SAKARYA ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ DERGİSİ

Sakarya University Journal of Science
SAUJS

ISSN 1301-4048 e-ISSN 2147-835X Period Bimonthly Founded 1997 Publisher Sakarya University
http://www.saujs.sakarya.edu.tr/

Title: Detection and Localization of Glioma and Meningioma Tumors in Brain MR Images using Deep Learning

Authors: Emine CENGİL, Yeşim EROĞLU,Ahmet ÇINAR, Muhammed YILDIRIM

Recieved: 2022-02-02 00:00:00

Accepted: 2023-03-02 00:00:00

Article Type: Research Article

Volume: 27
Issue: 3
Month: June
Year: 2023
Pages: 550-563

How to cite
Emine CENGİL, Yeşim EROĞLU,Ahmet ÇINAR, Muhammed YILDIRIM; (2023), Detection and Localization of Glioma and Meningioma Tumors in Brain MR Images using Deep Learning. Sakarya University Journal of Science, 27(3), 550-563, DOI: 10.16984/saufenbilder.1067061
Access link
https://dergipark.org.tr/en/pub/saufenbilder/issue/78131/1067061

Sakarya University Journal of Science 27(3), 550-563, 2023

Detection and Localization of Glioma and Meningioma Tumors in Brain MR Images using Deep Learning

Emine CENGİL*[1], Yeşim EROĞLU[2], Ahmet ÇINAR[3], Muhammed YILDIRIM[4]

Abstract

Brain tumors are common tumors arising from parenchymal cells in the brain and the membranes that surround the brain. The most common brain tumors are glioma and meningioma. They can be benign or malignant. Treatment modalities such as surgery and radiotherapy are applied in malignant tumors. Tumors may be very small in the early stages and may be missed by showing findings similar to normal brain parenchyma. The correct determination of the localization of the tumor and its neighborhood with the surrounding vital tissues contributes to the determination of the treatment algorithm. In this paper, we aim to determine the classification and localization of gliomas originating from the parenchymal cells of the brain and meningiomas originating from the membranes surrounding the brain in brain magnetic resonance images using artificial intelligence methods. At first, the two classes of meningioma and glioma tumors of interest are selected in a public dataset. Relevant tumors are then labeled with the object labeling tool. The resulting labeled data is passed through the EfficientNet for feature extraction. Then Path Aggregation Network (PANet) is examined to generate the feature pyramid. Finally, object detection is performed using the detection layer of the You Only Look Once (YOLO) algorithm. The performance of the suggested method is shown with precision, recall and mean Average Precision (mAP) performance metrics. The values obtained are 0.885, 1.0, and 0.856, respectively. In the presented study, meningioma, and glioma, are automatically detected. The results demonstrate that using the proposed method will benefit medical people.

Keywords: MRI, brain tumor detection, deep learning

* Corresponding author: ecengil@beu.edu.tr (E. CENGİL)
[1] Department of Computer Engineering, Bitlis Eren University, Bitlis, Turkey
[2] Department of Radiology, Firat University, Elazig, Turkey,
[3] Department of Computer Engineering, Firat University, Elazig, Turkey,
[4] Department of Computer Engineering, Malatya Turgut Ozal University, Malatya, Turkey,
E-mail: yeroglu@firat.edu.tr, acinar@firat.edu.tr, muhammed.yildirim@ozal.edu.tr
ORCID: https://orcid.org/0000-0003-4313-8694, https://orcid.org/ 0000-0003-3636-4810, https://orcid.org/ 0000-0001-5528-2226, https://orcid.org/ 0000-0003-1866-4721

1. INTRODUCTION

Brain tumors are tumors with high morbidity and mortality, the frequency of which increases with age. They are masses of cells that proliferate abnormally and uncontrollably in the brain. Primary brain tumors develop from the parenchymal components of the brain, or the membranes that surround the brain called the meninges. The most common primary brain tumors are gliomas originating from neuroepithelial cells and meningiomas originating from the membranes surrounding the brain. Gliomas are the most usual brain tumors that develop from neuroglial cells such as astrocytes, oligodendrocytes, and ependymal cells, and they can be benign or malignant [1, 2]. Meningiomas are mostly benign and constitute approximately 20% of brain tumors. They are extra-axial tumors because they arise from the membranes surrounding the brain [3]. Gliomas are more common in men and meningiomas in women. The main imaging modalities used in the identification of brain tumors are computed tomography (CT) and magnetic resonance imaging (MRI). The advantages of magnetic resonance imaging are its high soft-tissue resolution, noninvasiveness, and no radiation. Computed tomography is especially used in emergent pathologies such as bleeding, hydrocephalus, herniation, and for the determination of tumor calcification [4, 5]. With conventional MRI of the brain, the localization, borders and spread of the tumor are determined and treatment is planned. However, sometimes the imaging findings of tumors do not allow adequate anatomical detailing and it may be difficult to detect the tumor [6, 7].

The brain tumor is a common tumor with serious consequences. In this respect, it should be determined correctly. Routinely, radiologists and clinicians may encounter some difficulties when performing this procedure. In addition, the lack of experience of doctors may increase the rate of error. Therefore, the use of computer-assisted technology has become necessary to overcome these limitations. In this study, an expert system using artificial intelligence-based deep learning architecture, which detects the presence and localization of the tumor region on brain MR images, has been studied.

The study aims to determine the type of glioma and meningioma, which are the most common brain tumors, and in which regions they are located on MR images. A public dataset is labeled by an expert radiologist with ten years of experience [8]. Although the classification of brain tumors is widely studied, the studies determining the type and location of the tumor are not common. The knowledge of the location of the relevant region also provides convenience to the doctors.

Figure 1 shows the draft of the proposed model. Using the applied method, the two types of brain tumors are found with high accuracy. The performance of the method is evaluated according to performance metrics such as precision, recall, and mAP.

