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A Deep Learning-Based Multi-Model Approach for Brain Tumor Detection in MRI Images

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ABSTRACT

A brain tumor is a serious type of tumor that can be life-threatening. The most common tumor sites include the brain and nervous system tissues. Early and accurate diagnosis is crucial for brain tumor treatment. This study evaluated different deep learning models for the automatic classification of brain tumors using magnetic resonance imaging (MRI) data. Magnetic resonance imaging (MRI) provides very effective data for brain tumor diagnosis. This data significantly contributes to physicians' treatment process and helps achieve more successful outcomes compared to traditional treatment methods. Four different brain tumor types (glioma, pituitary, meningioma, and no tumor) were targeted in the classification process. The classification data were compared during the training and testing phases for a total of six different models commonly used in deep learning-based approaches: VGG16, ResNet-50, InceptionV3, Xception, MobileNetV2, and EfficientNet-B0 The model performance was evaluated using metrics such as accuracy, accuracy rate, loss function, and confusion matrix. Experiments revealed that the MobileNetV2 model achieved a classification accuracy of 90% compared to other models. This result demonstrates that lightweight models, particularly suitable for use in mobile and low-resource systems, can also be effective in complex medical imaging problems.

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MRI Görüntülerinde Beyin Tümörü Tespiti için Derin Öğrenme Tabanlı Çok Modelli Bir Yaklaşım

ÖZ

Beyin tümörü, yaşamı tehdit edebilen ciddi bir tümör türüdür. En sık görülen tümör bölgeleri beyin ve sinir sistemi dokularıdır. Beyin tümörü tedavisi için erken ve doğru tanı çok önemlidir. Bu çalışmada, manyetik rezonans görüntüleme (MRG) verileri kullanılarak beyin tümörlerinin otomatik sınıflandırılması için farklı derin öğrenme modelleri değerlendirilmiştir. Manyetik rezonans görüntüleme (MRG), beyin tümörü teşhisi için oldukça etkili veriler sağlar. Bu veriler, hekimlerin tedavi süreçlerine önemli ölçüde katkıda bulunur ve geleneksel tedavi yöntemlerine kıyasla daha başarılı sonuçlar elde edilmesine yardımcı olur. Sınıflandırma sürecinde dört farklı beyin tümörü tipi (glioma, hipofiz, menenjiyoma ve tümörsüz) hedeflenmiştir. Sınıflandırma verileri, derin öğrenmeye dayalı yaklaşımlarda yaygın olarak kullanılan altı farklı model için eğitim ve test aşamalarında karşılaştırılmıştır: VGG16, ResNet-50, InceptionV3, Xception, MobileNetV2 ve EfficientNet-B0 Model performansı, doğruluk, doğruluk oranı, kayıp fonksiyonu ve karışıklık matrisi gibi ölçütler kullanılarak değerlendirilmiştir. Yapılan deneyler, MobileNetV2 modelinin diğer modellere kıyasla %90'lık bir sınıflandırma doğruluğuna ulaştığını ortaya koymuştur. Bu sonuç, özellikle mobil ve düşük kaynaklı sistemlerde kullanıma uygun olan hafif modellerin, karmaşık tıbbi görüntüleme problemlerinde de etkili olabileceğini göstermektedir.

Anahtar Kelimeler: Beyin Tümörü Analizi, MRI Tabanlı Görüntüleme, Derin Öğrenme, Otomatik Sınıflandırma

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1. Introduction

With the rapid development of technology, artificial intelligence has begun to be used effectively in many areas [1]. One of these is healthcare. With the introduction of artificial intelligence in healthcare, early and accurate disease diagnosis has significantly increased [2]. In particular, the accurate processing of data obtained from medical imaging devices has led to promising advances in the early diagnosis and treatment of diseases such as tumors, which are detected with the help of medical imaging devices [3].
A brain tumor is a disease that occurs when cells in the brain grow uncontrollably and disproportionately, posing a significant threat to human health. The brain is structurally confined to a narrow space within the skull. The growth of cells caused by the tumor further reduces the brain's space, potentially rendering it unable to perform certain functions [4, 5].

