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A Deep Learning Model Collaborates with an Expert Radiologist to Classify Brain Tumors from MR Images

Tülin ÖZTÜRK[1], Oğuzhan KATAR[2*]
[1] Department of Radiology, Medikal Park Hospital, Elazig, Turkey
[2] Department of Software Engineering, Faculty of Technology, Firat University, Elazig, Turkey
[1] tulin58@hotmail.com, [*2] okatar@firat.edu.tr

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Abstract: The brain, which consists of nerve cells called neurons, is the center of the nervous system. The rapid and abnormal growth of nerve cells by interacting with each other is called a brain tumor. Undiagnosed or delayed diagnosis of brain tumors lead to death. Although it depends on experience, manually diagnosing and classifying brain tumors is challenging for physicians. Artificial intelligence-based computer systems can help doctors detect brain tumors using the developments in hardware technology and the amount of data increasing daily. This study proposes a deep learning-based system to classify brain MRI images as tumorous or normal using the pre-trained EfficientNet-B0 model. Our radiologist validated a public dataset containing 3000 brain MRI images. The dataset is divided into 70% train, 20% validation, and 10% test. In the test phase after the training, the pre-trained EfficientNet-B0 model achieved high performance with 99.33% accuracy, 99.33% sensitivity, and 99.33% F1 score. In addition, in the evaluation of the test images, the heat maps obtained by the Grad-CAM method were examined by our radiology specialist. The result of evaluations shows that the pre-trained EfficientNet-B0 deep model chooses the right focus areas in its predictions and can be used for clinical tumor detection due to its explainable structure.

Key words: Brain tumor, MRI, Deep learning, EfficientNet, Grad-CAM.

MR Görüntülerinden Beyin Tümörlerini Sınıflandırmak İçin Uzman Bir Radyolog ile İşbirliği Yapan Derin Öğrenme Modeli

Öz: Nöron adı verilen sinir hücrelerinden oluşan beyin, sinir sisteminin merkezidir. Sinir hücrelerinin birbirleriyle etkileşerek hızlı ve anormal büyümesine beyin tümörü denir. Beyin tümörlerinin teşhis edilmemiş veya gecikmiş teşhisi ölüme yol açmaktadır. Tecrübeye bağlı olmakla birlikte, beyin tümörlerini manuel olarak teşhis etmek ve sınıflandırmak hekimler için zordur. Yapay zeka tabanlı bilgisayar sistemleri, donanım teknolojisindeki gelişmeleri ve her geçen gün artan veri miktarını kullanarak doktorların beyin tümörlerini tespit etmelerine yardımcı olabilir. Bu çalışma, ön eğitimli EfficientNet-B0 modelini kullanarak beyin MRG görüntülerini tümörlü veya normal olarak sınıflandırmak için derin öğrenme tabanlı bir sistem önermektedir. Radyoloğumuz, 3000 beyin MRG görüntüsü içeren halka açık bir veri setini doğruladı. Veri seti %70 eğitim, %20 doğrulama ve %10 teste bölünmüştür. Eğitim sonrası test aşamasında, ön eğitimli EfficientNet-B0 modeli %99.33 doğruluk, %99.33 hassasiyet ve %99.33 F1 puanı ile yüksek performans elde etti. Ayrıca test görüntülerinin değerlendirilmesinde Grad-CAM yöntemi ile elde edilen ısı haritaları radyoloji uzmanımız tarafından incelendi. Değerlendirmelerin sonucunda, ön eğitimli EfficientNet-B0 derin modelinin tahminlerinde doğru odak alanlarını seçtiğini ve açıklanabilir yapısı sayesinde klinik olarak tümör tespiti için kullanılabileceğini göstermektedir.

Anahtar kelimeler: Beyin tümörü, MRG, Derin öğrenme, EfficientNet, Grad-CAM.

