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Brain Tumor Detection via Deep Learning Framework on MRI Images

Arun Karthick S
Department of Computer Science and Engineering
Thiagarajar College of Engineering
Madurai, India
arunkarthicks@student.tce.edu

Rahul Shiva Konar
Department of Computer Science and Engineering
Thiagarajar College of Engineering
Madurai, India
rahulshivakonar@student.tce.edu

Harshavarthini V S
Department of Computer Science and Engineering
Thiagarajar College of Engineering
Madurai, India
harshavarthini@student.tce.edu

Ramkumar M P
Department of Computer Science and Engineering
Thiagarajar College of Engineering
Madurai, India
ramkumar@tce.edu

Emil Selvan G S R
Department of Computer Science and Engineering
Thiagarajar College of Engineering
Madurai, India
emil@tce.edu

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***Abstract*—In medical imaging and diagnostics, identifying brain tumors is crucial. The objective of this study is the automated diagnosis of brain tumors using Magnetic Resonance Imaging (MRI) pictures, and the suggestion of a deep learning approach utilizing the YOLOv7 neural network model is presented. Initially a dataset had been collected which consists of 300 images. The image datasets are labelled in such a way that the area of tumor is correctly annotated. The dataset is then expanded in size as a result of the data augmentation approaches that are used. The model is trained on 80% of the photos, then tested on the remaining 20%. On a sizable dataset of brain MRI images, the suggested approach is assessed, and its performance is compared to that of earlier YOLO algorithm versions. The results demonstrate that the proposed approach of using YOLO7 achieves high accuracy in brain tumor detection, outperforming previous versions by a significant margin. The proposed model of YOLOv7 achieves a mAP score of 94%. These results prove that the YOLOv7 model is capable to detect the brain tumor along with its location which proves, that the model has potential in finding tumors using MRI.**

Keywords—Brain Tumor. Brain Tumor detection, YOLOv7, precision, Deep neural network, MRI

I. Introduction

In current era, the mortality due to tumors have been increased. Of which death due to brain tumor causes a major impact in the society [1]. When we talk about brain tumors, we mean abnormal cell growths inside the brain that can cause a variety of symptoms and potentially life-threatening. It can affect all ages of people starting from small children to old age people. Although it is a deadly disease, the survival chances are high if the identification of tumor is carried out at an early stage [1]. For the condition to be effectively treated and managed, early and precise diagnosis of brain tumors is essential. Medical Imaging techniques such as MRI, Computed Tomography (CT), Electroencephalography (EEG) and Positron Emission Tomography (PET) are commonly used for brain tumor detection, but the interpretation of these images can be challenging and often requires expert knowledge. Many radiologists prefer MRI scans for accurate detection of brain tumor [2].

In the early years of this decade, deep learning methods based on ANNs have demonstrated significant promise for a variety of image processing tasks in the medical industry, including the detection of brain tumors [3]. These methods can help identify and cure brain tumors by using massive volumes of data to automatically learn to recognize patterns and characteristics in medical pictures [4]. Advanced characteristics of DL-based artificial neural networks include the ability to apply these algorithms directly to data without the requirement for feature extraction [5].

The rest of the paper is organized as follows: Literature Review in section II. Materials and methods for dataset preparation in section III. In section IV, the proposed method of Yolov7. As in section V the experimental analysis of training, validation, and testing of the images are presented. Then, results and discussions are presented in section VI, and finally, the concluding statements and future work are in section VII.

II. Literature review

Vidyarthi, R. Agarwal et al., [1] presented a machine learning based approach to classify the type of tumors. Here, the authors put forth the Cumulative Variance Method (CVM), a unique feature selection strategy. This feature selection extracts important elements from brain imaging scans. Using a feature ranking matrix, the redundant and unnecessary features are removed from the feature pool. K-Nearest Neighbour, multi-class SVM, and neural network (NN) are three types of techniques that are utilized for classification. The neural network technique produces noteworthy results for these classifiers.

Shahid Eqbal et al., [2] presented a feature extraction approach of MRI brain tumor using wavelet transform approach. Wavelet transform approach uses superposition of wavelets generated from the MRI machine. Typically, a wavelet representation of a picture is relatively minimal and powerful. The brain MRI images are categorized using a hybrid method that combines support vector machine (SVM) and fuzzy c-means methods.

