Research Mentor, Department of Software Engineering, Daffodil International University(DIU), Ashulia, Savar, Dhaka, Bangladesh.

It is also declared that neither this thesis nor any part thereof has been submitted anywhere else for the award of any degree, diploma, Ph.D., or other qualifications.

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APPROVAL

This **thesis** entitled on ***"MRI based Brain Tumor Detection Using Deep Learning Methods-YOLOv5"***, submitted by ***Md. Shahriar Parvez*** **(ID: 181-35-310)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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I dedicate this work to my father Md.Shahjahan Mia and express my gratitude to him for supporting me from the childhood.

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Abstract

The brain is the main nervous system in the human body. The brain provides all the instructions to the whole human body. The brain can be affected by a tumor or irregular tissues when our brain is affected by a tumor we called it a brain tumor. The brain tumor is mainly of two types first one is the Primary Tumor and the second one is the Secondary Tumor. This tumor can be a cause of human death. Brain tumors have mainly three different classes first one is Meningioma tumor second one is the Glioma tumor and the last one is the Pituitary tumor. Among these several classes of tumor Gliomas are the most dangerous and life-threatening brain tumor with exceptionally quick development. Gliomas detection using CAD (Computer-Aided Detection) is a very challenging task. Because of different shapes, sizes, and boundaries of tumors with the surrounding area. Magnetic Resonance Imaging (MRI) is the most widely used method for imaging structures in the human brain. In this study, a deep learning-based method is used which has different modalities for the detection of brain tumors. The proposed YOLOv5 deep learning method is used for detecting brain tumors. YOLO stands for You Only Look Once. YOLOv5 model is mainly a branch of CNN (Convolution Neural Network) with 32 layers. This model is used because it has the power to detect small things. The proposed method is validated on the BRATS dataset. We have used this data with the process of data preprocessing, normalization, and data labeling with different classes of brain tumors. We used 80% of the data for training and 20% of the data for validation. After training the YOLOv5 model we have tested 20% of different data and got an accuracy of 91%.

Key Words: Brain Tumor, Glioma, Meningioma, Pituitary, Images, CAD, CNN, MRI, YOLO.

Chapter I

Background

1.1 Introduction

The brain is a massive and complicated organ in the human body that governs the whole nervous system. Our brain has around 100 billion nerve cells. This vital organ develops at the core of the nervous system. For that reason, any type of disorder in the brain may cause danger to human health. The brain tumor is the most serious of this disorder. Brain tumors are unregulated and abnormal cell development in the brain that may be caused a human death. Brain tumors may be divided into two types mainly the first one is Primary tumor and the Second one is Secondary Tumor. Primary tumors are found in human brain tissue, on the other hand, secondary tumors spread from the other regions or organs of the human body and affect our brain via the bloodstream. Among these main tumors have four different classes first one is Meningioma, the second one is Glioma, the third one is Malignant, and the last one is Pituitary tumor. Among these tumors, Glioma and Malignant tumors are two dangerous kinds of brain tumors that can kill a patient if it is not detected at early stages. Brain tumors are divided into four classes by the World Health Organization (WHO). They divided the tumor into two different levels the first one is the Lower Level and the second one is the Higher Level. In the lower level, they defined two different grades the first one is grade 1, and the second one is grade 2. Lower level tumors are meningioma tumors. In the Higher level, they defined two different grades the first one is grade 3, and the second one is grade 4. Higher-level tumors are glioma tumors and pituitary tumors. Treatment for brain tumors is varies depending on the tumor's location, size, boundaries, and class or kind. Currently, Surgery is the most often used treatment for brain tumors. Because it has no negative effects on the human body and brain. Medical imaging methods such as Computerized Tomography (CT) scan, Positron Emission (PET), and Magnetic Resonance Images (MRI) are the available technology which is used for observing the inside state of the human body and brain or any organ. MRI is used as the most ideal imaging modality since it has no side effects and it provides useful or valuable information in 2D and 3D formats images regarding the brain tumors kind, shape, class, and location. In this modern era, manually examining these photos is time-consuming for physicians and doctors. Because it was an error full task, they can make mistakes for detecting the location of the tumor exactly. To resolve this vital issue, the creation of an automatic Computer-Aided Diagnosis (CAD) system is necessary to reduce the workload of physicians and doctors for categorizing and diagnosis the brain tumors MR images. Now, it is a need to make a tool or model for radiologists to detect the brain tumors' location, size, and shape exactly.

1.2 Motivation

Our brain is the central nervous system in our body. Our brain gives the command to our whole body and it is also called the control center of our human body because it is in charge of all processes in the human body. Brain tumors can directly endanger a person's life. If a tumor is found at the early stage then the patient has chances of survival. In this modern era, Magnetic Resonance Images (MRI) are commonly utilized by clinicians to assess the presence or extent of malignant tumors. The quality of brain tumors or cancers therapy is determined by the physician's and an expert's knowledge. As a result, adopting an automated and functioning tumor detection system is needed to help our physicians. Detection of brain cancers using MR imaging has become a critical issue, and various research has been undertaken in recent years. The most common cancer in the world is a brain tumor. The majority of brain tumors evolve into malignant tumors over time. Brain tumor causes our brain tissues and organs. During Magnetic Imaging of Brain Tumors, a greater rate of identification is achieved, resulting in improved tumor therapy. Several researchers have explored a variety of strategies to improve the detection rate of brain tumors. In this work, we will demonstrate a best-fitted model to boost the sensitivity and accuracy rate. We expect that the model will show a new age in biomedical engineering or medical science by detecting the brain tumors with the highest accuracy.

1.3 Objectives Of The Report

The research objectives in this paper are as follows:

1. There are several people around us with a brain tumor. But we can't take the necessary steps and care of them since we do not know that they are suffering from a brain tumor.
2. Help to detect the brain tumor in the early stage.
3. Help the physician for detecting the brain tumor with the highest accuracy.
4. Helps to reduce deaths.
5. Wants to analyze the previous year's brain tumor patient records in Bangladesh.
6. Wants to detect brain tumors based on MR images using deep learning methods.
7. Brain tumors can be cured in the early stage if they can be detected in an early stage.
8. An efficient deep learning methodology will be designed to get the best efficiency and highest accuracy for detecting the brain tumor.