1. Introduction

The incidence of brain tumors is five to 13 cases per 100,000, with a five-year survival rate of %33.4. The incidence of brain tumors increases with age. The most common symptoms of these tumors are headache, nausea, vomiting, and seizures [1]. As the tumor grows, focal neurological findings can be seen. In some patients, there may be no symptoms at all, and the patient may be detected incidentally by medical imaging methods taken for some other reasons. The present findings of the patient are usually first evaluated with CT, MRI [2]. Magnetic Resonance Imaging (MRI) technology is widely applied to create high-resolution images for brain tumor diagnosis. It has been shown that the treatments applied when brain tumors are detected early in small size are very effective. Radiologically, the diagnosis is difficult because the tumors are small in size, resemble blood vessels, and can be easily missed in non-contrast series. In addition, manual image reading takes a lot of time and effort [3]. The diagnosis process becomes an error-prone process with the emergence of human factors such as

[*] Corresponding author: okatar@firat.edu.tr. ORCID Number of authors: [1] 0000-0001-8942-5264, [2] 0000-0002-5628-3543

fatigue due to the excess time spent. Computers with fast processing capacity and the ability to be unaffected by human factors can help radiologists in this process [4].

Artificial intelligence-based systems are actively used to detect various diseases or monitor the process of treatments [5]. Today, studies involving the use and development of deep learning models for disease-based classification of medical images and marking important disease areas on the image have gained attention [6]. Khan et al. [7] proposed a method for automatic detection of brain tumors with the help of a deep learning-based system. They used a publicly available MRI dataset to detect brain tumors containing 253 images; 155 of them were labeled as tumor, while the remaining 98 images were marked as normal. They used the Canny Edge Detection method to contain minimal background area. Due to the small dataset, synthetic images were produced by data multiplexing. Using these images, four different models, including the CNN-based deep model proposed by the authors. The proposed model correctly classified all 28 test images.

Singh et al. [8] proposed a CNN model to classify MR images. They used a pre-trained VGG-16 model to classify brain tumor MR images into the tumor or normal classes. The dataset was resized to 224x224 and used in model training for 16 epochs. When the test images were examined, it was seen VGG-16 model reached %90 accuracy.

Pundir and Kumar [9] proposed a deep model that can classify normal and tumor brain MRI images. Training dataset consists of images produced by data multiplexing methods. The pre-trained VGG-16 model was trained for 100 epochs. 431 out of 500 tumor images and 487 of 500 normal images allocated for the test phase were predicted correctly by the trained classifier model. Therefore, the VGG-16 model reached 91.8% accuracy.

The primary purpose of this study is to automatically classify tumor and normal images on brain MRI images by a deep learning model and to visualize which areas are focused on the image in the classification predictions it has made. In this way, it is aimed to explain the black-box structure of deep models and to spread the use of deep models in the health sector. The rest of this paper is organized as follows. Section 2 contains information about the method proposed for this study, the used dataset, the classifier deep learning model, and the performance metrics used in classification studies. The numerical values obtained during the training phase of the classifier and the Grad-CAM outputs are given in Section 3. The conclusion part of the study is in Section 4.

2. Materials and Methods

This study proposes a deep learning model to detect brain tumors from MR images. A large number of training data and high-capacity hardware that can process the given data are needed to train deep learning models from scratch. For this reason, it is very costly to train a model from scratch. In order to reduce the computational cost during the training process, CNN models that have been pre-trained on a different dataset are used on the current task. The pre-trained models have learned various features and have optimized weights for the classification task. In this study, a deep learning system is designed to classify brain MRI images with or without tumor. Using the Grad-CAM algorithm, which areas on the image the CNN model pays attention to in its predictions are visualized using the heat map technique. In this way, it was determined by an expert radiologist whether the areas that the deep learning model focuses on are the areas that play an active role in determining the class. Fig.1 shows a block representation of the proposed approach employed in this study.

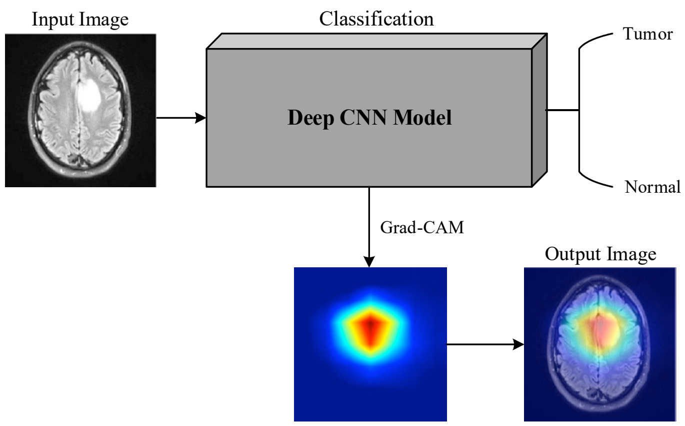

Figure 1. A block representation of the proposed method in this study.