S. Ahmad and P.K et al., [3] compared several transfer learning methods in a study and evaluated their effectiveness. Here, ResNet50, InceptionResNetV2, InceptionV3, Xception, and DenseNet201 are used along with the algorithms VGG-16, VGG-19, and Inception. VGG19 stands out among them in terms of performance. The output of each transfer learning method is provided to different machine learning classification algorithms. AdaBoost, Gradient Boosting, Random Forest, Decision Tree, Support Vector Machine. The VGG19 and SVM combination outperforms the others. The authors intended to do more research on the detection of various malignant brain tumor kinds.

III. Material and Method

A. Data Collection

The dataset for this work is collected from fig share [6]. The data source's original creator claims that the dataset consists of MRI of 300 patients. Further the original author of the data claims that these data are verified and pre-sorted by a radiology expert. The images in the dataset have a standard dimension of 512x512 [6]. The data images are initially in the original format of the MRI (i.e.) MAT format. In order to work with the images, the MAT format of the data images is converted into JPG format so that the YOLO algorithm can easily access the data images. There was no suitable label format for the collected data. which is necessary for YOLO algorithm. The YOLO algorithm makes use of the image as well as the label to recognize and localize objects. The label consists of the object class and bounding box coordinates. After the model is trained, the testing is done with the help of these labels. By comparing the predicted bounding boxes with the label's bounding box coordinates, one may determine the accuracy of detection. Due to lack of proper labelling of tumor, we performed a precise labelling of coordinates around the tumor is performed using appropriate labelling tool. Thus, we get the labelled dataset required by the YOLO algorithm [4]. The dataset is intended to be used in the creation and testing of for MRI image-based brain tumor detection with deep learning model [6].

B. Data Augmentation

Normally deep learning models requires a huge dataset to process the results. Since medical data are confidential, we cannot get a large amount of data related to medical domain [5]. This encouraged the development of many data augmentation strategies' such as transforming complex images geometrically. This will increase the amount of data and boost the model's overall accuracy. Some of the data augmentation techniques are

- Translation
- Rotation
- Flip
- Resizing
- Distortion
- Cropping
- Image overlay
- Noise injection
- Color space
- Linear filters
- Random deletion of frames

Of these techniques, we used Resizing, Flip, Rotation and Cropping as data augmentation methods [7]. By doing so we increased the total dataset from 300 to 1196 data.

IV. Proposed Method

The methodology we proposed here, is to find the brain tumor using object detection algorithm YOLOv7.

YOLO processes photos relatively rapidly since it just utilizes one neural network to predict the item classes and bounding boxes. The neural network is trained using a sizable dataset of labelled pictures, and throughout training, it discovers the characteristics and patterns connected to various object classes [8].

A. YOLOv7 Model

YOLO – You Only Look Once is a popular object identification algorithm. It has many versions of which version 7 has a more reliable architecture. This reliable architecture was very faster when compared to other object detectors. The most effective object identification algorithm for demanding computer vision tasks is YOLOv7. It facilitates a stronger network architecture that results effective integration of features, performance of object detection is more accurate, a powerful loss function and increased model training efficiency. Moreover, YOLOv7 re-quires less computation hardware when compared to other DL models. So, using this algorithm training the model can be done at a faster rate [9].

Fig. 1. Blueprint of proposed YOLOv7 model

The YOLOv7 makes use of MS COCO dataset to pretrain the model for object detection. The YOLOv7 architecture is composed of three components: the backbone network, the feature pyramid network, and the detection head. As shown in fig. 1 [10], the backbone network extracts feature from the picture while the feature pyramid network and detection head focus on the detection component.

B. *YOLOv7 Detection Unit*

The bounding boxes and class probabilities of the items in a picture are predicted by the detection unit of the YOLOv7. The feature pyramid network (FPN) extracts the features, which are processed by a number of convolutional layers to provide the final predictions [11]. The detection unit consists of 3 main parts namely, a set of convolutional layers for extracting features, a set of neural layers for detecting the final output and prediction of results. Convolutional layers with stride 2 or 3 are frequently included in the feature extraction layers, which degrade the feature maps and broaden the network's receptive field [12].