1.4 Thesis Outline

Consecutively, in the rest of the report, I discuss object detection background and all the version of YOLO in Chapter 2. After that, I reviewed some related work in Chapter 3. Then, I designed the methodology in Chapter4. In my methodology section, I have given dataset explanation, data augmentation step and technique, data labeling, model development for brain tumor detection with the diagram in Chapter 4. After performing a new version of the YOLO model

YOLOv5. I investigate the model in Chapter 5. In my result and discussion part, I have given three evaluation processes:

1. Training and validation period evaluation.
2. Performance and loss metrics evaluation.
3. Object detection evaluation.

Finally, I told overall research works in the part of the Conclusions and Discussion in Chapter 6. Then I have given all the references in Chapter 7.

Chapter II

Background Analysis

2.1 Introduction

Object detection is critical in today's world. Several industries, including security, defense, healthcare, transport, and everyday life, have adopted real-time object detection techniques to make our lives easier, healthier, and more secure. Deep learning technology is constantly advancing, and it is having a significant influence on our daily lives. The object detection model was invented using a CNN architecture based on deep learning. Currently, two techniques are utilized to identify objects: a single-stage algorithm known as YOLO and a two-stage approach known as R-CNN. A single-stage technique has a lot quicker detection speed than a two-stage algorithm and has a higher detection accuracy. Because the detection rate of the two-stage algorithm technique is much lower than that of the one-stage algorithm. It is not a superior choice for real-time objection detection. The YOLO (You Only Look Once) method is highly lightweight in a single stage. It has a high rate of detection accuracy.

2.2 Five Version of YOLO

2.2.1 YOLOv1

In 2016, Redmon et all released the inaugural edition of the YOLO series. To improve the model's performance, five different versions have been presented. The YOLOv1 approach creates a candidate zone before detecting the item. Although the algorithm had a high detection rate, its execution speed was quite slow. YOLOv1 can identify the item in each photograph and where it is located.

2.2.2 YOLOv2

The YOLOv2 algorithm is an improved version of the YOLOv1 method. Objects passing across the level link maximum and minimum regulations feature pyramid got multi-scaled detection in YOLOv2, which primarily employed a cross features pyramid based on SSD. To reduce overfitting and expedite convergence, YOLOv2 uses an anchors approach based on grid limitations and a batch normalizing approach.

2.2.3 YOLOv3

Modification of YOLOv2 in YOLOv3. It has two significant improvements. The residual model, for example, might well be utilized to further deepen the network architecture, while the FPN structure can be employed to enable multi-scale detection. Darknet-53, the foundation network for extracting features for the building of YOLOv3, was designed using Res Net. It creates three various sizes and depicts FPN's multiscale concept based on YOLOv2. YOLov3 overcomes the instabilities of the regression model and the previous frame mechanism by employing the frame regression approach to forecast location. And the bounding box was predicted using numerous item categorizations.

2.2.4 YOLOv4

Alexey et al. proposed in YOLOv4 to boost the accurateness and performance. To retrieve target characteristics, YOLo4 mostly leveraged CSP Darknet. YOLOv4 adds CSP to each massive Darknet53 dense block, separates the extracted features of the sublayer into two half, and merges them throughout a cross-stage architecture, building on the CSP Net's expertise with preserving correctness, reducing computational obstacles, and cutting memory costs. This reduces the number of computations needed while also ensuring correctness. CSPDarknet53 uses the Mish activation function, however, the following network uses the leaky rectified function, leading to a much more effective target detection setup. Following upsampling, information was circulated on PA Net and the level crate features pyramid was fused.

2.2.5 YOLOv5

YOLOv5 is the fifth installment of the YOLO series. Ultralytrics is primarily responsible for its development. To extract significant information from a picture, the YOLOv5 detector network employs CSPDarknet as the extracting features network. Spent is a huge neural network that overcomes the challenge of network optimization. It also incorporates gradients variations into the feature map, resulting in a reduction in regression coefficients and FLOPS. The Focus method is proposed by YOLOv5 for use in the computation of the framework is an important region, which considerably enhances detection performance. To make real progress in the accuracy of the vision-based framework, many sophisticated data augmentation techniques are applied to optimize the utilization of data sets.

Chapter III

Literature Review

3.1 Introduction

In recent years, there were published different works based on Deep Learning algorithms. Automated tumor area segmentation and detection is the focus of the majority of current medical MR imaging research. Much recent research has shown several ways for identifying and segmenting the tumor zone in magnetic resonance imaging. After the tumor has been segmented on the MRI, it must be categorized into different classes. Prior research has utilized binary classifiers to discriminate between glioma and malignant groups. Some of them are briefly discussed in this chapter.

3.2 Related Work

In 2019, Sidra Sajid et all published a paper named is Brain Tumor Detection and Segmentation in MR Images Using Deep Learning. They used a pre-processing step, a feed-forward pass through a CNN, and a post-processing step to detect the tumors. Finally, they achieved a score of 86 percent accuracy on BRATS-2018 datasets.

In 2020, Dipale Nanware et all published a paper named is Brain Tumor Detection Using Deep Learning. They used Convolution Neural Network (CNN) based classifier. After using this classifier they compared the trained and test data and they get the best result.

In 2020, Tanzila Sabaa et all published a paper named is Brain Tumor detection using the fusion of handcrafted and deep learning features. They used a fusion of handcrafted and deep learning models for detecting brain tumor. Finally, they achieved a score of 99 percent accuracy on the BRATS -2015 dataset.

In 2021, Hari Mohan Raj et all published a paper named 2D MRI image analysis and brain tumor detection using deep learning CNN model LeU-Net. They used Convolution Neural Network (CNN) based LeU-Net model for detecting the brain tumor. Finally, they achieved a score of 94 percent accuracy.

In 2020, Anindya Apriliyanti et all published a paper named UNet-VGG16 with transfer learning for MRI-based brain tumor segmentation. They used UNet-VGG16 with a transfer learning model. Finally, they achieved UNet-VGG16 could recognize the brain tumor area with a mean of CCR value is about 95.69%.

In 2018, Ali Ari et all published a paper named Deep learning-based brain tumor classification and detection system. They used Extreme Learning Methods (ELM) and Local Receptive Fields (LRF) method for detecting the brain tumor. In the experimental studies, the classification accuracy of cranial MR images is 97.18%.

In 2021, Jaeyong Kang et all published a paper named MRI-based brain tumor classification using Ensemble of deep features and machine learning classifiers. They used Ensemble pf deep features and machine learning classifiers. They classified the brain tumor in MRI dataset with four different classes (Normal, Glioma, Meningioma, Pituitary).