2.1. Brain MRI Dataset

A publicly available dataset called Br35H was used in this study [10]. This dataset includes 1500 tumor and 1500 normal brain MRI images. The experts verified the class labels of the images in the dataset. Sample brain MR images with tumor and normal labels are shown in Fig.2.

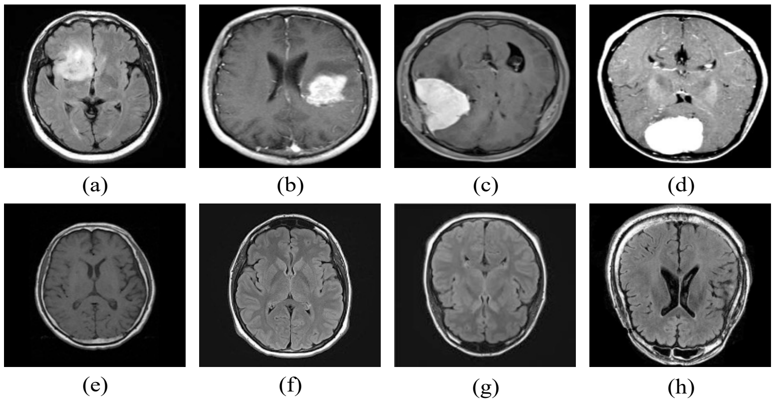

Figure 2. (a), (b), (c), (d) Brain Tumor Axial MR slices, (e), (f), (g), (h) Normal Axial Brain MR slices.

2.2. Proposed Classification Method

This study uses a CNN-based EfficientNet-B0 architecture as the classifier deep learning model. The selected model is state-of-the-art in ImageNet classification computation. The models trained on large datasets achieve significantly higher performance than model training with small data. Tan M. et al. [11] proposed a new method to scale CNNs in a structured way. In the proposed method, a fixed size scaling was used instead of traditional approaches such as increasing the depth, width, or input resolution. The EfficientNet model family, which is smaller and faster than the current computing models, has been developed in the specified new scaling method. This family has eight members, sequentially named from EfficientNet-B0 to EfficientNet-B7. EfficientNet-B0 is designed as the base model, and all other models have scaled versions. The architecture of the EfficientNet-B0 model is given in Table 1.

Table 1. EfficientNet-B0 Model Architecture [11].

Stage	Operators	Resolutions	Channels	Layers
1	Conv3×3	224×224	32	1
2	MBConv1,3×3	112×112	16	1
3	MBConv6,3×3	112×112	24	2
4	MBConv6,5×5	56×56	40	2
5	MBconv6,3×3	28×28	80	3
6	MBConv6,5×5	14×14	112	3
7	MBConv6,5×5	14×14	192	4
8	MBConv6,3×3	7×7	320	1
9	Conv1×1 & Pooling & FC	7×7	1280	1

The basic network structure block diagram of the EfficientNet-B0 deep learning model is shown in Fig.3.

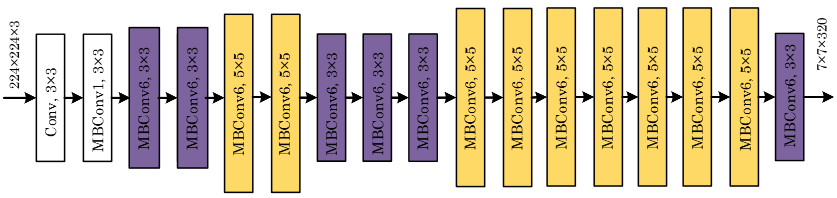

Figure 3. The Block diagram of the EfficientNet-B0 model.

2.3. Experimental Setups

EfficientNet-B0, the basic model of the EfficientNet model family, was used in training the classifier deep learning model. The model with a default input size of 224x224 pixels was trained using the Keras library created with the Python programming language. During the model training, we preferred to use ImageNet [12] weights instead of random initial weights to optimize the parameters. The last layers of the model have been revised to produce only two values in accordance with the binary classification method at the output. In the final layer of the model, the softmax activation function is used as the activation function. Adam optimization was carried out for the training process with cross-entropy loss, batch size of 16, and early termination function active for 50 epochs with a learning rate of 0.001. The performance value followed during training was the accuracy rate. When the verified accuracy rate does not exceed the highest value for five consecutive rounds, the early stop function was activated, and the step with the highest value was saved in the '.hd5' format. This way, it aims to reach the step with the most successful classification ability. All of these processes were carried out in the Google Colab environment.