In YOLOv7, the detection layers include a set of neural layers that forecast the objectness score and boundary box coordinates for every anchor box. The objectness score shows how likely it is that an object will be discovered within the bounding box, while the bounding box coordinates describe its location and size [13]. Since YOLOv7 employs anchor-free detection, it does not make use of pre-defined anchor boxes [8]. Instead, the detection unit predicts the locations and sizes of objects directly, which allows it to detect objects of various dimensions and aspect ratios [14]. YOLOv7 does this by predicting the center point of each item as well as the dimensional ratios of the bounding box in relation to the size of the picture using a collection of convolutional layers [15].

The SoftMax function is used to determine the class probabilities based on the characteristics that were retrieved from the image [16].

Overall, the detection unit in YOLOv7 is designed to process the features extracted by the FPN and output the final predictions for object detection. The use of anchor-free detection and advanced detection techniques, such as feature fusion and multi-scale detection, allows YOLOv7 to achieve high accuracy and real-time performance on a wide range of object detection tasks [17].

V. EXPERIMENTAL ANALYSIS

A. *Transfer Learning, Fine-Tuning, and Model Training*

Using insufficient learning data might result in a weak and erroneous performance on the majority of DL tasks. Transfer learning, however, made it possible to train models and get meaningful results without the requirement for a lot of data. This method was used in conjunction with the COCO dataset's pre-trained weights to improve the model's capacity to identify different types of brain tumors. The previously learned COCO features provided the model with additional picture recognition requirements needed for the detection process[5]. Furthermore, the pre-trained model can be further improved by using fine-tuning to regulate resource allocation and prevent memory exhaustion during training and testing.

The default class numbers were changed from 80 to 2, where 2 represents the two categories of benign and malignant brain tumors, as the initial step in fine-tuning the model. Here 80 stands for the COCO classes from before. The default value of Conv filter must be changed from 255 to 24, as C stands for the number of classes as indicated in Eq (1). This is for the five YOLO coordinates and three multiple scaled bounding boxes K [10].

$$filters = 2 * (5 + C) \tag{1}$$

Batch size, subdivisions, learning rate, momentum, decay, and iterations are the appropriate hyper-parameters for this application, according to Table I [10]. Following that, the model was trained using 2775 iterations, a subdivision size of 55, and a batch size of 16. The training process's learning rate, momentum, and decay were set at 0.00261, 0.9, and 0.0005, respectively, based on the resources available. Weights are serialized automatically every 1000 iterations in order to offer early feedback on performance during the training phase [11].

TABLE I. HYPER-PARAMETERS OF THE YOLOV7 MODEL

Hyper-Parameter	**Value**
Batch Size	16
Subdivision	8
Learning Rate	0.00261
Momentum	0.9
Decay	0.0005
Iterations	2775

B. *Evaluation Metrics*

After the training and testing phases of the model are finished, the next step is to evaluate the model's performance using the established metrics for object detection.

The True Positives (TP), False Positives (FP), and False Negatives (FN) detections on a test set. TP refers to a tumor class identified correctly, FP denotes a non-tumor that is wrongly recognized, and FN is a tumor that the model fails to detect [7]. The confusion matrix results are shown in Fig 2.

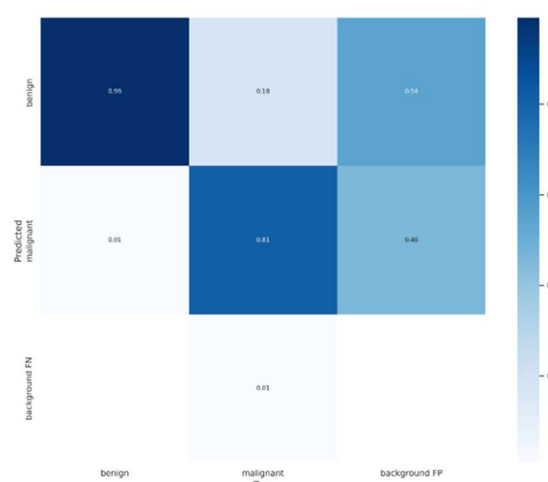

Fig 2. Confusion Matrix of Brain Tumor

Average Precision (AP) is the worldwide standard for evaluating the overall detecting capabilities of object detection algorithms, rather than accuracy. This statistic accounts for the number of samples of a certain class instance that were properly and mistakenly recognized. P(k) is the accuracy at a specific threshold, k, and rΔ(k) is the change in recall (RC). The AP is officially presented in Equation (2). The AP is shown in fig3

$$AP = \frac{1}{N} \sum_{k=1}^{N} P(k)\Delta r(k) \tag{2}$$

The mAP (mean average precision) is a well-liked metric for judging how well object recognition algorithms work. The accuracy and thoroughness of the model's predictions are assessed by contrasting the predicted bounding boxes with the ground truth bounding boxes in a dataset. mAP is frequently used in computer vision research and applications to evaluate and compare the efficacy of various object recognition models.