In 2021, Nadim Mahmud Dipu et all published a paper named Deep learning based brain tumor detection ad classification. They used FastAi classification model which is a deep learning library for detecting the tumor. Finally, they got accuracy of 85.78 %.

Selvaraj et al, built a binary classifier to characterize normal and abnormal brain Magnetic Resonance (MR) images using first-order and second-order statistics along with the regression Support Vector Machine (SVM).

Khwaldeh et al. proposed a CNN model for categorizing brain MR images' normalcy and abnormality, as well as high-grade and low-grade glioma tumors. They adopted the AlexNet CNN model and used it as the basis for their network architecture, reaching an 89 percent accuracy rate.

Chapter IV

Methodology

4.1 Introduction

Object recognition with excellent performance is achieved using YOLO (You Only Look Once) models. YOLO splits a picture into grids, each of which identifies things inside its boundaries. They may be used to detect objects in real-time using data streams. YOLO is an abbreviation meaning You Only Look Once. We're using Ultralytics' Version 5, which was released in June 2020 and is now the most powerful object recognition algorithm available. It's a brand-new neural network (NN) that accurately recognizes objects in real-time. This method processes the entire image with a neural network classifier, then divides it into pieces and guesses boundary boxes and probability for each element. The predicted probability is used to weigh these bounding boxes. In the sense that it produces forecasts after only one forward's propagation through to the neural network approach.

4.2 Proposed Method

A brain tumor is an extremely delicate condition. Glioma is a tumor that develops from tissue. If the tumor is little, medical technology can't identify it. It will be extremely essential to both patients and the medical community to detect the small tumor. As a result, our research built a model that will be extremely useful if the tumor is quite little. The YOLOv5 algorithm, which is based on CNN, was primarily employed in this investigation (Convolutions Neural Network). The most recent iteration of the YOLO series is the YOLOv5. Object categorization and bounding box prediction were combined in a single end-to-end differential network for the first time in YOLO. Darknet weight is responsible for its development and upkeep.YOLov5 is the first YOLO model developed on the PyTorch framework, making it easier and lighter to use. On a conventional benchmark COCO dataset, however, YOLOv5 does not beat YOLOv4 since YOLOv4 did not make significant structural changes to the network. We implemented different versions of the YOLOv5s model. The work flow of our findings are given in below on Fig – 4.1 .

4.3 Dataset Explanation

Using the BRATS -2018 data set, the suggested object detection algorithm is trained and tested. The data collection contains 600 MRI pictures of brain tumors. The picture data set is 512x512 in size. Because the dataset is so inadequate, we employed the data augmentation approach to improve it. We employed a variety of tactics in the augmentation methodology, including rotation, translation, scaling, horizontal and vertical flipping, and so on. After finishing the pre-process and augmentation techniques, we produce new training picture data for the YOLOv5 framework using our real data collection. The dataset comprises 1600 photos with a 512x512 pixel dimension once the pre-processing and augmentation techniques are completed. The sample of dataset is given in below on Fig – 4.2 .

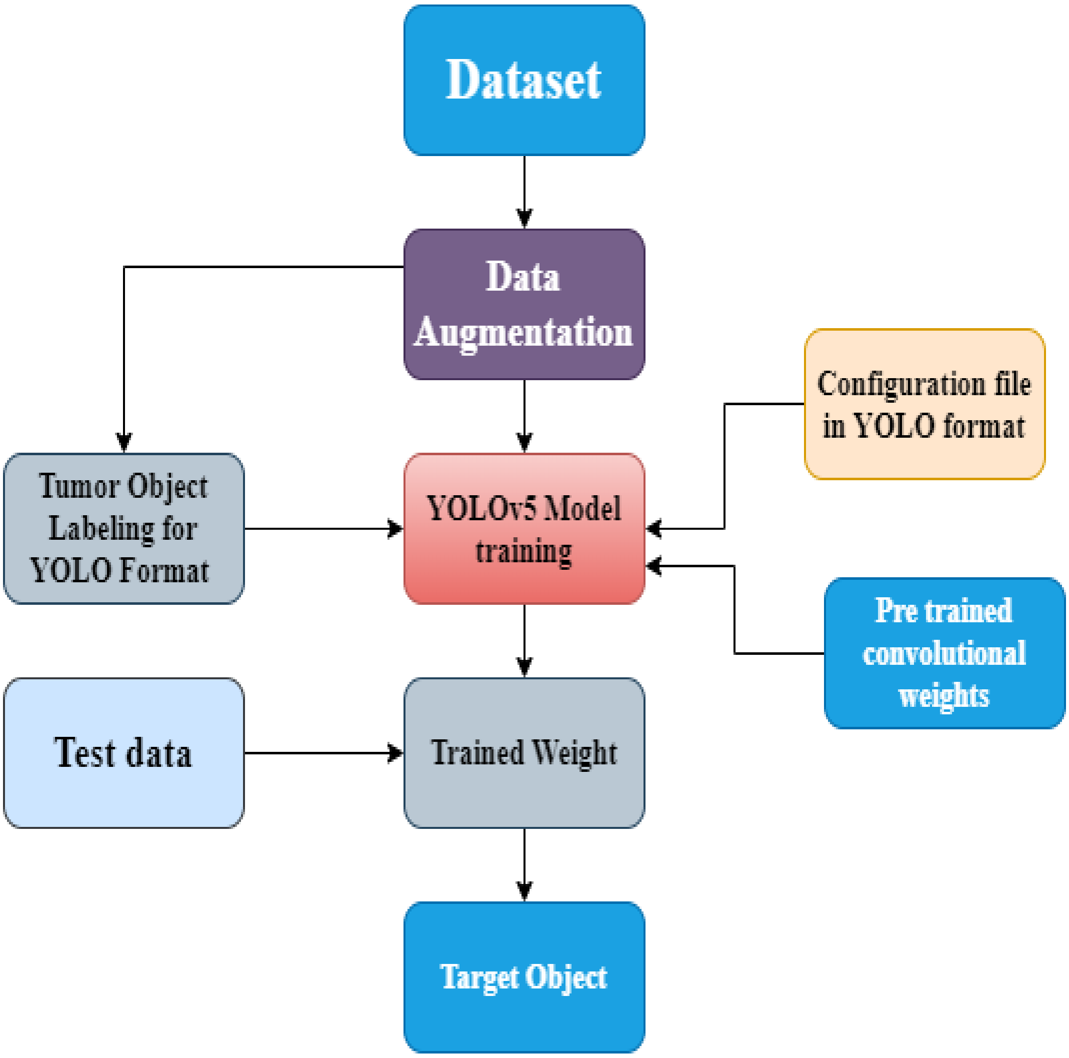

Fig – 4.1: Brain Tumor detection experimental Workflow.