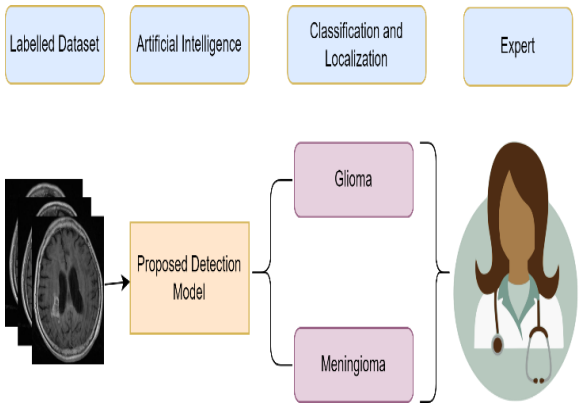

Figure 1 Draft diagram of the proposed model

The organization of the work is as follows. In section 2, artificial intelligence-based methods for the detection of brain tumors are given. In the third section, the dataset used and the proposed method are presented. The fourth section includes the experimental

results of the method. Finally, the results of the study are evaluated in section 5.

2. LITERATURE

Brain tumor classification, segmentation, and detection are the most studied topics in medical image processing. G. Garg et al. [9] intend to determine the tumor region's area and identify brain tumors as benign or malignant. For this, a hybrid ensemble method based on the Majority Voting Method is proposed, which employs Random Forest, K-Nearest Neighbor, and Decision Tree. First, Otsu's Threshold method is used to segment the data. The Stationary Wavelet Transform, Principal Component Analysis, and Gray Level Co-occurrence Matrix are used to extract thirteen features for classification. The hybrid ensemble classifier (KNN-RFDT) is used for classification, which is based on the majority voting method. In general, it is intended to improve traditional classifier performance rather than going deep learning. In the dataset of 2556 images, the proposed method had an accuracy of 97.305 percent.

V. V. Kumar and P. G. K. Prince [10] use Deep belief network and Quadratic Logit BoostClassifier (DBNQLBC) technique for brain tumor detection. The proposed technique includes differen types of layers such as input layer, hidden layers and output layer. The method yielded 70.83% Specificity on 250 MRI images The RCNN technique was proposed by N. Kesav and M.G. Jibukumar [11] for brain tumor classification and tumor-type object detection. Two publicly available datasets were used to analyze the architecture. First, Dual Channel CNN, a low-complexity architecture, is used to distinguish between glioma and meningioma tumor MRI samples. The same structure is then used as a feature extractor of an RCNN to detect tumor regions in the previously classified Glioma MRI sample. Bounding boxes are utilized to define the tumor region. The methodology yielded a confidence level of 98.83 percent on average.

M. F. Khan, et al. [12] used AdaBoost and random forest algorithms to classify brain tumors. In the related dataset, 95% accuracy was obtained for the AdaBoost algorithm, while 89% accuracy was obtained for the Random Forest algorithm.

In [13], the Whale Harris Hawks optimization (WHHO) method is proposed for detecting brain tumors using MR images. Cellular automata and rough set theory are used for segmentation. Tumor size, Local Optically Oriented Pattern, Mean, and Variance are extracted from segments. A deep convolutional neural network is utilized to detect brain tumors, with training using the recommended WHHO. The proposed WHO is created by combining the Whale optimization algorithm (WOA) and the Harris hawk optimization algorithm (HHO). The WHO-based DeepCNN has a maximum accuracy of 81.6%, a maximum specificity of 79.1%, and a maximum sensitivity of 97.4%.

The authors in [14] offer a method for identifying brain tumors that relies on a deep autoencoder and spectral data augmentation. Brain images were subjected to morphological cropping in order to downsize and decrease noise. The data space problem with feature reduction is then resolved using the discrete wavelet transform (DWT). For easier feature extraction and categorization of images of brain tumors, a dense layer is lastly proposed. The proposed algorithm gave 97% accuracy and 99.46% AUC ROC score.

Q. Chuandong, et al. [15] proposed a shared memory-based parallel optimization approach to resolve the SVM classifier for brain tumor identification. First, the wavelet transform method is utilized to compare the features of the extracted brain tumor MR image using the HOG algorithm. After, SVM was used as a classifier. Finally, the classifier solution is proposed and applied using the SMP-SGD, SMP-Momentum, SMP-Adagrad, and SMP-Adam algorithms. According to experimental

findings, the HOG algorithm extracts MRI features of brain tumors more successfully than the discrete wavelet transform technique. The SMP-SGD method that was suggested offered 96% accuracy.

S. Sangeeta and H. Nagendra [16] aimed to classify brain tumors as meningiomas, gliomas, and pituitary. For this purpose, K means and Fuzzy C-Means Clustering (FCM) algorithms were used. In the study where the two methods were compared, both reached 80% accuracy. In addition, K means performed better in terms of processing time.

M. Arif et al. [17] classify the brain glioma tumor or a meningioma tumor. In the paper, a deep learning classifier and Berkeley's wavelet transform (BWT)-based technique are suggested. Using the gray level co-occurrence matrix (GLCM) method, significant features are retrieved from each segmented tissue, and then those features are optimized using a genetic algorithm. The method achieved 98.5% accuracy on MRI brain images (normal, abnormal) from 66 patients.

G. Ramkumar et al. [18] suggested a novel method and strategy based on the Deep CNN Algorithm (DCNNA). A fuzzy-based strategy is also inserted to the suggested segmentation processing steps in brain tumor classifications, increasing the accuracy of the proposed DCNNA approach.

In [19], human brain images are classified as normal, benign, and malignant tumors. Preprocessing and Segmentation, Feature Reduction, and Feature Extraction and Classification are the four stages of the system. The Threshold function is used to process preprocessing and segmentation in the first stage. The features associated with MR images are obtained in the second step by employing the discrete wavelet transform. The third step includes of Principal component analysis, which is used to reduce the MRI features to more essential features. The final stage is the classification, in which a classifier KSVM is used to classify the site of infection in the brain tumor. The method obtained an accuracy of around 90%.

M. Jian et al. [20] proposed a tumor detection method for MRI brain images based on salience modeling. First, to overcome the skull effect, the morphological method was used to strip the skull of MRI brain images. Next, a basic local contrast-based salience detection method is introduced to enhance foreground regions that make it easier to obtain the lesion site. Eventually, noise removal, segmentation, and morphological methods are utilized to improve the results.

