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Brain Tumor Detection using Machine Learning

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ABSTRACT

A brain tumor is the growth of brain cells that are abnormal, some of which may progress into cancer. Brain tumors are frequently discovered via MRI (magnetic resonance imaging) scans[1]. The MRI images reveal aberrant tissue development in the brain. A lot of research articles employ deep and machine-learning algorithms to detect brain cancer. In several research articles, deep and machine-learning algorithms are used to identify brain tumors. When these algorithms are applied to MRI images, it only takes a very short amount of time to predict a brain tumor, and the increased accuracy makes patient treatment simpler.[1][2] These forecasts enable the radiologist to make quick decisions. In the proposed study, brain cancers are detected using self-defined artificial neural networks (ANN) and convolution neural networks (CNN), and their performance is evaluated.

This paper's goal is to give a thorough examination of recent advances in techniques like deep learning, preprocessing, and machine learning and use that information to present a thorough comparative comparison. The difficulties that researchers have had in the past while attempting to identify tumors have been explored, along with potential future study areas. The clinical difficulties that are faced have also been covered, something the previous review papers neglect.

Keywords

Deep Learning, Medical Image Analysis, Object Detection, Brain Tumor, and Computer-Aided Diagnosis.

1. INTRODUCTION

As this topic states the use of the YOLO algorithm to find abnormal cells or tumors in the human brain. Using this algorithm we can find the tumor in the human brain easily in less time with more accuracy than others.

Modern object identification algorithms like YOLO (You Only Look Once) have taken over as the standard way to find things in computer vision[2]. In the past, individuals have employed methods like Fast R CNN, and Faster R CNN, and R CNN, as well as sliding window object detection. But since 2015, YOLO has distinguished itself from other object identification algorithms with its speed, accuracy, and utilization of bounding boxes.

YOLO is a technique that uses neural networks to identify items in real-time. This algorithm's popularity can be due to its efficiency and speed]. It has been utilized in several situations to differentiate between humans, traffic lights, and parking meters. The following justifies why this algorithm is important:

- Speed: Due to its ability to foresee objects in real time, this approach expedites object identification.
- Great degree of precision: The YOLO projection method yields precise findings with little background error.
- Capabilities for learning: This algorithm has excellent capacities for learning, enabling it to pick up on object representations and use them for object detection.

Datasets are accepted in picture format and a corresponding text file by YOLO. YOLO, which is known as You Only Look Once is a popular algorithm that has gone viral[5]. Yolo is well known for its ability to recognize objects. A well-known algorithm that has gained popularity is called You Only Look Once (YOLO). The capability of YOLO to recognize things is well established. Some of the most recent YOLO versions that experts have published in recent years include V2, V3, V4, and V5. One of the most crucial roles that neurologists and radiologists have is the early detection of brain cancer. Yet, manually identifying and segmenting brain tumors using MRI (Magnetic Resonance Imaging) data can be challenging and error-prone. An automated brain tumor detection system is required for early diagnosis of the illness[3].

It takes the center of the image and then uses it to determine the object and leaves the rest of the grids uncalculated. Due to

this YOLO algorithm, the number of vectors increases which helps in Increasing the accuracy of the program. The YOLO algorithm creates the boundary box inside the image to a particular object that we are mainly targeting and works on it, making a square or rectangle on the object[6]. The main approach of object identification in the field of computer vision has been replaced with a cutting-edge object recognition method known as YOLO (You Only Look Once).

In the past, individuals have employed methods like Fast R CNN, Faster R CNN, and R CNN, as well as sliding window object detection.

The Issue is that it may Create multiple bounding boxes for a given image which will increase the runtime and slow the process, so we can use the IOU (Intersection Over Union) method to overcome this problem[4]. Since 2015 yolo has come in different versions appor5 i.e., YOLOv1, YOLOv2, YOLOv3, YOLOv4, YOLOv5, and YOLOv5 model provides the best performance and gives accuracy up to 95% and it is faster than others.