Since the images in the dataset are of different resolutions, they have been resized to 224x224px. Before starting the training of the model, 70% of the resized dataset samples were randomly divided to be used in the training, 20% validation, and 10% testing phases, preserving the class distribution. The visual setup of the data splitting process is shown in Fig.4.

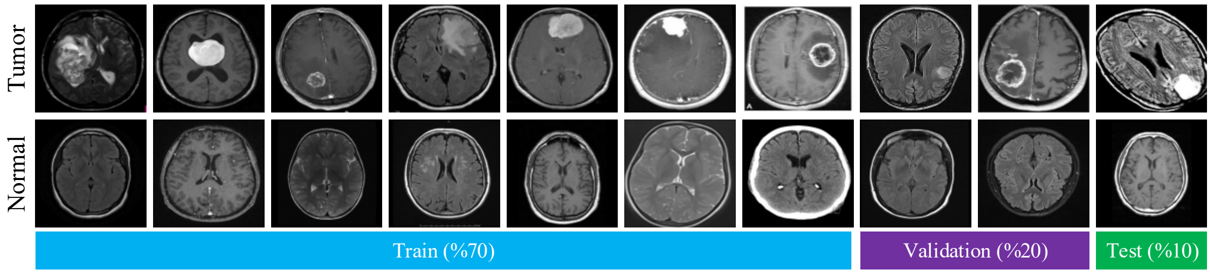

Figure 4. A representation of brain MRI images showing the division rates during model training and testing phases.

The detailed information about the numerical distributions of the data set samples after data division is given in Table 2.

Table 2. Numerical distribution of MR images after data distribution.

Phase	Number of Tumor MR Images	Number of Normal MR Images	Total
Train	1050	1050	2100
Validation	300	300	600
Test	150	150	300
Total	1500	1500	3000

2.4. Performance Evaluation Metrics

In artificial intelligence-based classification studies, confusion matrix-based performance measurements are commonly used to evaluate the performance of the deep learning model in the testing phase. The confusion matrix provides information about the relationship between the predicted label and the actual class label, with reference to the image given as input to the deep learning model. In the studies carried out on the binary classification setup, the model can only predict two different classes at the output. For this reason, only four different situations can arise by examining the predictions of the model. These situations and their details are as follows.

- The prediction of an image with a tumor labeled as tumorous by the classifier deep learning model is called True Positive (TP).
- The prediction of an image with a normal label as tumorous by the classifier deep learning model is called False Positive (FP).

- Normal prediction of an image with tumor label by the classifier deep learning model is called False Negative (FN).
- Normal prediction of an image labeled Normal by the classifier deep learning model is called True Negative (TN).

In order to represent the confusion matrix visually, the values of TP, FP, FN, and TN must be placed in a 2×2 matrix. It is understood that the classification ability of the classifier deep learning model is developed when the TP and TN values are higher than the values of other cases. Various performance metrics have been standardized to express this classification ability mathematically. Some standardized metrics and the equations used for their calculations are as follows.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{1}$$

$$Sensitivitiy = \frac{TP}{TP+FN} \tag{2}$$

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

$$Specificitiy = \frac{TN}{TN+FP} \tag{4}$$

$$F1\ Score = \frac{2*(Precision*Sensitivitiy)}{(Precision+Sensitivitiy)} \tag{5}$$

$$Matthews\ Corelation\ Coefficient\ (MCC) = \frac{(TP*TN)-(FP*FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{6}$$

3. Experimental Results

For automatic detection of tumor and normal brain MR images, the pre-trained EfficientNet-B0 model was trained for 50 epochs with the help of the early termination function. The EfficientNet-B0 model achieved the highest validation accuracy rate of 0.9967 in the 10th epoch. The loss and accuracy graphs of EfficientNet-B0 model obtained during training are shown in Fig. 5.