M. K. Islam et al. [21] proposes a brain tumor detection scheme based on the superpixel, template-based K-means algorithm, and PCA. At first, basic features are extracted using PCA. The image is then enhanced using a filter that helps enhance accuracy. Lastly, segmentation to detect brain tumors is performed via the TK-vehicle clustering algorithm. The proposed detection scheme showed 95% success for detecting brain tumors on MR images.

There are numerous papers in the literature on the detection of brain tumors. A large part of these studies focuses only on the presence of the tumor. Some classify tumors according to their types but are not concerned with the knowledge of where the tumor is. Our motivation is to suggest an artificial intelligence-based system to assist doctors. For this purpose, the type and localization of the two most common tumors are determined.

3. METHODOLOGY

In this section, information about the data set utilized and the proposed method are detailed.

3.1. Data Set

In the presented study, we use a dataset consisting of a total of 4 classes containing brain MRI images [22]. In the classes, images of the normal brain, images of glioma tumors originating from neuroepithelial cells, images of meningioma tumors originating from the membranes of the brain, and images of pituitary tumors originating from the sellar region are available, respectively.
The dataset was examined by a specialist radiologist. The class with normal brain MR images and the class with pituitary tumors in the sellar region were excluded from the study. Images of glioma and meningioma, the two most common classes of brain tumors, were also analyzed, and postoperative MR images and images with poor image quality and artifacts were excluded from the dataset. Some examples of such images are given in Figure 2. As a result, the dataset to be applied to the method consists of 602 glioma and 818 meningioma images. The images to be used are labeled with the labelImg [23]. Examples of original and labeled images of the dataset are given in Figure 3.

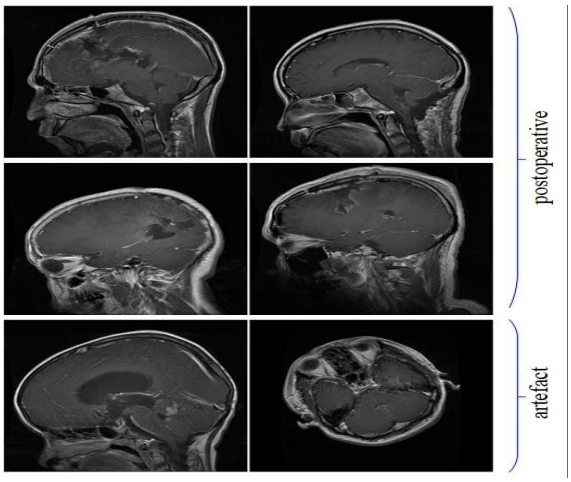

Figure 2 Samples of images extracted from the dataset

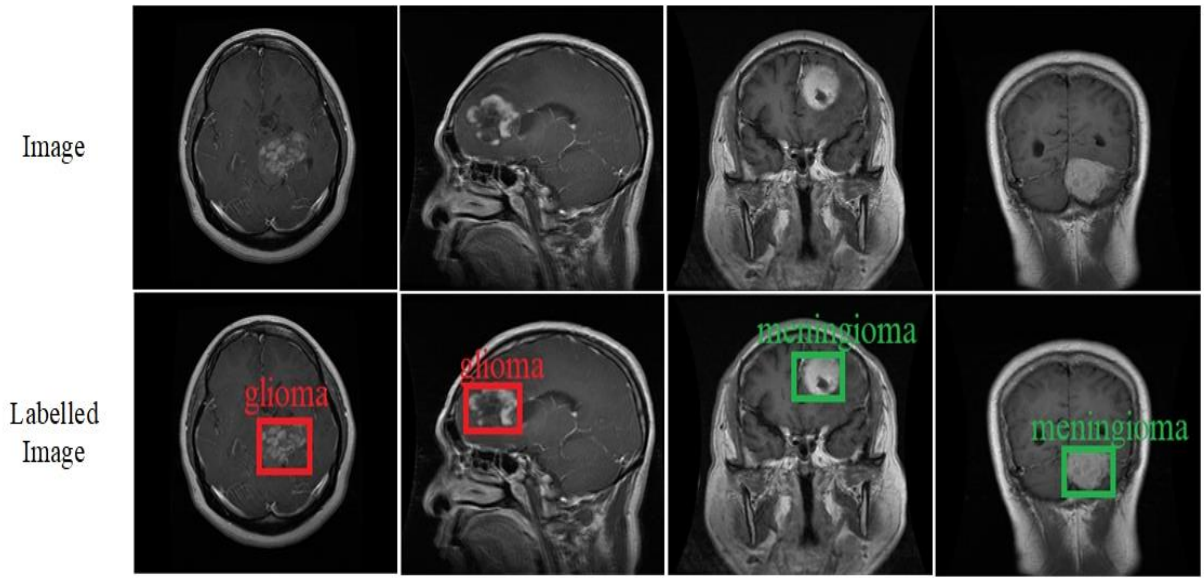

Figure 3 Samples of original and labelled images of the data set.

3.2. Convolutional Neural Network (CNN)

CNN are multi-layer architectures based on deep learning, which is a popular technique of recent times. CNN provides classification by extracting the characteristics of the labeled training data. CNN models are frequently used in image processing in academic and scientific areas. CNN architecture has convolution, pooling, and fully connected layers, etc. The convolution function is presented in equation (1) [24].

$$(a * k)(x) = \sum_{m=-\infty}^{+\infty} a(m)k(x-m) \quad (1)$$

where, a: input image, k: kernel, x: variable representing range of shifting and, m: shifting against x. The mathematical operation aids in calculating the similarity of the two signals. The depth of the network is increased by applying filters to the entered data, with the goal of producing more accurate results [25].

Activation layers are often used in CNN architectures. The most common activation functions are Tanh, Sigmoid, Relu, and Leaky ReLU [26].