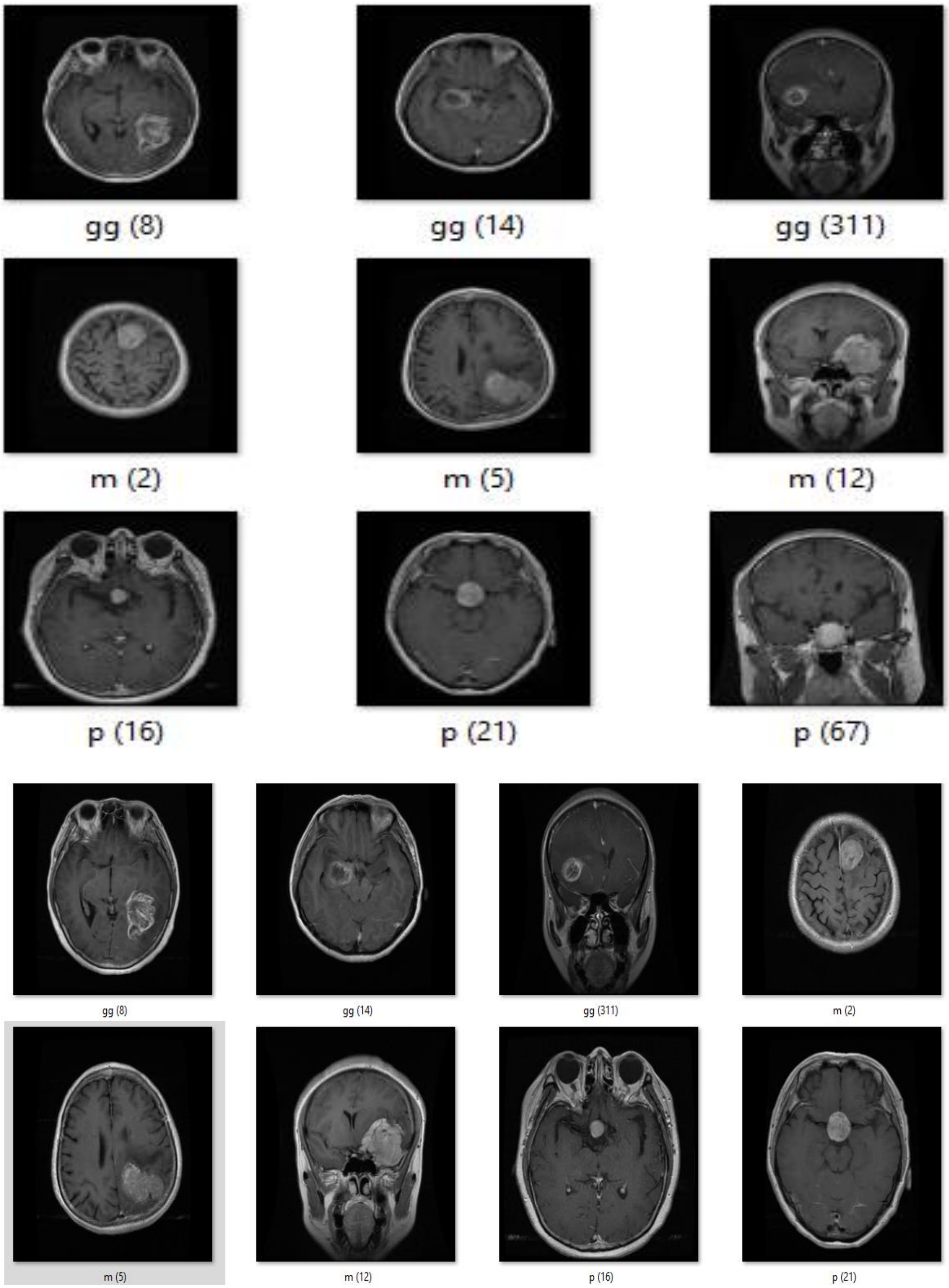

Fig – 4.2: Brain Tumor Dataset Sample

4.4 Data Augmentation Technique

We know that if a model has a decent dataset and a particular quantity of data, it will perform much better. We don't have enough datasets to train our chosen model since we don't even have enough data. As a result, Dataset contains 195 samples that are unsuitable for training our chosen model. To improve the dataset, deep learning algorithms and data augmentation methods are implemented. The fundamental purpose of data augmentation techniques is to change or blend genuine and artificially manufactured data. In this study, an augmentation strategy was applied to the original dataset to build a sufficient tumor dataset for our model to work with. It increases the framework's dependability.

Data augmentation approaches often employed picture contrast, color, lighting, intensity, and geometrical modification, as well as distortion correction for resizing, expanding, and rotating photos, among other things. This project uses data augmentation techniques including resizing, horizontally filliping, vertically flipping, widths, and thickness moving to create our required dataset. Rotate the image round and counterclockwise with a 2 to 48-degrees angle in the rotations formula. As a result, the picture object moves in many directions. In addition, the height and breadth of the tumor object were shifted by 5% and 18%, respectively. The picture reduction procedure was then employed for augmentation purpose in the scaling scenario, with 2 percent and 18 percent applied. Furthermore, the tumor object was translated in several areas using 2% to 10% vertical and horizontal shifting for picture translation reasons. In addition, a probability value of 0.2 to 0.5 was employed in the vertical and horizontal filliping perspectives to ensure that the tumor item flipped between different positions. After applying the four augmentation procedures to one image from the original 600 datasets, the set of data became 1600 data. Finally, we obtained 1600 data points, including genuine data, for use with the YOLOv5 models. Our random enhanced approach is depicted in figure 4.3 after completing the augmentation procedure.