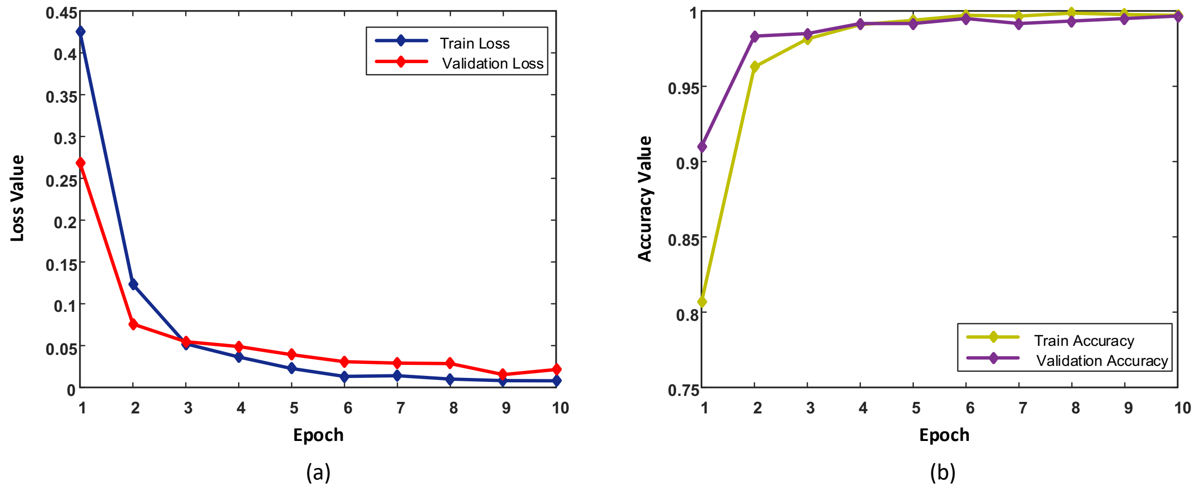

Figure 5. Training graphs EfficientNet a) loss graph b) accuracy graph.

The images reserved for use only in the testing phase are given as input to the EfficientNet-B0 model. The confusion matrix created by reference to the predictions made by the model for the test images is shown in Fig.6.

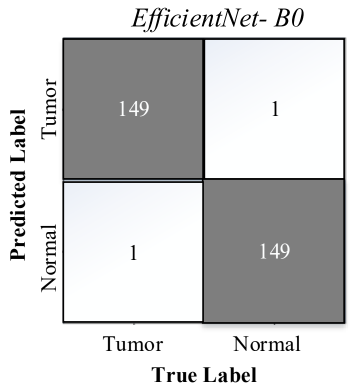

Figure 6. The confusion matrix was obtained by the model on the test images.

It seems that the EfficientNet-B0 model can gain the ability to classify brain MRI images as tumorous or normal according to the findings it contains. In Table 3, the values of the performance metrics achieved by the model during the testing phase are given.

Table 3. Performance values of the classifier model on test data.

Accuracy	Sensitivity	Specificity	Precision	F1 Score	MCC
0.9933	0.9933	0.9933	0.9933	0.9933	0.9867

When the performances of deep learning models are examined, the specified mathematical equations are usually used. However, it is not known which feature of the deep learning model takes into account the class prediction on the image, so the deep models are in a black-box structure. Especially in areas that directly affect human life, such as health, proving that deep learning models focus on which areas in predictions will lead to the emergence of more reliable systems. In this study, Grad-CAM [13] method was applied to examine whether the EfficientNet-B0 model focuses on tumor areas while deciding on brain MRI images. A visualization of the use of the Grad-CAM algorithm in this study is given in Fig.7.