The Fully Connected layer is another popular layer in CNN architectures [27]. The feature maps are fed into the fully connected layer. These feature maps are being prepared for classification. Also, multidimensional feature maps are converted to a single dimension.

The first step in object-finding problems is to extract distinctive attributes from the image. The success of the method is largely parallel to the success of this stage. Convolutional neural networks have models that have proven themselves in this field. Some of the popular ones are AlexNet [28], VGG [29], ResNet [30], and EfficientNet [31]. In the EfficientNet model, all three of the depth, width, and resolution are scaled to make the model smaller. The EfficientNet group includes of 8 models from B0 to B7, and the larger the number, the higher the number of calculated parameters and the accuracy. EfficientNet is frequently used in image processing applications in the medical field and achieves successful results [32-34]. For this reasons, the EfficientNet network is preferred in the feature extraction step.

3.3. Proposed Method

Artificial intelligence is present in many fields today. The rapid progress of technology necessitates the use of artificial intelligence in the area of medical image processing, as in most areas. The graphical depiction of the model is as in Figure 4.

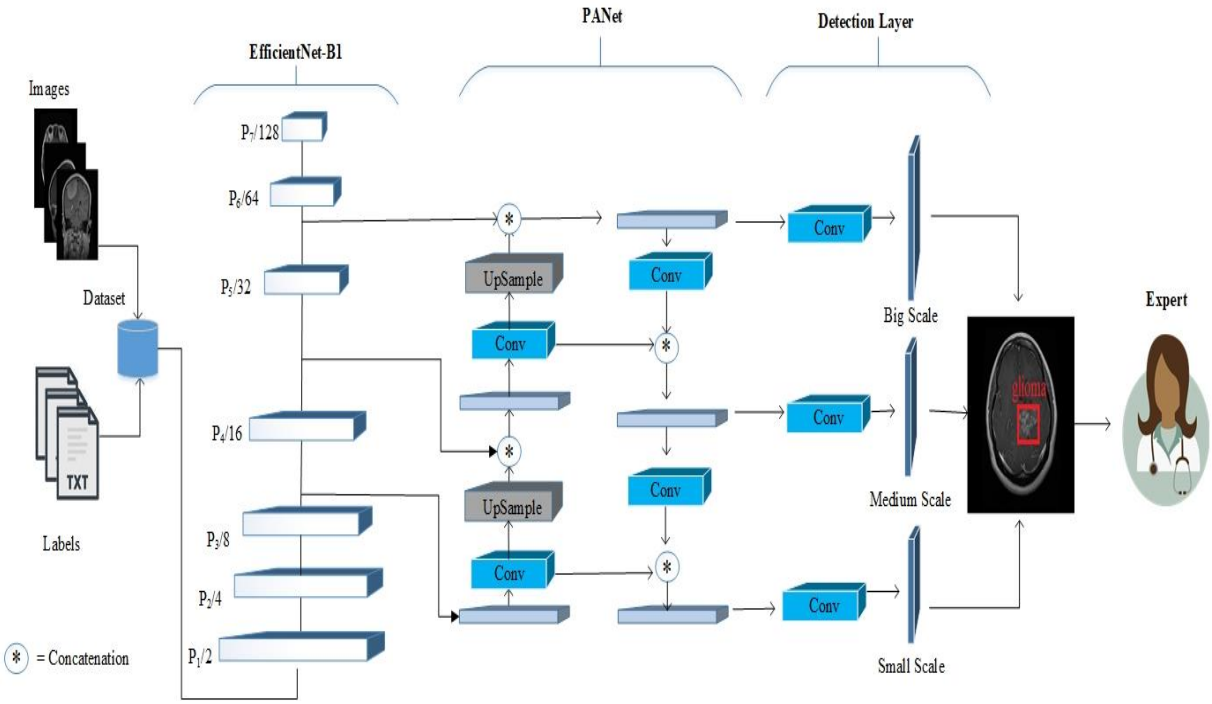

Figure 4 Graphical depiction of proposed model

In the study, a dataset containing two types of tumors labeled by the expert radiologist with the labelImg tool is used as input. In YOLOv5, CSPDarkNet is used as a backbone.

In the proposed method, features are provided with the EfficientNet model from the input images. Then PANet [35] is used to generate the feature pyramid. The utilization of accurate localization signals in the lower layers is improved by PANet, which can obviously increase the object's position accuracy. Finally, object finding is performed using the detection layer used in versions 3-4 and 5 [36, 37] of the YOLO object detection algorithm. The Yolo layer generates feature maps in 3 different sizes (18×18, 36×36, 72×72) to obtain a multi-scale prediction. In this way, it is ensured that Small, Medium, and Big Scale tumors in MR images.

4. EXPERIMENTAL RESULTS

This study was carried out with the python language. While 70% of the images in the dataset were used for training, 15% were used for validation and 15% were used for testing. The training parameters used are important for the performance of the model. In the model, the initial learning rate is 0.01 and the momentum is 0.937. Other training parameters are given in Table 1. System requirements for the experiment; Windows 10 operating system is 16GB RAM, NVIDIA GeForce 950M GPU, and Intel(R) Core(TM) i7-7500U CPU.

Table 1 Train Parameter of model

Momentum	0.937
Learning Rate	0.01
Weight Decay	0.0005
Epoch	20
Batch size	2
Opt. Alg.	SGD/Adam
Library	PyTorch

The method is run under the same conditions as SGD and Adam optimization algorithms. In terms of training time, model training is completed in 4.409 hours with SGD. On the other hand, when Adam is used, the training is completed in 4,143 hours. In terms of accuracy criteria, 0.775 mAP is provided with SGD, while 0.856 mAP is provided with Adam. Therefore, it was decided to conduct model training and testing with Adam optimization, which provided advantages in terms of both speed and accuracy criteria. The confusion matrix acquired after the training with the prepared dataset is as in Figure 5.