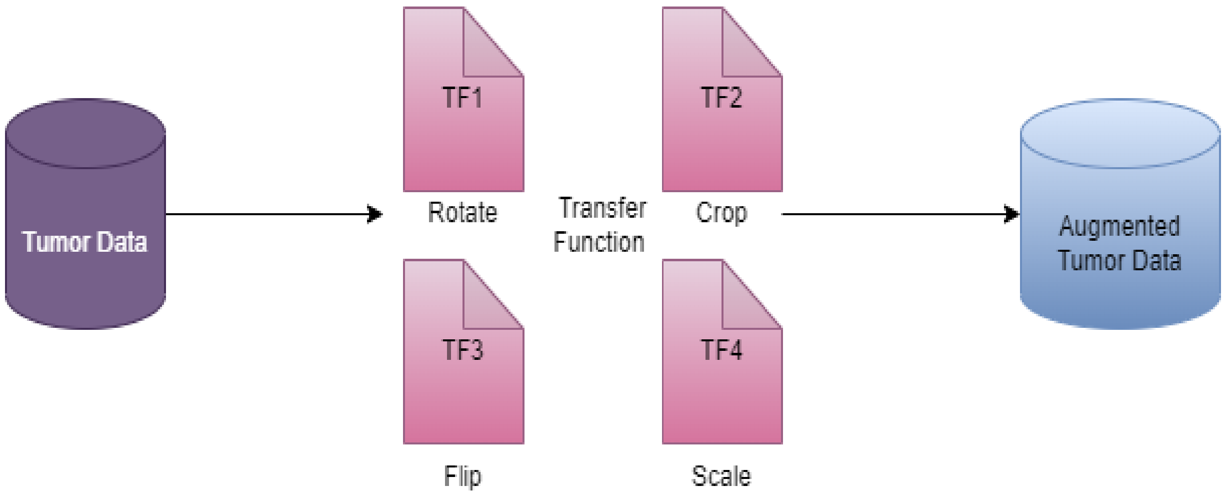

Fig – 4.3: Data augmentation technique using Transfer Function (TF)

4.5 Dataset Classes with Description

A dataset table is shown for the dataset classes and description.

Serial No	Classes	Description
01	No Tumor	This class means that there is no tumor in brain tumor MRI images.
02	Glioma Tumor	This class means that having a tumor at vast stage in brain tumor MRI images.
03	Meningioma Tumor	This class means that having tumor at early stages in brain tumor MRI images.
04	Pituitary Tumor	This class means that having a tumor at critical place in brain tumor MRI images

Table 4.1: Dataset Class and Description

4.6 Data Labeling

All object recognition procedure needs knowledge about the target area. The YOLOv5 algorithm detects the target position using a unique format. The process of marking target items in object detection is known as object detection. The YOLO algorithm requires a file to be labeled during the training and validation phases. Microsoft Common Objects in Context (MSCOCO) dataset has been used to pre-train the YOLOv5 model. All types reserved in the "koko.yaml" file are included in this data set, which has 100 preset object classes. In our study, we build another yaml class file and a YOLO brain tumor object labeling formate file named "data.yaml" in the same way. There is just one class in the "data.yaml" file, which is a tumor. Only tumors in various formats, such as glioma, meningioma, and pituitary tumor, are included in the dataset. As a result, we employed three distinct classes for different tumors when labeling. The annotation procedure is used to generate tumor object labeling files as a YOLO fashion file in the final dataset. YOLOv5 uses a text format file with the same name as the photos throughout the training and validation phase. The tumor class id, center coordinates of the tumor object, object height, and object width are all included in the text formatted file. The makesense.ai dataset labeling aim is a graphical annotation website that is used to construct every picture annotation file. These tumor training and validation samples are annotated using the website in general. Finally, the YOLOv5 network model was trained and used all tumors training and validating text format datasets, as well as training pictures and recognizing objects datasets. This graphic depicts the mostly tumor-related file. For each target tumor object, the text context file has three elements: the tumor class id, the bounding box of tumor coordinates (X0,Y0), and the tumor area (width, height). The tumor classes are represented by the ids ‘0’, ‘1’, and ‘2’.

4.7 Yolov5 Model for Brain Tumor Detection

Because of its particular benefits, we used the YOLOv5 model in this investigation. The model has several advantages, including accurate object identification, tumor localization, increased speed, and improved detection performance. In contrast, the model can detect tiny tumors in photographs that are noisy, blurry, or foggy. The YOLOv5 model is a single-stage object detector. Core, Neck, and Head are three different key aspects of every stage object detector (Prediction).The Bottleneck Cross Stage Partial Network is the YOLOv5 model's fundamental backbone (BCSPN). The method uses an image dimension of 512x512x3 pixels as input. When our data is fed into the model, the framework result might be any mix of predicted classes. First, the input picture travels via the FOCUS module of the backbone. The picture is divided into four tiny sections by the FOCUS module for convolutional operations. The 512x512x3 pixels photographs are divided into four smaller photos with image dimensions of 220x220x3 pixels each. The picture will be a 220x220x3 feature pyramid after 32 convolutional processes. The CoBL module is a simple convolutional module with the following features: Conv2D + Batch Normalization (BN) + Leaky ReLu activation. The BCSP collects crucial information from the training pictures by pulling features from the feature pyramid. It reduces input parameters and model size by eliminating repetition of gradient information in CNN's optimization procedure and incorporating gradient changes into the feature pyramid. The BCSP includes two CoBL modules: the residual unit and the 1times1 Conv2D kernels. A residual unit has two CoBL modules and an adder, with the adder accumulating the features of the previous CoBL module result as well as the features of two CoBL modules, and then transferring the endemic qualities as 1times1 Conv2D layers. The BCSP module also links the backbone's spatial pyramid pooling (SPP). The SPP module expands the receptive field of the network and provides scale-specific capabilities. The Paths Aggregation Network (PA Net), which is embedded into the model to optimize the flow of information, is the second portion of YOLOv5. To convey strong semantic qualities from top to bottom, PA Net is primarily built utilizing a feature pyramid network (FPN). From the bottom to the top, the FNR layer conveys string positional features. Furthermore, PA Net improves low-level characteristic transmission and the utilization of accurate localization signals. As a result, the target object's location accuracy will increase. Finally, the prediction, detection, or YOLO layer is referred to as the head layer. To achieve multi-scale prediction, the prediction layer built three independent feature pyramids. Whatever the case may be, the model can identify and distinguish a small, medium, and big item in the detection layer.