The mAP, which averages all AP values for each category, can be used to determine which model is best at detecting brain tumors. This may be used to defend the model that outperformed all others. The formal presentation of the mAP mathematical equation is made in Eq (3). The mAP result is shown in fig 4.

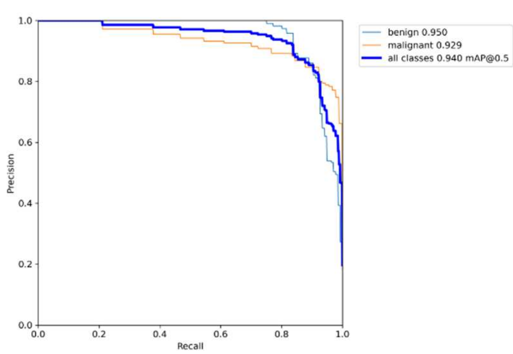

Fig 3. Average Precision of all classes

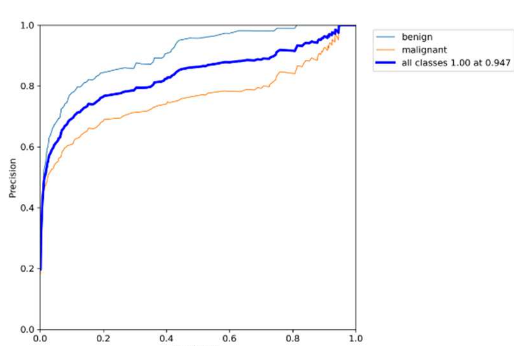

Fig. 4. Mean Average Precision of all classes

In the field of medicine, these measures are critical for assessing the ratio of precisely predicted positives to all detections, expected detections, and the balance between recall and accuracy. With the use of the offered metrics, a model's effectiveness and dependability for a particular job, such deep learning, may be assessed. The precision and F1 scores are mathematically determined using Eq (3) and (4) [6]. The subsequent result graphs are shown in fig 5 and 6.

$$PR = \frac{TP}{TP + FP} \tag{3}$$

$$F1 - Score = \frac{2*(PR*RC)}{PR + RC} \tag{4}$$

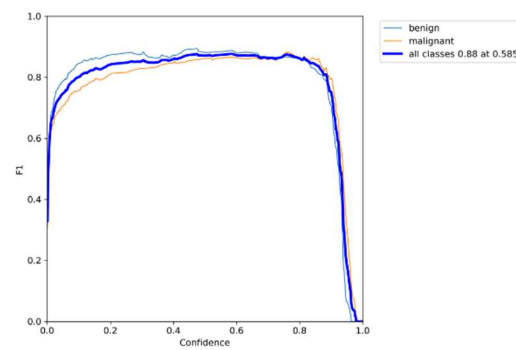

Fig. 5. F1 score of all classes

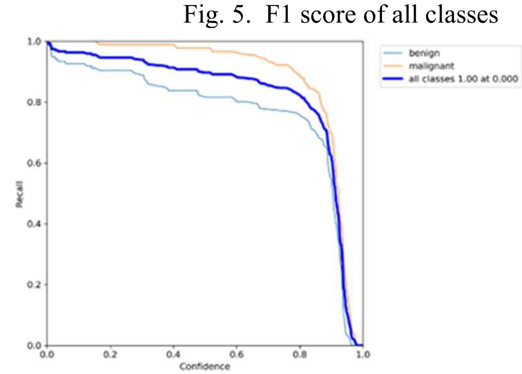

Fig. 6. Recall – Confidence of all classes

VI. Result and Discussion

A. Average Loss and Convergence

To ascertain whether the model had been effectively trained with the training data, the convergence of loss to the local minima was demonstrated by the loss graphs in Fig. 7 of this work, indicate that the models did not make many mistakes or losses when validating from the picture dataset. This ideal loss line characteristic shows that the models verified the pictures precisely and with little mistake, and that the model learnt progressively with no fitting issues. The blue line concurrently showed that the model's accuracy from the training dataset improved with time. The fig 7 shows the overall results of the proposed YOLOv7 model.