Glioma, pituitary tumor, and meningioma are among the most common types of brain tumors [6]. With the development of artificial intelligence, significant progress has been made in the detection of brain tumors. Significant successes have been achieved, particularly through the processing of data obtained from medical imaging devices using deep learning methods [7]. Before the advancement of artificial intelligence in image processing, doctors used traditional methods to analyze diseases like brain tumors. Doctors' personal knowledge, skills, and experience directly impact diagnosis, and because these skills vary from doctor to doctor, results may not always be highly accurate. Artificial intelligence has accelerated this process and achieved high levels of accuracy [8]. Although brain tumors usually present with symptoms such as fatigue and nausea, in some cases they can progress without any symptoms, making diagnosis of the disease quite difficult [9].

In recent years, studies in this area have seen widespread use of machine learning, and particularly deep learning methods. It is noteworthy that deep learning approaches generally provide higher accuracy rates in high-dimensional and complex datasets [10, 11].

The structure of the paper is organized as follows: Section 2 reviews recent research related to brain tumor detection. Section 3 describes the dataset and the methodological approach adopted in this study. Section 4 discusses the experimental design along with the obtained findings. Finally, Section 5 provides an evaluation of the results and outlines several recommendations.

2. Related Works

Much research has been conducted on the detection of brain tumors, and much of this work is currently conducted using deep learning methods. The human brain is quite complex, and accurately analyzing it using medical images is crucial.
In Hashemzehi's study, a hybrid method consisting of Convolutional Neural Network (CNN) and neural autoregressive distribution estimation was proposed. They demonstrated that this method achieved 95% classification accuracy [12]. In a study conducted by Al-Rumaihi and colleagues, they examined artificial intelligence studies in brain tumor diagnosis between 2000 and 2024. Seventy-nine studies were studied according to their established criteria. These criteria included the use of MRI for brain tumor detection and classification, as well as clearly defined performance metrics such as sensitivity, recall, F1 score, accuracy, precision, and specificity. In their study, they found that the overall F1 score ranged from 94% to 96%, with an accuracy rate of 95% [13].

In a study conducted by Gao and colleagues, a study was conducted to diagnose 18 tumor classes using MRI image data collected from 37,871 patients between 2000 and 2019. They achieved an average success rate of 92% [14]. In their study, Halimeh and Teshnehab proposed the use of MRI, a common approach for detecting brain tumors and multiple sclerosis. Brain tumors occur when brain cells grow. Multiple sclerosis (MS) is a chronic condition that damages the brain. Because these two diseases are so similar and often confused, this can lead to death. The authors used an ESA to detect brain tumors and MS, achieving a 96% accuracy rate [15]. In a study by Wong et al., deep learning-based accuracy determination was performed using four different brain tumor classes (glioma, meningioma, pituitary, and normal). A pre-trained VGG16 model and a convolutional neural network (CNN) model were used as the base model. A total of 17,136 MRI images were obtained for each of the four classes using data augmentation techniques. The model's accuracy was found to be 99.24% [16]. In a study conducted by Srinivasan and colleagues using three different deep convolutional neural networks (CNNs), the first model achieved a 99.53% success rate in brain tumor detection. The second model identified five different brain tumor classes (normal, glioma, meningioma, pituitary, and metastatic) with a 93.81% success rate. The third model achieved a 98.56% success rate in classification [17]. In another study, a four-class dataset consisting of meningioma and pituitary images, but not brain tumors, was used. The VGG-19 architecture was used on the dataset, and classification was achieved with a 95% success rate [18].

The aim of this study is to contribute to the literature by classifying four different brain tumor classes (glioma, meningioma, pituitary, and no tumor) with rapid and high accuracy, even on low-performance systems. Six different deep learning methods (VGG16, ResNet-50, InceptionV3, Xception, MobileNetV2, and EfficientNet-B0) were trained and tested under the same conditions. The results were evaluated comparatively. The study's contributions to the literature are summarized below:

1. Classification of 4 different brain tumors was made under the same conditions with 6 different deep learning methods and the results were compared in detail..
2. It has been observed that fast and high accuracy results are obtained for low-end systems.
3. The classification accuracies obtained were presented together with confusion matrices and other statistical measures to make a comparison between the models.

The MobileNetV2 model demonstrated the highest performance compared to other architectures, demonstrating that high accuracy is possible for low-end systems.