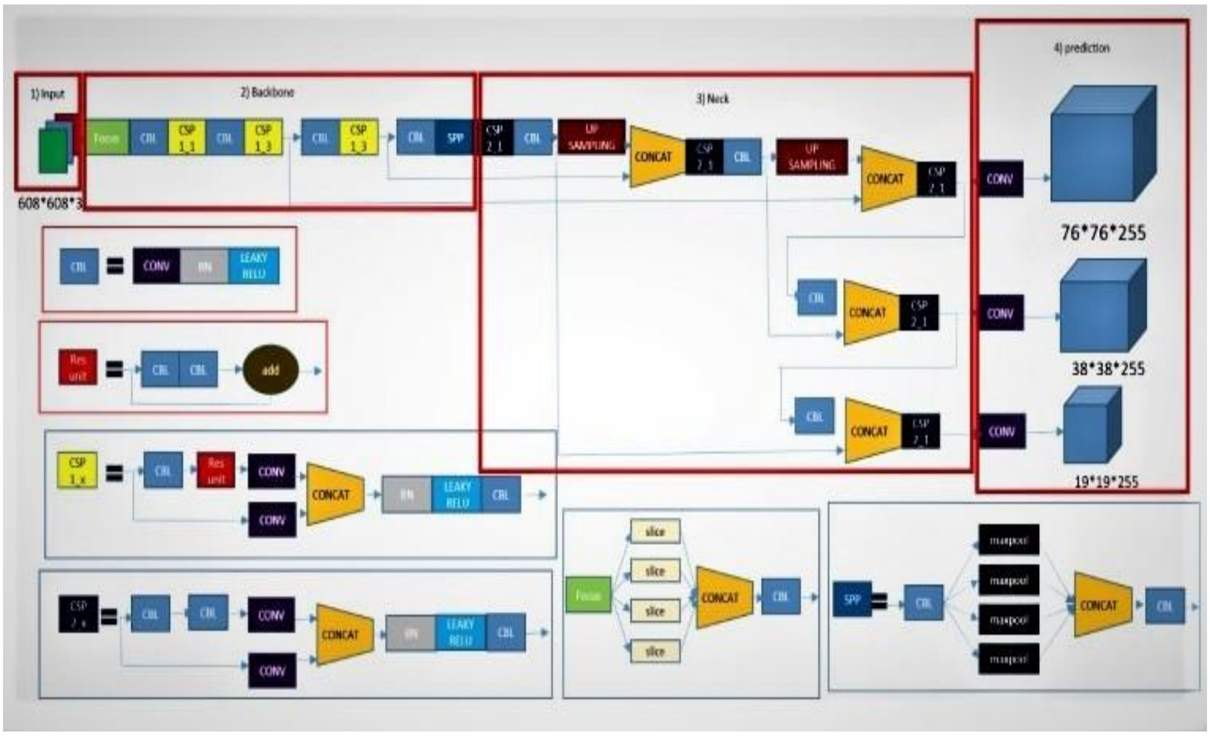

Fig – 4.4: Network diagram of YOLOv5

4.8 Environment Setup and Training Explanation

We made this experiment in Google Colab Platform. We used Google Colab Platform because it has an NVDIA graphics card and also a higher powerful processor with much amount of memory. Our model is mainly trained by the PyTorch deep learning framework. We also used python 3.8 version. In our experiment, we demonstrate a new versions of YOLO which is YOLOv5. Then we compared each of the class performance of this brain tumor data. Then, our experimental phase used our final augmented dataset for training with the annotation of each classes. We train 1600 data in our model. In the experiment time we used 80% of data for training and 20% of data for testing. In training phase, 80% data is divided into two different part one is training another one is validating. We used validation for overcoming the model from overfitting.

The model hyper parameters summary is shown in Table 4.2.

Parameter's Name	Type	Value
Initial Learning Rate	Numerical	0.01
Momentum	Numerical	0.941
Optimizer	Text	SGD
Learning Factor	Numerical	0.21
IoU Training Threshold	Numerical	0.21
Anchors	Numerical	3.1
Weight Decay	Numerical	0.0006
Warmup epochs	Numerical	3.1
Warmup momentum	Numerical	0.9
Warmup bias learning rate	Numerical	0.1
Box loss gain	Numerical	0.5
Anchor multiple thresholds	Numerical	4.1

Table- 4.2: YOLOv5 model training hyper parameter

Chapter V

Result and Analysis

5.1 Introduction

To evaluate the performance, we have used Accuracy, Precision, Recall, and F1-score. Classification accuracy is the ratio of correct predictions to total number of predictions made by the model. Precision is the ratio of true positive to the true positive and false positive prediction. Recall is defined as the ratio of true positives to the true positive and false negative. F1-score or F-measure is the balance measure to express the performance in a single quantity. It is the harmonic mean of precision and recall.

They are formulated as follows:

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{Positive} + \text{Negative}}$$

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

$$\text{F} - \text{measure} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

5.2 Performance Analysis

$$Mean\ Average\ Precision\ (mAP) = 1/\text{M} + \sum_{J=1}^{M} (\text{APj})$$

The bounding box loss regression define as follows:

$$l_{box} = \lambda_{crd} \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{i,j}^{ojb} b j(2 - w_i \times h_i) \left[\left(x_i - \hat{x}_i^j \right)^2 + \left(y_i - \hat{y}_i^j \right)^2 + \left(w_i - \hat{w}_i^j \right)^2 + \left(h_i - \hat{h}_i^j \right)^2 \right]$$

5.3 Experimental Result

After completing all experiments, this section discusses the experiment performance and compares the performance of the YOLOv5 model. The model trained by the latest YOLO series is highly responsible to detect the small object. In our experiment, we used 1600 image dataset, 80% of data for training and 20% of data for validation purposes. In real-time direction machines sometimes avoid very small tumors, which are very risky for any patient. But YOLOv5 employed model performed better for small tumor detection.

5.4 Training and Validation Evaluation

A fresh version of YOLOv5 was used. Again for calibration and validation phases, a variety of models are available. Various epochs were used to improve model performance and reduce calibration and validation loss. After completing all of the processes on our chosen models, we discovered that the YOLOv5 performed better than the others. For training and validation, we employed 50, 70, and 100 epochs for all of the models. Our model was tested for 50 epochs. We have a poor level of precision. Then, for models with improved performance over the prior training, 70 epochs were run. Finally, we ran 100 epochs for all object detection models, which showed that our model prediction accuracy performance was superior. Figure 5 depicts the results of our model's investigation into trained boundary box failures, trained object failures, validating boundary box losses, and validating object failures.