In fig 7 showed that all models had been effectively trained for a constant duration of 2775 iterations. Throughout the training phase, the CIoU loss function quickly converged without exhibiting any overfitting or underfitting symptoms [10].

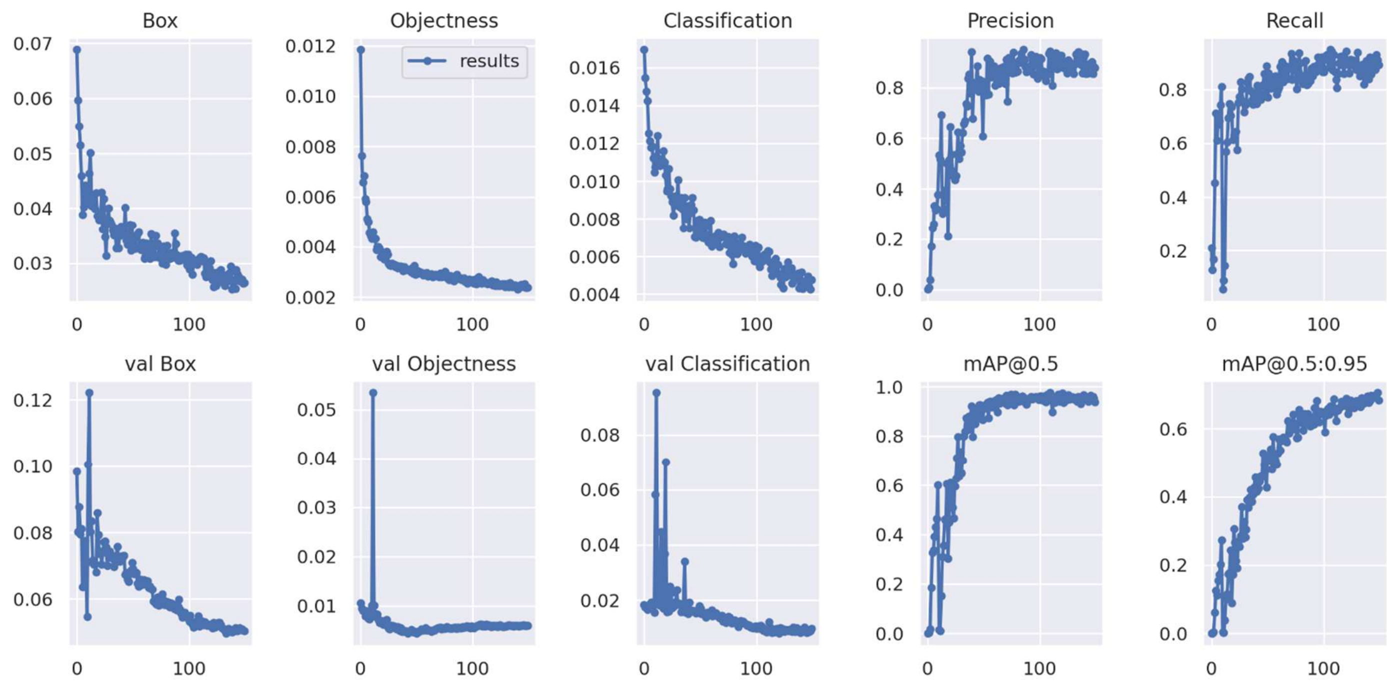

Fig. 7. Results of the proposed YOLOv7 model

B. Average Precision and Detection Count

In Table 2 it displays the AP determined by the ratio of TP and FP detections for each model's class. The findings showed that YOLOv7 (640x640) has the greatest AP for tumor detection with 94%. This score is followed by the 416x416 with 92.62% and the YOLOv3 with 87.23%.

It is difficult to establish which model is the most effective because, upon ex-amination, all three models have demonstrated varying capabilities in detecting different types of tumors [7]. Additional metrics are employed in a second evaluation set to choose the most effective brain tumor detection model.