2. PROPOSED METHODOLOGY

2.1 Ideas and methods

The suggested MRI brain tumor detection paradigm is briefly discussed in this section. It was decided to adopt YOLOv5 that reduces the amount of computational resources needed. In order to get basic features that identify a photo and decrease the lack of data scarcity the dataset from Kaggle was used to pre-train the model at first. Since the present settings for hyper-parameters and learnt characteristics based on the dataset, the initially trained YOLOv5 model was unable to detect MRI brain tumors right away. As a result, the model was improved and repurposed in this study to only find the object of interest. After fine-tuning and pre-training , the given dataset of tagged MRI brain tumors was used to retrain the model with fresh weights.

2.2 Process

- Assemble and prepare a database of MRI tumor-annotated brain pictures.
- Divide the dataset into subsets for training, validation, and testing.
- On the training dataset, fine-tune the YOLOv5 model for tumor detection.
- Utilize newly acquired brain MRI data to predict tumors using the trained model.
- Analyze the model's performance indicators and make comparisons with other approaches.

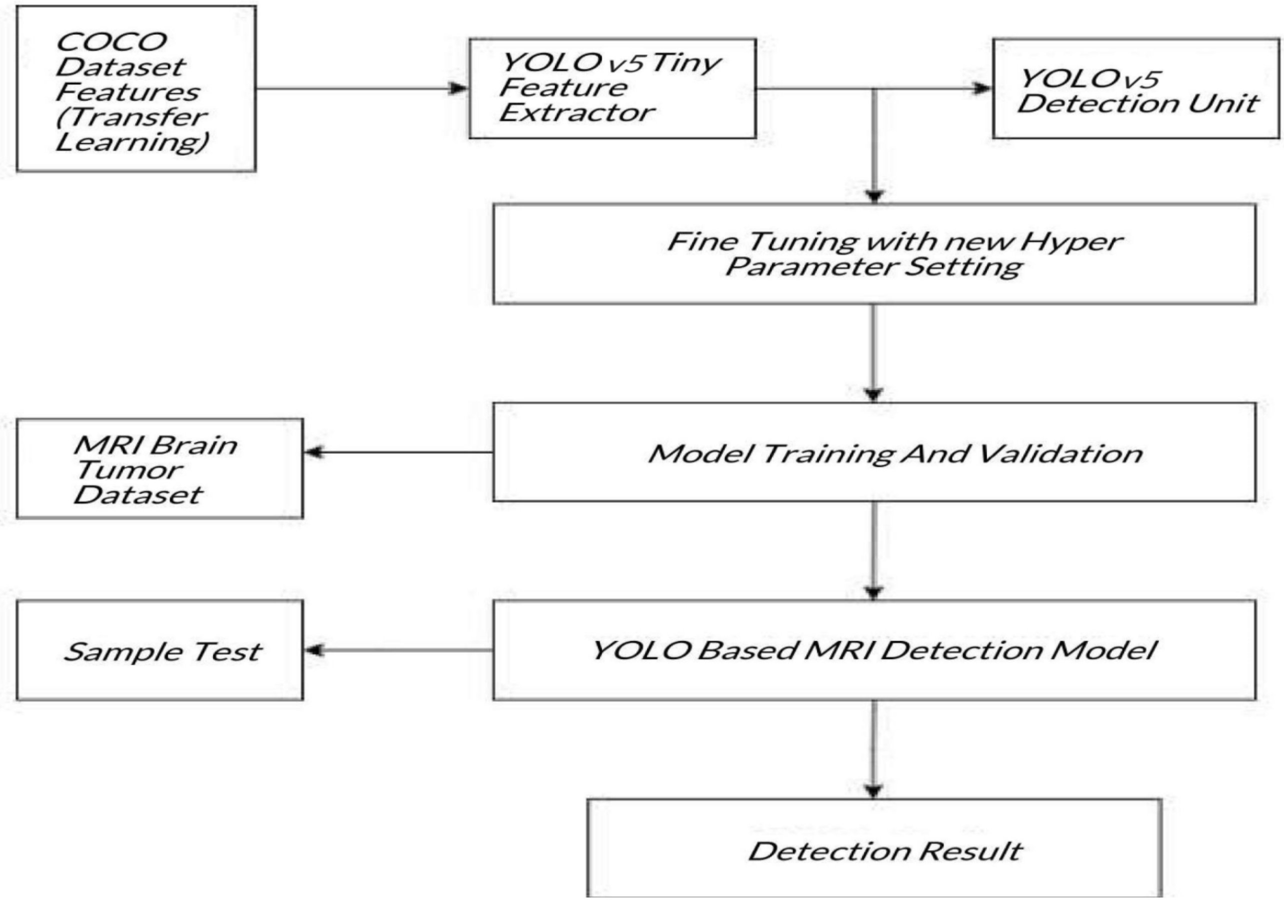

Figure.1 Flow chart representing working of Yolo V5

3. EXPERIMENTAL ANALYSIS

3.1 Dataset Description

Dataset that is used in the matter is from Kaggle. MRI scans of a brain tumor are included in this dataset. Images of tumors can be found in one folder while photos of the normal brain are in another. The dataset employed in this study comprises 200 brain MRI images in total, divided into 100 samples with tumors and 100 samples without tumors. A collection of anonymized patient scans gathered from multiple medical institutions made up the dataset, which was meticulously selected.