The training set includes 482 gliomas and 654 meningioma tumors. The validation set includes 120 gliomas and 164 meningiomas. Precision and recall curves obtained as a result of applying these images with the suggested method are as in Figure 6. Precision is obtained by dividing the number of objects found as True Positive (TP) by the sum of the number of TP and FP objects. The precision of all classes is 0.885. Recall TP is obtained by dividing the samples by the sum of the TP and FN samples [38]. The confusion matrix in Figure 5 shows that the FN value is 0. There is no object as FN in the dataset. Therefore, the recall metric was obtained as 1.

The mAP is often used to measure the performance of object detection problems. The Precision-Recall curve of the model is demonstrated in Figure 7. The AP value of the glioma class is 0.786, and the AP value of the meningioma class is 0.926. The mAP value of the two classes is provided as 0.856.

Studies done in the literature are given in section 2. Information about some of these studies is also given in Table 2 as a comparison table.

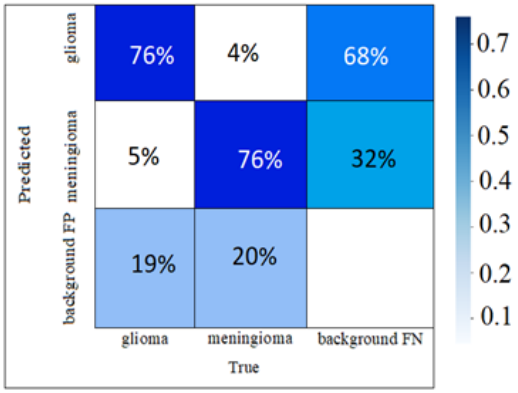

Figure 5 Confusion matrix of the model

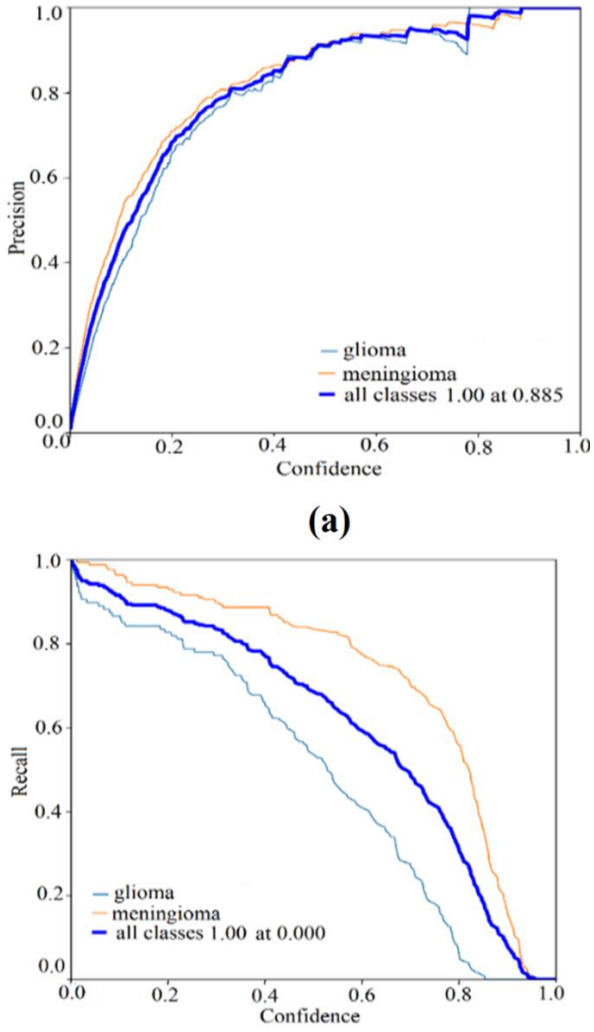

Figure 6 (a) Precision and, (b) recall curve of the model

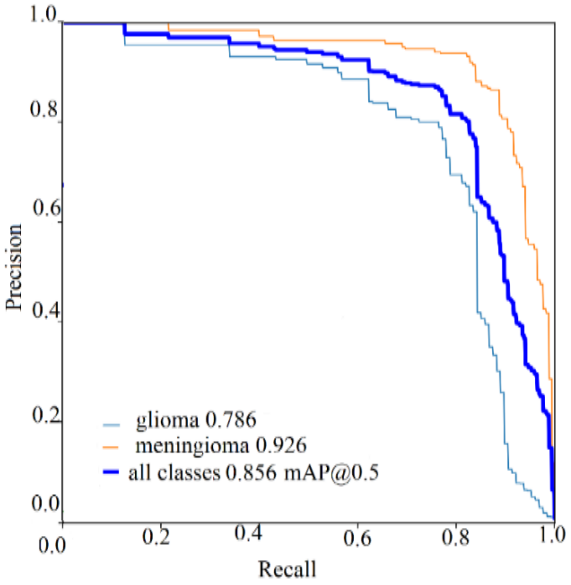

Figure 7 Precision-Recall curve of the model

The test process was carried out with the best-weighted model obtained as a result of the training. A total of 215 images are used. Some of the results obtained as a result of the test are as in Figure 8.

Table 2 Studies on classification, segmentation and detection of brain tumor

Ref No./ Year	**Dataset**	**Method**	**Performance metrics**	**Classes/Task**
[9]/2021	2556 images	Hybrid Ensemble Model	97.305 % Acc.	Benign, Malignant/ Classification
[10]/2023	250 MR images	DBNQLBC	70.83 % Specificity 94% Acc.	Normal, Abnormal/ Classification
[11[/2021	Two public datasets	RCNN & Two channel CNN	98.83 average confidence	Meningioma, Glioma, Pituitory/ Classification and detection
[12]/2021	Brain MRI Dataset	Adaboost Random Forest	95 % Acc. 89 % Sensitivity	Meningioma, Glioma, No tumor/ Classification
[14]/2022	Brain Tumor Detection MRI	Autoencoder+ DWT	97% Acc.	No, Yes/ Classification
[15]/2023	3064 MR Images	SMP-SGD	96% Acc.	Meningioma, Glioma, Pituitory/ Classification
[16]/2022	3680 MR Images	K means FCM	80% Acc. 80% Acc.	Meningioma, Glioma, Pituitory/ Classification
[17]/2022	150 MRI brain images	GLCM+BWT+CNN	98.5 % acc.	Normal, Abnormal/Classification
[18]/2021	BRATS dataset	DCNNA	95 % Acc.	Glioma tumor/ Segmentation
[19]/2021	MR Image Dataset	KPCA+ KSVM	90% Acc.	Normal, Benign, Malignant/ Segmentation
[20]/2020	100 MRI brain images	saliency computational modeling	0.8255 Precision 0.8206 Recall 0.8244 F-Measure	Brain tumor/ Segmentation
[21]/2021	40 MR images	PCA &TK-means	95% Acc.	Brain tumor/ Segmentation
Proposed model	**Brain tumor detection dataset**	**EfficientNet& PANet& YOLO**	**0.885 Precision, 1.0 Recall 0.856 mAP**	**Glioma, Meningioma/ Detection**