C. Detections

The following detections, produced by YOLOv7(640x640) model from randomly chosen test data, are shown in Fig. 8. Interestingly, other models from 416x416 failed to identify the tumor with the greatest mAP. Moreover, the 640x640 even worked better and found the tumor in YOLOv3. With the provided collection of randomly chosen samples in the above figure, only the YOLOv7 640x640 succeeded to achieve full detections. This does not, however, completely capture the total effectiveness of any approach. Simply said, this section shows how YOLO can identify a range of minor to big brain tumors from the test set. As the detected output is shown in fig 8.

D. Comparison

In the context of brain tumor detection, YOLOv7 appears to outperform YOLOv3 in terms of mean average precision (mAP) as shown in Table 1. With a higher mAP of 94, YOLOv7 is able to more accurately detect brain tumors than YOLOv3's mAP of 87.23. This improvement in performance is likely due to the larger architecture of YOLOv7, which includes a feature extractor with 120 convolutional layers

. Because of this, YOLOv7 can recognize more intricate characteristics in photos of brain tumors, leading to more precise and reliable identification. But it's crucial to keep in mind that other elements, such as the size and quality of the dataset, pre-processing techniques, and training methods, may also have an influence on how well these models perform in terms of spotting brain tumors. The comparison results are shown in Table II.

TABLE II. COMPARISON OF VARIOUS YOLO MODELS

Model	**Value**		
	Precision	Recall	mAP
YOLOv7 (640x640)	93.45	98.7	94%
YOLOv7 (416x416)	87.9	89	92.62%
YOLOv3 (640x640)	65.9	84.1	87.23%

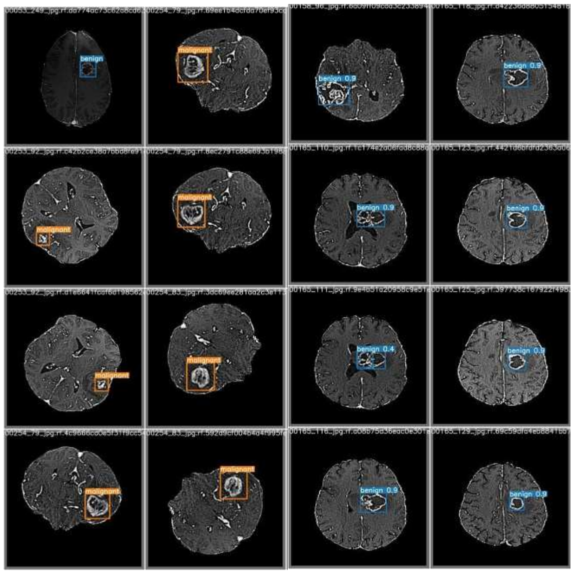

Fig. 8. Detection Results

VII. CONCLUSION AND FUTURE WORK

YOLOv7, the most up-to-date object recognition algorithm, for the detection of brain tumors in MRI data is proposed. To train the YOLOv7 model, transfer learning and fine-tuning techniques were employed on a large dataset of MRI images depicting brain malignancies. The suggested model effectively identified brain tumors with high accuracy and precision, with an average precision of 94%. The findings show how well deep learning-based object identification algorithms work for automatically spotting brain malignancies in MRI images. Radiologists and physicians can utilize the suggested model as a useful tool to quickly and effectively identify brain tumors in their early stages, improving treatment results and patient survival rates.

The usage of YOLOv7 for the identification of other tumor types in medical imaging, as well as performance optimization of the model architecture and hyperparameters, can be explored in future study. Moreover, the accuracy and effectiveness of brain tumor identification may be increased by utilizing other data augmentation approaches and integrating the suggested model into clinical processes. In future the work can be further extended to classify different tumor types including gliomas, meningiomas, and pituitary using MRI. The accuracy of the outputs and the rate of the model calculations can also be improved by using a larger dataset. The use of better GPU-based processing too improves the accuracy of the output.

REFERENCES

[1] A. Vidyarthi, R. Agarwal, D. Gupta, R. Sharma, D. Draheim and P. Tiwari, "Machine Learning Assisted Methodology for Multiclass Classification of Malignant Brain Tumors," in IEEE Access, vol. 10, pp. 50624-50640, 2022, doi: 10.1109/ACCESS.2022.3172303.