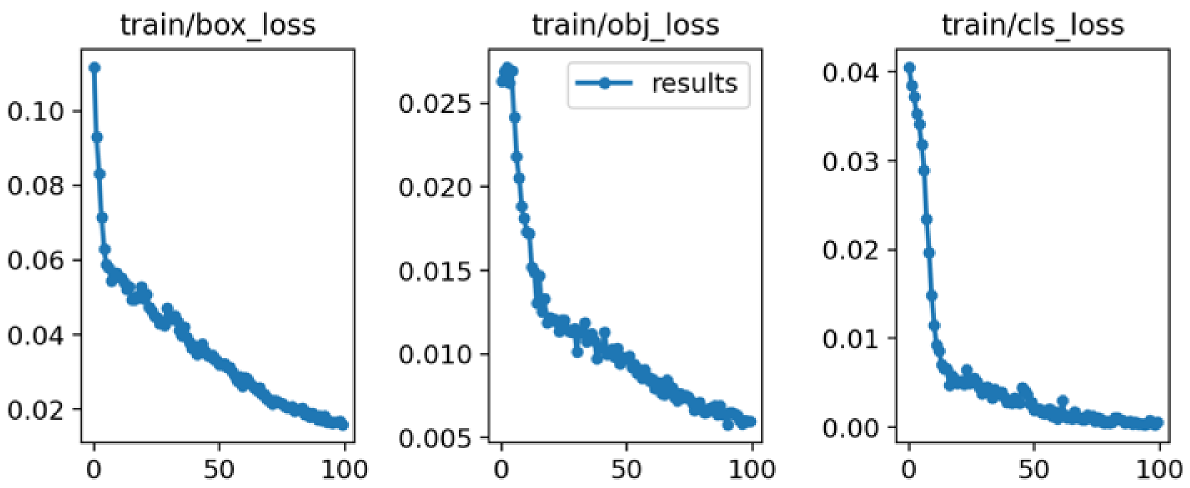

Fig- 5.1 – Training losses

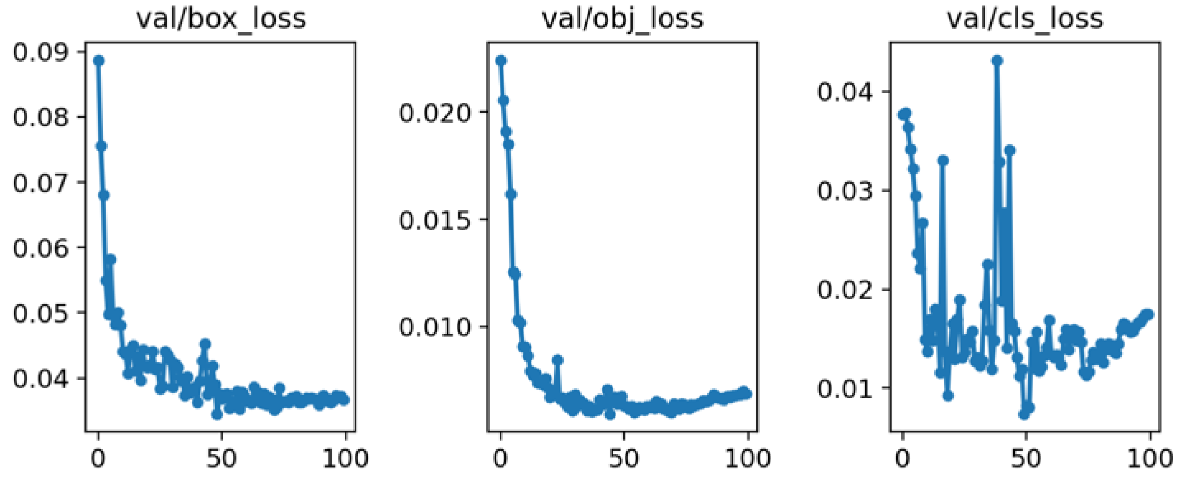

Fig- 5.2: Validation losses

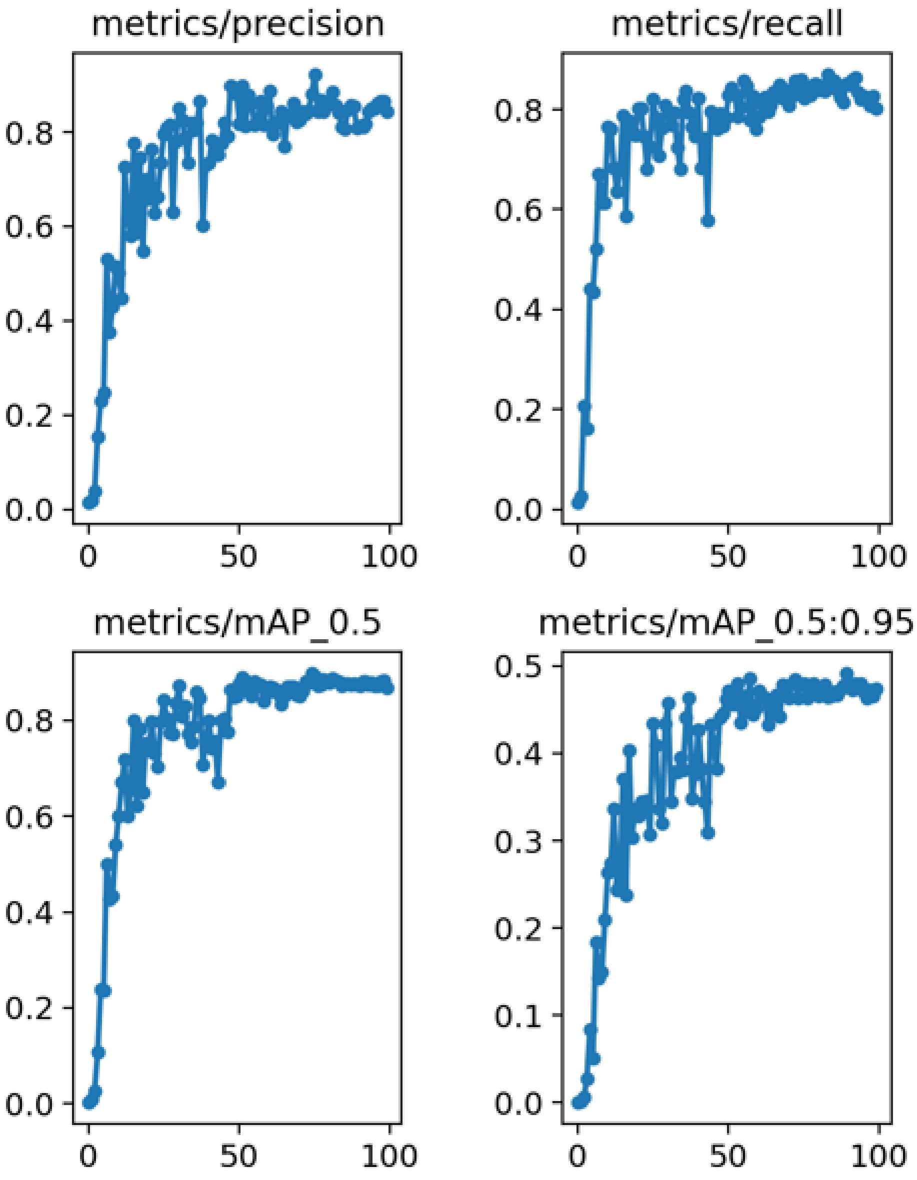

Fig- 5.3: Accuracy, Recall, Precision, and MAP

5.5 Object Detection Result Evaluation

Several measurement criteria are performed to analyze the prediction results throughout the object detection phase. Our various models provide a variety of detection results, which are measured using the Intersection over Union (IoU) approach. The detection component of the IoU technique is mostly performed, and the detection score is displayed. The procedure produces numerous bounding boxes, however the search stage only shows the boundary of the target item. Create a boundary and add the results together throughout the intersections over unions step. During our testing phase, we evaluated the IoU using a variety of photos. Various models we used yielded different IoU. Glioma tumors ranged from 90 percent to 95 percent, meningioma tumors from 85 percent to 93 percent, and pituitary tumors from 70 percent to 90 percent. The overall accuracy we got is 91%.

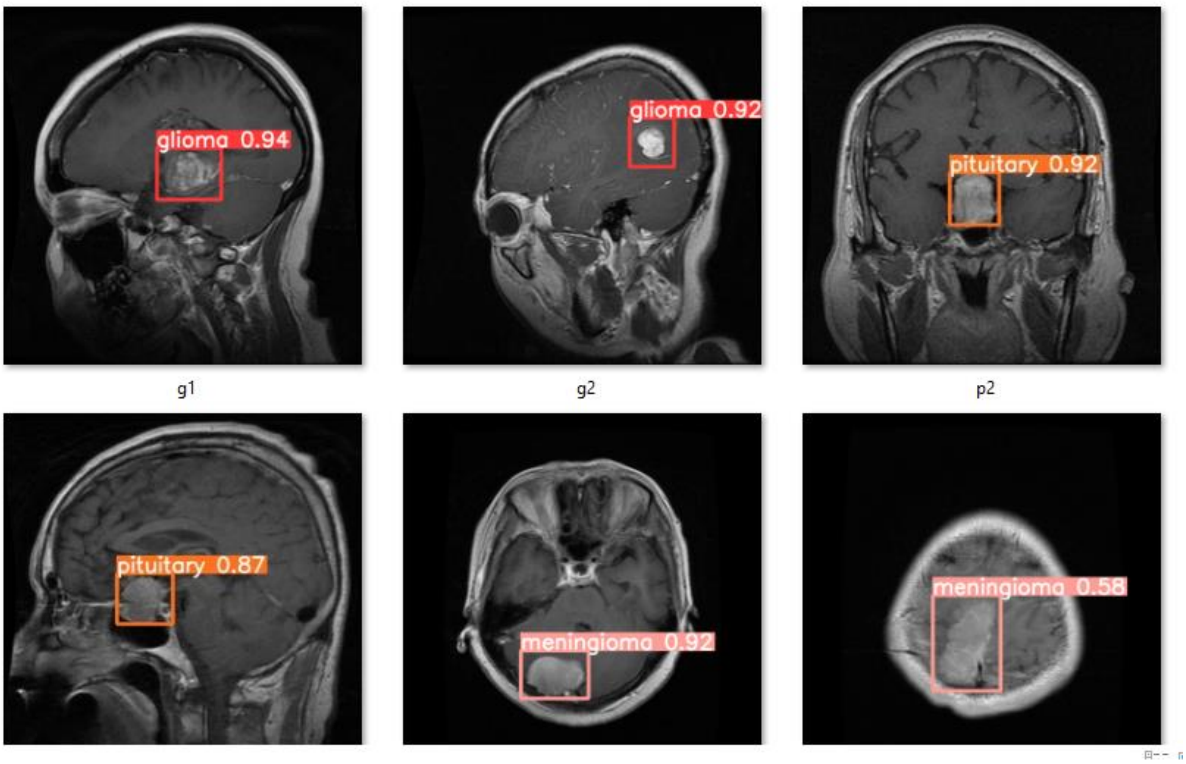

Fig 5.4: YOLOv5 Brain Tumor Detection Result

Chapter VI

Conclusion and Discussion

6.1 Conclusion

This research begins with a basic analysis of object detection methods and concludes that object detection method can solve a variety of difficulties in the medical industry. After reviewing our dataset, we used a variety of data augmentation approaches to expand it in order to improve model performance. With the use of the YOLOv5 model, we trained, validated, and tested the data set, which included 1600 photos, including original photographs. For this research, we used 80% of