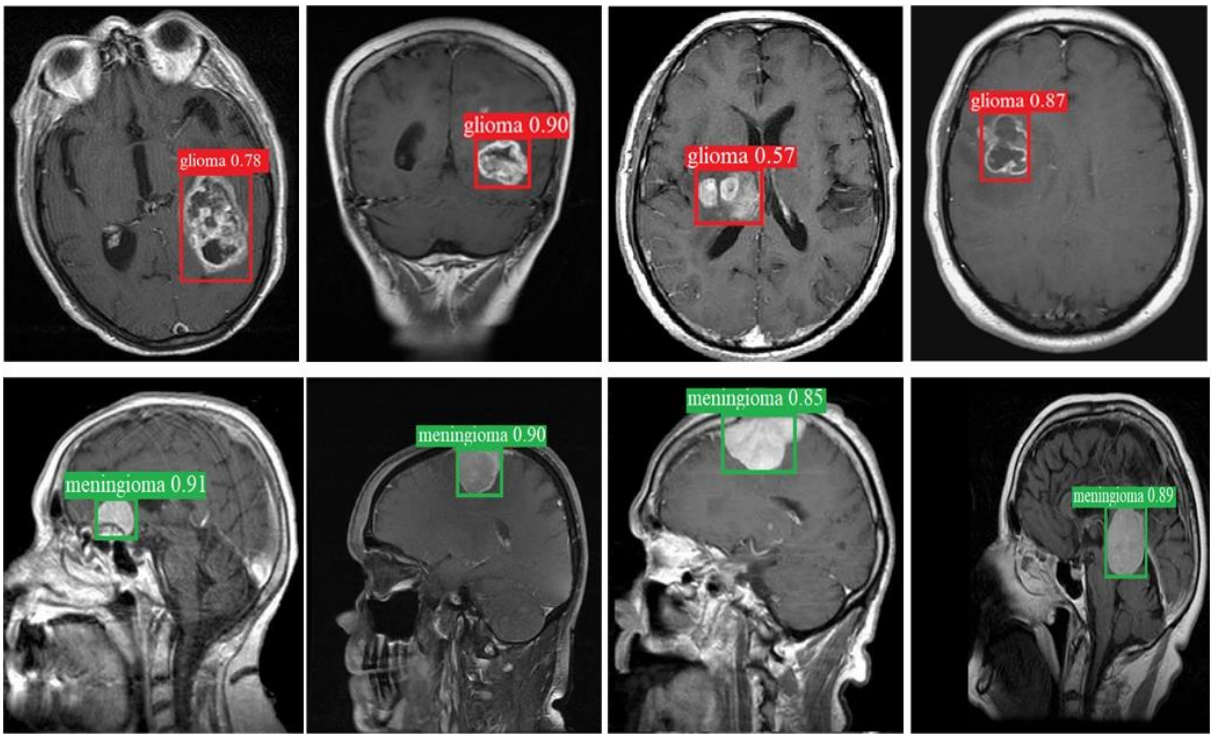

Figure 8 Samples of test results

5. DISCUSSIONS

The glioma and meningioma classes in our study can be differentiated from each other by some imaging findings in MRI. These tumors can be benign or malignant. Gliomas can be malignant more often, while meningiomas are more often benign. Gliomas are intra-axial tumors as they arise from the parenchymal cells of the brain. On MRI, especially malignant gliomas are more heterogeneous, irregularly circumscribed, and peripherally enhanced. There is edema around it [39]. Meningiomas, on the other hand, are extra-axial tumors because they arise from the membranes surrounding the brain. Therefore, they are meninges-based, more homogeneous, and well-circumscribed tumors on MRI. There is usually no edema around them [40].

However, there may be differences in imaging findings of some atypical tumors or variants. Therefore, they may not always be easily distinguished radiological and may be confused with each other.
Some images that the proposed method finds incorrect are given in Figure 9. In the axial contrast-enhanced MR image in Figure 9 (a), the localization of the glioma-class lesion in the left posterior parietal was correctly determined by our model. However, the type of the lesion was determined as meningioma and mistyped. Since the lesion is based on interhemispheric fissure, we think that our model included it in the class of meningioma, thinking that the lesion originates from the membranes surrounding the brain. In Figure 9 (b), the localization of the left frontal glioma-class lesion in the axial contrast-enhanced MR image was correctly determined by our model. However, the type of lesion was mistyped as meningioma. We think that our model included it in the class of meningioma because the lesion is located in the periphery of the cerebral hemisphere, there is no edema around it, and it is more homogeneous and well-circumscribed.

In the axial contrast-enhanced MR image in Figure 9 (c), the type of meningioma extending from the lobe to the orbit in the right temporal lobe was correctly determined by our model. However, the lesion is partially localized. We think that the inability to localize the part of the lesion extending to the orbit may be due to the complex anatomy of this region. In the coronal contrast-enhanced MR image in Figure 8(d), the localization of the glioma class lesion crossing the midline frontally from right to left was correctly determined by our model. However, the type of lesion was misclassified as meningioma. We think that since the lesion is of relatively homogeneous intensity and closer to the midline, it was misclassified as an extra-axial lesion.