3. Materials and Methods

In this study, artificial intelligence-based deep learning methods such as VGG16 [19], ResNet-50 [20], Inception [21], Xception [22], MobilenetV2 [23], EfficientNet-B0 [24] were used for the classification of brain tumor disease and Brain Tumor MRI Dataset [25] was used. This dataset consists of four classes, including medical images of three different types of brain tumors and brain MRI images of healthy individuals. This dataset consists of a total of 7023 medical images: 1621 gliomas, 1757 pituitary tumors, 1645 meningiomas, and 2000 tumor-free brain MRI images. Detailed numerical information regarding the training and test data is provided in Table 1.

Table 1. Detailed Numerical Information on Training and Test Data of Brain Tumor Images

Tumor Test	Train	Test	Total
Glioma	1321	300	1621
Pituitary	1457	300	1757
Meningioma	1339	306	1645
No tumor	1595	405	2000
Total	5712	1311	7023

3.1. Data Preprocessing and General Structure of the Model

The epoch number for training all deep learning models used in the study was set to 10. To prevent the system from memorizing, Earlystop was selected as 3. Sample images from the training and test datasets are shown in Figure 1, and the general flow and methodology of the study are shown in Figure 2. The image dimensions in the raw data were defined as 512×512 pixels. During data preprocessing, all images were rescaled to 128×128 pixels to make them suitable for model training. The resized images were subjected to preprocessing such as zooming in, zooming out, and rotating. Following preprocessing, the design, implementation, and analysis of the deep learning models were performed on the Google Colaboratory [26] platform using the Python programming language.