the data for training the model and 20% of the data to validate the model. To maximize model features and decrease the featured hierarchy on three classes, the YOLOv5 framework employs the CoBL components, BCSP component, Leaky Linear transfer function, and multiple 33% and 11% fully connected layers. Following the experiment, YOLOv5l models outperform YOLOv3 models in terms of tumor object recognition. Furthermore, with low training and validation loss, the YOLOv5 framework displayed great accurate, recalls, trained precision F1 score, and maP. Furthermore, the YOLOv5 model performed better in the testing stage than that of the other models. In the tumor object photos, the model delivers a suitable detecting position with a detection score. The YOLOv5 model we used appears to be effective in detecting small objects. Our approach aids in the detection of tiny tumors from MRI scans, undergoing a revolution era in medicine. The overall accuracy we got 91%.

6.2 Future Prospects of Our Work

For medical research, having a large data collection is critical, especially if the topic is closely related to our daily lives. Another crucial step is to choose an effective and appropriate model for the given dataset. The investigation started with 600 original photos and then used an augmentation process to get 1600 photographs. For this delicate task, there was a relatively little dataset. So, in the future, the first task will be to gather high-resolution and high-quality photographs, after which the YOLOv5 model's performance will be improved, and various versions of YOLOv5 will be investigated. After that, we suggested a better model for detecting brain cancers in real time.

Chapter VII

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