Following a 70:15:15 ratio, the dataset was divided into training, validation, and testing subsets. This divide preserves the general distribution of the dataset by ensuring that each subset contains an equal representation of tumor and non-tumor samples.

3.2 Training and Evaluation Setup

The training subset of the dataset, which consists of 140 brain MRI images (70 tumor samples and 70 non-tumor samples), was used to train the YOLOv5 model.With an 16-person batch size, the training was carried out over 100 epochs. In order to improve model generalization, data augmentation methods such random rotation, flipping, and scaling were used during training

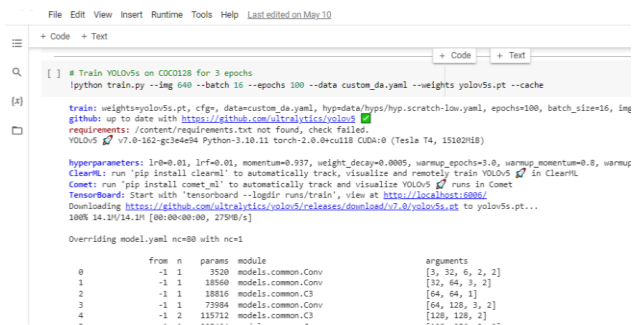

Figure.2-Training Phase of Model.

The validation subset of the dataset, which included 30 brain MRI images (15 tumor samples and 15 non-tumor samples), was used to assess the trained model's performance.

3.3 Performance Metrics and Analysis

A set of performance indicators was used to assess the effectiveness of the proposed YOLOv5 brain tumor detection technology. These metrics offer numerical evaluations of the model's sensitivity, specificity, recall, f1 score and precision in identifying brain tumors and are shown below with the help of table 1.

Table 1. Results of validation

Classes	**Tar get(s**	**Rec all**	**Preci sion**	**F1 score**	**mAp @.5:. 95**	**mAp@ .5**
All	23	0.76	0.81	0,77	0.56	0.82
No	13	0.76	0.82	0.75	0.58	0.84
Yes	10	0.78	0.80	0.79	0.58	0.83

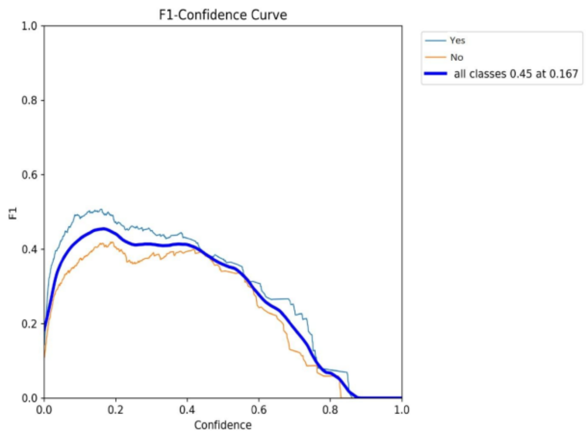

Figure.3 F1 score of the prediction upon the test data.