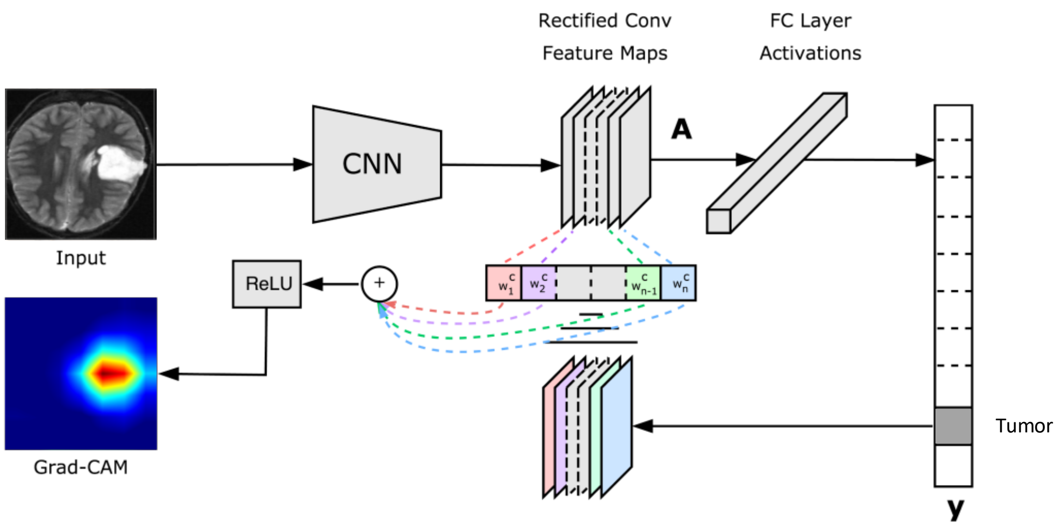

Figure 7. An illustration of the use of the Grad-CAM algorithm.

The Grad-CAM algorithm processes the feature maps generated in the last convolution layer in the CNN architecture. For this reason, the last convolution layer of the classifier model is referenced with the naming of the Grad-CAM algorithm. The heat map corresponding to the input image is created with the help of feature maps and gradients in the relevant layer. The areas expressed in red and yellow in these heat maps represent the areas that the classifier deep learning model focuses on in class prediction. The comparison of the areas focused on by the radiologist and the classifier model on some randomly selected test images in the study is shown in Fig.8.

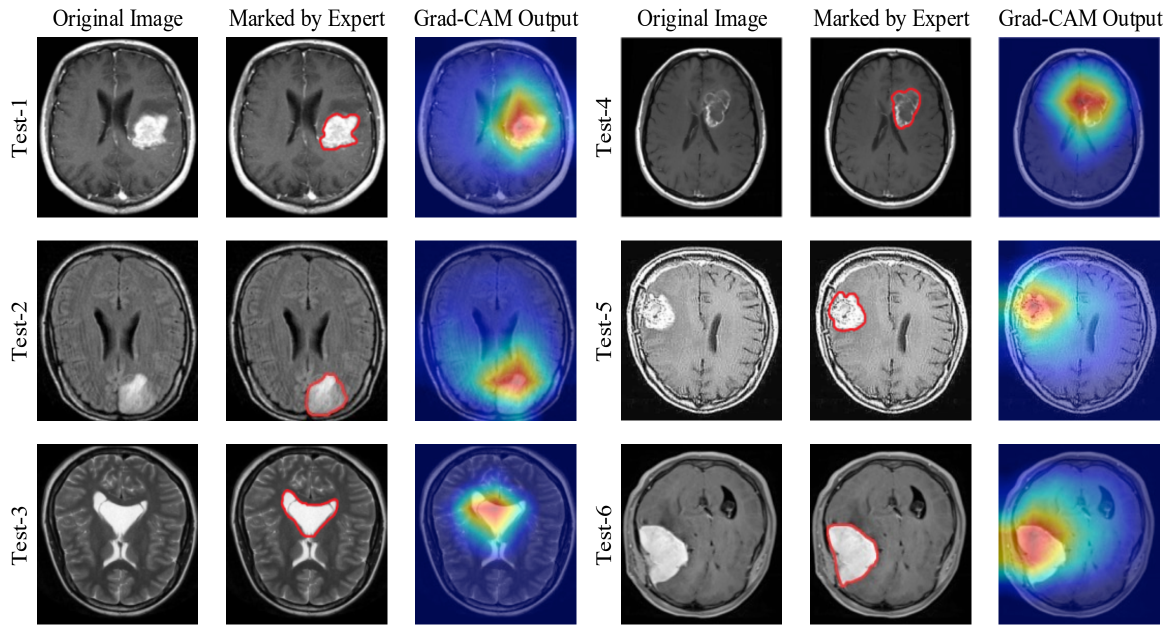

Figure 8. The output of the Grad-CAM algorithm and marks of the expert radiologist.