6. CONCLUSIONS

Brain tumors constitute a significant portion of cancer-related deaths. Brain MRI images constitute a significant part of the daily workload of medical imaging. Knowing the location of brain tumors as well as the type is important in determining the treatment of patients. Therefore, the need to use artificial intelligence methods to determine the type and localization of brain tumors is increasing.

In our study, two common types of brain tumors were detected using the method consisting of EfficientNet architecture, PANet architecture, and YOLO algorithm. The resulting values showed that the method would be useful for detecting brain tumors.

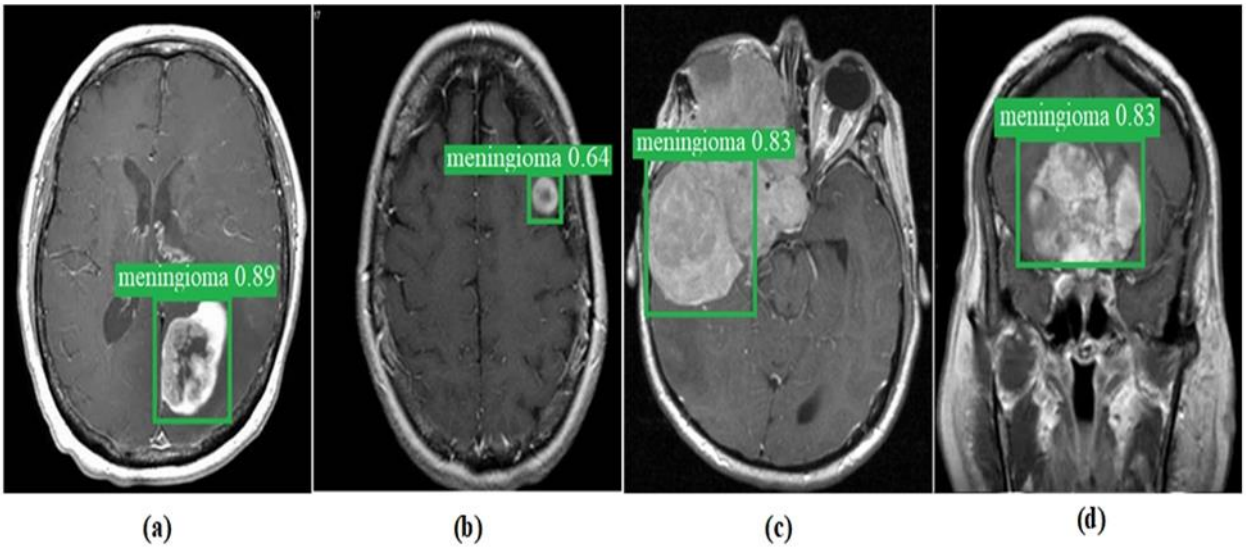

Figure 9 Some images found wrong by the proposed method

Acknowledgments
Dataset link created by authors: https://github.com/ecengil/Brain-tumor-detection-dataset.

Funding
The authors has no received any financial support for the research, authorship or publication of this study.

The Declaration of Conflict of Interest/ Common Interest
No conflict of interest or common interest has been declared by the authors.

Authors' Contribution
The first author contributed 40%, the second author 20%, the third author 20% and, the fourth author 20%."

The Declaration of Ethics Committee Approval
This study does not require ethics committee permission or any special permission

The Declaration of Research and Publication Ethics
"The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science."

REFERENCES

[1] J. M. Hempel, C. Brendle, B. Bender, G. Bier, M. Skardelly, I. Gepfner-Tuma, J. Schittenhelm, "Contrast enhancement predicting survival in integrated molecular subtypes of diffuse glioma: an observational cohort study," Journal of neuro-oncology, vol. 139, no.2, pp. 373-381, 2018.

[2] J. Howard, Central Nervous System Tumors. Neurology Video Textbook DVD, C., Demos and Medical.

[3] T. Ong, A. Bharatha, R. Alsufayan, S. Das, A. W. Lin, "MRI predictors for brain invasion in meningiomas," The Neuroradiology Journal, vol. 34, no.1, pp.3-7, 2021.

[4] B. Garzín, K. E. Emblem, K. Mouridsen, B. Nedregaard, P. Due-Tønnessen, T. Nome, J. K. Hald, A. Bjørnerud, A. K. Håberg, Y. Kvinnsland, "Multiparametric analysis of magnetic resonance images for glioma grading and patient survival time prediction," Acta radiologica, vol. 52 no. 9, pp. 1052-1060, 2011.

[5] C. J. Belden, P. A. Valdes, C. Ran, d. A. Pastel, B. T. Harris, C. E. Fadul, M. A. Israel, K. Paulsen, D. W. Roberts, "Genetics of glioblastoma: a window into its imaging and histopathologic variability," Radiographics, vol. 31, no. 6, pp.1717-1740, 2011.

[6] M. A. Baig, J. P. Klein, L. L. Mechtler, "Imaging of brain tumors," CONTINUUM: Lifelong Learning in Neurology, vol. 22, no. 5, pp. 1529-1552, 2016.

[7] M. C. Mabray, R. F. Barajas, S. Cha, "Modern brain tumor imaging," Brain tumor research and treatment, vol. 3, no. 1, pp. 8-23, 2015.

[8] E. Cengil, Brain tumor detection dataset [online], Available: https://github.com/ecengil/Brain-tumor-detection-dataset.

[9] G. Garg, R. Garg, "Brain Tumor Detection and Classification based on Hybrid Ensemble Classifier." arXiv preprint arXiv:2101.00216, 2021.

[10] V. V. Kumar, P. G. K. Prince, "Deep belief network Assisted quadratic logit boost classifier for brain tumor detection using MR images." Biomedical Signal Processing and Control, *81*, 104415, 2023.

[11] N. Kesav, M. Jibukumar, "Efficient and low complex architecture for detection and classification of Brain Tumor using RCNN with Two Channel CNN." Journal of King Saud University-Computer and Information Sciences, *vol.* 34, no. 8, pp. 6229-6242, 2021.