[2] Shahid Eqbal, M.A.Ansari, "Medical Image Feature Extraction Using Wavelet Transform" International Journal of Engineering Science Invention Research & Development; Vol. IV, Issue IV, OCTOBER 2017, E-ISSN: 2349-6185

[3] S. Ahmad and P. K. Choudhury, "On the Performance of Deep Transfer Learning Networks for Brain Tumor Detection Using MR Images," in IEEE Access, vol. 10, pp. 59099-59114, 2022, doi: 10.1109/ACCESS.2022.3179376.

[4] P. Kumar Mallick, S. H. Ryu, S. K. Satapathy, S. Mishra, G. N. Nguyen and P. Tiwari, "Brain MRI Image Classification for Cancer Detection Using Deep Wavelet Autoencoder-Based Deep Neural Network," in IEEE Access, vol. 7, pp. 46278-46287, 2019, doi: 10.1109/ACCESS.2019.2902252.

[5] A. Anaya-Isaza and L. Mera-Jiménez, "Data Augmentation and Transfer Learning for Brain Tumor Detection in Magnetic Resonance Imaging," in IEEE Access, vol. 10, pp. 23217-23233, 2022, doi: 10.1109/ACCESS.2022.3154061.

[6] https://figshare.com/articles/dataset/brain_tumor_dataset/1512427

[7] A. Hossain et al., "A YOLOv3 Deep Neural Network Model to Detect Brain Tumor in Portable Electromagnetic Imaging System," in IEEE Access, vol. 9, pp. 82647-82660, 2021, doi: 10.1109/ACCESS.2021.3086624.

[8] Akram, M. & Usman, Anam. (2011). Computer aided system for brain tumor detection and segmentation. Proceedings - International Conference on Computer Networks and Information Technology. 299-302. 10.1109/ICCNIT.2011.6020885.

[9] Wang, C., Bochkovskiy, A., & Liao, H. (2022). YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. ArXiv. https://doi.org/10.48550/arXiv.2207.02696.

[10] "A Computer-Aided Diagnosis of Brain Tumors Using a Fine-Tuned YOLO-based Model with Transfer Learning." The Free Library. 2020 KSII, the Korean Society for Internet Information 02 Mar. 2023 https://www.thefreelibrary.com/A+Computer-Aided+Diagnosis+of+Brain+Tumors+Using+a+Fine-Tuned...-a0649749903.

[11] J. Cheng, W. Yang, M. Huang, W. Huang, J. Jiang, Y. Zhou, R. Yang, J. Zhao, Y. Feng, Q. Feng, and W. Chen, "Retrieval of Brain Tumors by Adaptive Spatial Pooling and Fisher Vector Representation,"

[12] F. Fang, Y. Yao, T. Zhou, G. Xie and J. Lu, "Self-Supervised Multi-Modal Hybrid Fusion Network for Brain Tumor Segmentation," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 11, pp. 5310-5320, Nov. 2022, doi: 10.1109/JBHI.2021.3109301.

[13] A. H. Abdel-Gawad, L. A. Said and A. G. Radwan, "Optimized Edge Detection Technique for Brain Tumor Detection in MR Images," in IEEE Access, vol. 8, pp. 136243-136259, 2020, doi: 10.1109/ACCESS.2020.3009898.

[14] S. Solanki, U. P. Singh, S. S. Chouhan and S. Jain, "Brain Tumor Detection and Classification Using Intelligence Techniques: An Overview," in IEEE Access, vol. 11, pp. 12870-12886, 2023, doi: 10.1109/ACCESS.2023.3242666.

[15] Ramkumar, M. P., Mano Paul, P. D., Maram, B., & Ananth, J. P. (2022). Deep maxout network for lung cancer detection using optimization algorithm in smart Internet of Things. Concurrency and Computation: Practice and Experience, 34(25), e7264.

[16] M. A. Ottom, H. A. Rahman and I. D. Dinov, "Znet: Deep Learning Approach for 2D MRI Brain Tumor Segmentation," in IEEE Journal of Translational Engineering in Health and Medicine, vol. 10, pp. 1-8, 2022, Art no. 1800508, doi: 10.1109/JTEHM.2022.3176737.

[17] A. S. Musallam, A. S. Sherif and M. K. Hussein, "A New Convolutional Neural Network Architecture for Automatic Detection of Brain Tumors in Magnetic Resonance Imaging Images," in IEEE Access, vol. 10, pp. 2775-2782, 2022, doi: 10.1109/ACCESS.2022.3140289.