The comments of the radiologist regarding the areas focused by each original image and deep learning model in Fig.8 are as follows.

- The mass lesion detected by the radiologist in the T1W axial MR image, named Test-1, was correctly focused by the model.
- The mass lesion detected by the radiologist in the non-contrast T1W axial MR image called Test-2 was correctly focused by the model.
- The mass lesion detected by the radiologist in the FLAIR axial MR images, named Test-3, was correctly focused by the model.
- The model correctly focused on the mass lesion detected by the radiologist in the non-contrast T1W axial MR image called Test-4.
- The mass lesion detected by the radiologist in the T2W axial MR image, named Test-5, was correctly focused by the model.
- The model is correctly focused on the mass lesion detected by the radiologist in the contrast-enhanced T1W axial MR image called Test-6.

The model accurately focused on brain tumors that the radiologist detected and localized on the available MR images. The model also detected existing brain tumors in the unenhanced series. In addition, the model marked the masses without distinguishing between benign and malignant.

4. Conclusion

The use of machine learning methods in the health field is becoming more common daily, with the computer having more substantial computational power and increased labeled health data daily. Computer-based automatic detection systems have gained importance in processes such as diagnosing disease and monitoring the progression of the disease by physicians. Since the approaches developed in this context directly affect human life, they must have a high success rate and an explainable structure to gain trust of physicians. In this study, brain MRI images were classified as a tumor or normal with the help of the pre-trained EfficientNet-B0 deep model. The classification performance of the model and the consistency of its focus areas on the image were verified by the radiology specialist. In this way, a reliable artificial intelligence-based system that can help physicians clinically detect brain tumors has been presented. In future studies, we aim to perform model training and testing on larger datasets by using different deep learning models.

References

[1] Perkins A, Liu G. Primary brain tumors in adults: diagnosis and treatment. American family physician, 2016; 93(3): 211-217.

[2] Villanueva-Meyer J. E, Mabray M. C, Cha S. Current clinical brain tumor imaging. Neurosurgery, 2017; 81(3): 397-415.

[3] Zhang Y, Wang S, Wu H, Hu K, Ji S. Brain Tumors Classification for MR images based on Attention Guided Deep Learning Model. 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), 2021; 3233-3236.

[4] Chartrand G, Cheng P. M, Vorontsov E, Drozdzal M, Turcotte S, Pal C. J, Tang A. Deep learning: a primer for radiologists. Radiographics, 2017; 37(7): 2113-2131.

[5] Arsalan M, Owais M, Mahmood T, Choi J, Park K. R. Artificial intelligence-based diagnosis of cardiac and related diseases. Journal of Clinical Medicine, 2020; 9(3): 871.

[6] Biswas M, Kuppili V, Saba L, Edla D. R, Suri H. S, Cuadrado-Godia, E, Suri J. S. State-of-the-art review on deep learning in medical imaging. Front Biosci (Landmark Ed), 2019; 24: 392-426.

[7] Khan, H. A, Jue W, Mushtaq M, Mushtaq M. U. Brain tumor classification in MRI image using convolutional neural network. Math. Biosci. Eng, 2020; 17(5): 6203-6216.

[8] Singh V, Sharma S, Goel S, Lamba S, Garg N. Brain Tumor Prediction by Binary Classification Using VGG-16. Smart and Sustainable Intelligent Systems, 2021; 127-138.

[9] Pundir A, Kumar R. Brain Tumor Classification in MRI Images Using Transfer Learning. Machine Learning for Intelligent Multimedia Analytics, 2021; 307-319.

[10] A. Hamada, Br35h: Brain Tumor Detection 2020, version 5, 2020, https://www.kaggle.com/ahmedhamada0/brain-tumordetection.

[11] Tan M, Le Q. Efficientnet: Rethinking model scaling for convolutional neural networks. International conference on machine learning, 2019; 6105-6114.

[12] Deng J, Dong W, Socher R, Li L. J, Li K, Fei-Fei L. Imagenet: A large-scale hierarchical image database. Computer vision and pattern recognition, 2009; 248-255.

[13] Selvaraju R. R, Cogswell M, Das A, Vedantam R, Parikh D, Batra D. Grad-cam: Visual explanations from deep networks via gradient-based localization. International conference on computer vision, 2017; 618-626.