[12] M. F. Khan, P. Khatri, S. Lenka, D. Anuhya, A. Sanyal. "Detection of Brain Tumor from the MRI Images using Deep Hybrid Boosted based on Ensemble Techniques," in 2022 3rd International Conference on Smart Electronics and Communication (ICOSEC) , 2022, pp. 1464-1467.

[13] D. Rammurthy, P. Mahesh, "Whale Harris Hawks optimization based deep learning classifier for brain tumor detection using MRI images," Journal of King Saud University-Computer and Information Sciences, vol. 34, no. 6, pp. 3259-3272, 2020.

[14] D. R. Nayak, N. Padhy, P. K. Mallick, A. Singh, "A deep autoencoder approach for detection of brain tumor images," Computers and Electrical Engineering, 102, 108238, 2022.

[15] Q. Chuandong, L. Baosheng, H. Baole, "Fast brain tumor detection using adaptive stochastic gradient descent on shared-memory parallel environment," Engineering Applications of Artificial Intelligence, 120, 105816, 2023.

[16] S. Sangeeta, H. Nagendra. "Brain Tumor Detection and Classification Using Clustering and Comparison with FCM, " in 2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), pp. 1-6, 2022.

[17] M. Arif, F. Ajesh, S. Shamsudheen, O. Geman, D. Izdrui, D. Vicoveanu, "Brain tumor detection and classification by

MRI using biologically inspired orthogonal wavelet transform and deep learning techniques." Journal of Healthcare Engineering, 2022.

[18] G. Ramkumar, R. T. Prabu, N. P. Singh, U. Maheswaran, "WITHDRAWN: Experimental analysis of brain tumor detection system using Machine learning approach." Materials Today: Proceedings, 2021.

[19] V. Sabitha, J. Nayak, P. R. Reddy, "MRI brain tumor detection and classification using KPCA and KSVM." Materials Today: Proceedings, 2021.

[20] M. Jian, X. Zhang, L. Ma, H. Yu, "Tumor detection in MRI brain images based on saliency computational modeling." IFAC-PapersOnLine, vol. 53, no. 5, pp. 43-46, 2020.

[21] M. K. Islam, M. S. Ali, M. S. Miah, M. M. Rahman, M.S Alam, M. A. Hossain, "Brain tumor detection in MR image using superpixels, principal component analysis and template based K-means clustering algorithm." Machine Learning with Applications, 5, 100044, 2021.

[22] SartajBhuvaji, Available: https://github.com/SartajBhuvaji/Brain-Tumor-Classification-DataSet/tree/master/Training.

[23] tzutalin. labelImg. (2021). Available: https://github.com/tzutalin/labelImg.

[24] F. Keller, "Computational Foundations of Cognitive Science." Reading, 2: 2, 2010.

[25] E. Cengil, A. Çınar, "A new approach for image classification: convolutional neural network." European Journal of Technique (EJT), vol. 6, no. 2, pp. 96-103, 2016.

[26] A. D. Jagtap, K. Kawaguchi, G. E. Karniadakis, "Adaptive activation functions accelerate convergence in deep and physics-informed neural networks. "Journal of Computational Physics 404 : 109136, 2020.

[27] E. Zisselman, A. Adler, M. Elad, "Compressed learning for image classification: A deep neural network approach." In Handbook of Numerical Analysis, Elsevier. Vol. 19, pp. 3-17, 2018.

[28] A. Krizhevsky, I. Sutskever, G.E. Hinton, "Imagenet classification with deep convolutional neural networks." Communications of the ACM, vol. 60, no.6, pp. 84-90, 2017.

[29] K. Simonyan, A. Zisserman, "Very deep convolutional networks for large-scale image recognition." arXiv preprint arXiv:1409.1556, 2014.

[30] H. Kaiming, X. Zhang, S. Ren, J. Sun, "Deep residual learning for image recognition." İn Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778, 2016.

[31] M. Tan, Q. Le, "Efficientnet: Rethinking model scaling for convolutional neural networks." in international Conference on Machine Learning, PMLR, 2019.

[32] G. Marques, D. Agarwal, I. de la Torre Díez, "Automated medical diagnosis of COVID-19 through Efficient Net convolutional neural network." Applied soft computing, 96, 106691, 2020.

[33] J. Wang, Q. Liu, H. Xie, Z.Yang, H. Zhou, "Boosted efficientnet: Detection of lymph node metastases in breast cancer using convolutional neural networks." Cancers, vol. 13, no. 4, pp. 661, 2021.

[34] N. K. Chowdhury, M. A. Kabir, M. Rahman, N. Rezoana, "Ecovnet: An ensemble of deep convolutional neural networks based on efficientnet to detect covid-19 from chest x-rays." arXiv preprint arXiv:2009.11850, 2020.

[35] K. Wang, J. H. Liew, Y. Zou, D. Zhou, J. Feng, "Panet: Few-shot image semantic segmentation with prototype alignment." In proceedings of the IEEE/CVF international conference on computer vision, pp. 9197-9206, 2019.

[36] J. Redmon, A. Farhadi, "Yolov3: An incremental improvement." arXiv preprint arXiv:1804.02767, 2018.

[37] A. Bochkovskiy, C. Y. Wang, and H. Y. M. Liao, "Yolov4: Optimal speed and accuracy of object detection." arXiv preprint arXiv:2004.10934, 2020.

[38] E. Cengil, A. Çınar, "Poisonous Mushroom Detection using YOLOV5." Turkish Journal of Science and Technology, vol. 6, no. 1, pp. 119-127, 2021.

[39] C. H. Suh, H. S. Kim, S. C. Jung, C. G. Choi, S. J. Kim, "Clinically Relevant Imaging Features for MGMT Promoter Methylation in Multiple Glioblastoma Studies: A Systematic Review and Meta-Analysis." American Journal of Neuroradiology, vol 39, no. 8: 1439, 2018

[40] B. Tamrazi, M. S. Shiroishi, C. S. Liu, "Advanced Imaging of Intracranial Meningiomas." Neurosurgery clinics of North America, vol. 27, no. 2, pp. 137-43, 2016.