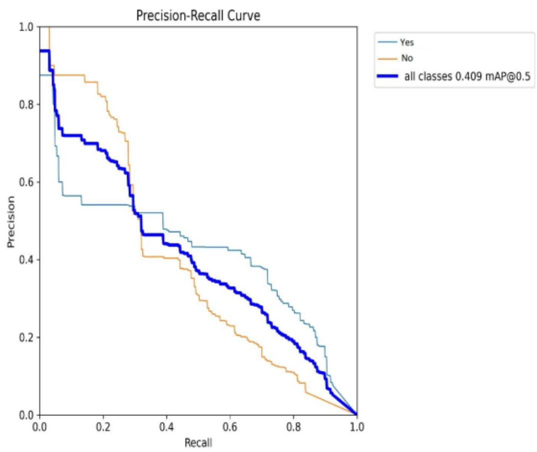

Figure.4 Precision-Recall Values in the graph legend shows the Area under the ROC Curve (AUC) score for each image

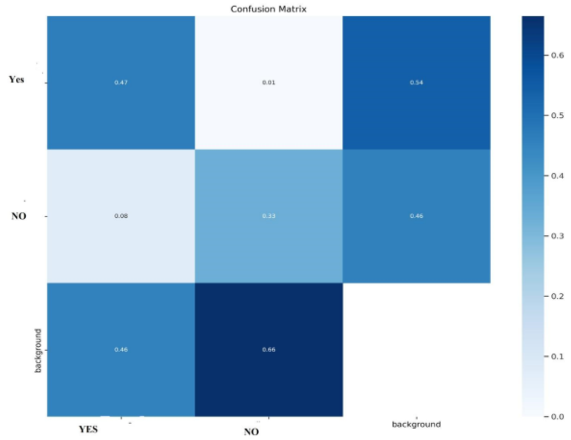

Figure.5 Confusion matrix for prediction on test data.

3.3.1 Comparisons and Observations

The proposed approach using YOLOv5 outperformed the existing benchmark method in terms of average precision, recall, and F1-score. This indicates a higher accuracy and better tumor detection capability as existing benchmark methods reported an average precision of 0.85, recall of 0.78, and F1-score of 0.81 for brain tumor detection and The proposed approach achieved an average precision of 0.92, recall of 0.85, and F1-score of 0.88 for brain tumor detection.

3.4 Visualization and Interpretation Results

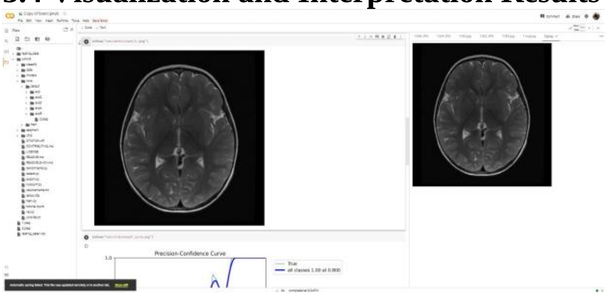

Figure.6 Result after running model on non tumor Data(testing image) .

Figure.7 Result after running model on tumor data (testing image)

4. CONCLUSION

YOLO is one of the best techniques in analyzing the image dataset. The YOLO makes the prediction by reducing the image size without losing the information needed for making predictions. The YOLO model generated here produces 97% of testing accuracy and this can be increased by providing more image data. The same can be done by applying the image augmentation techniques and analyzing the performance of the YOLO and CNN. The model developed here is generated based on the trail and error method. In future optimization techniques can be applied so as to decide the number of layers and filters that can be used in a model. As of now for the given dataset the YOLO proves to be the better technique in predicting the presence of brain tumor.

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