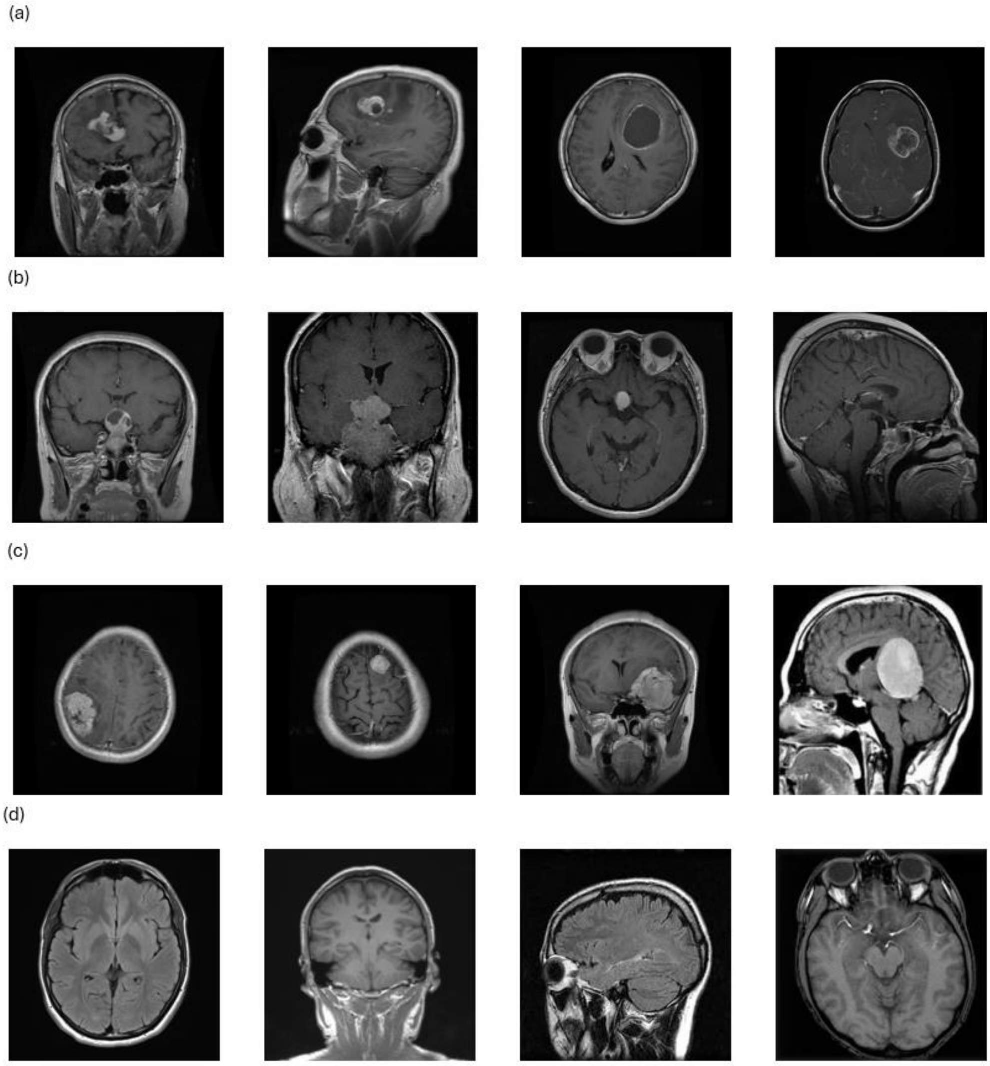


Figure 1. Images in the dataset: (a) Glioma, (b) Pituitary tumor, (c) Meningioma, (d) No Tumor

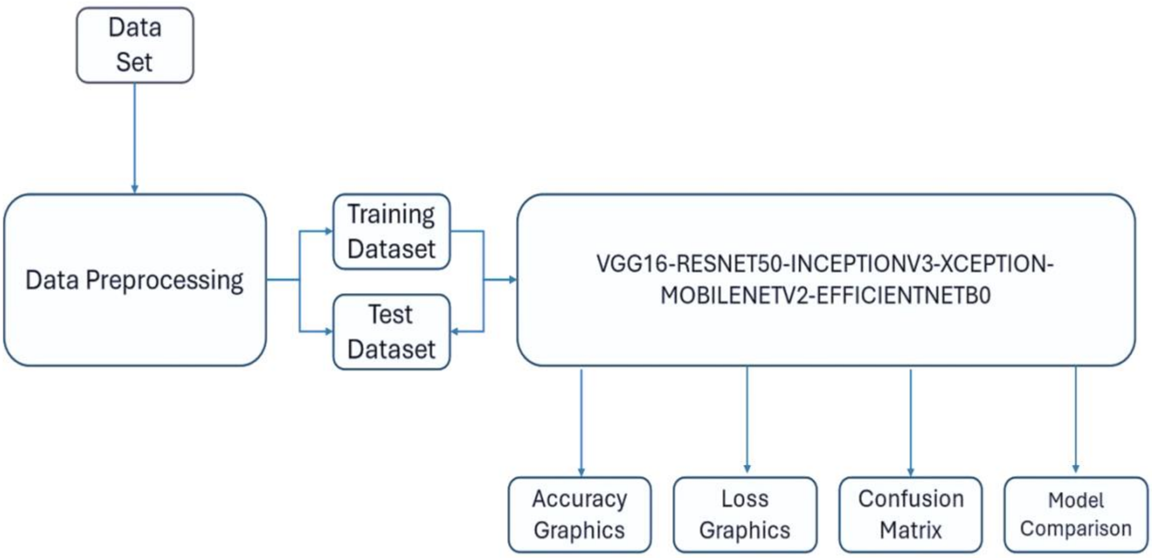


Figure 2. Simplified general structure of the model

Figure 2 shows the simplified model design of the study. The operation of the model can be explained as follows:

- A total of 7023 brain tumor images in 4 different classes (Glioma, Pituitary, Meningioma, No Tumor) were used as a dataset.
- The data was pre-processed and made suitable for the system.
- The total number of images used for training is 5712, while the number of images used for testing is 1311.
- The study was conducted using 6 different deep learning methods.

Success graphs, loss graphs, confidence matrix and model comparisons of the results of each model were made.

4. Results and Discussion

In this study, a four-class brain tumor dataset was used to contribute to early disease diagnosis. Six different deep learning methods were used to successfully detect medical images in this dataset. These methods were VGG16, ResNet-50, InceptionV3, Xception, MobileNetV2, and EfficientNet-B0, respectively. Training, test data, and data preprocessing were used identically for all models.

Experimental results obtained using training and test datasets, along with accuracy, precision, recall, and F1 score values, are presented in Table 2. Furthermore, the changes in accuracy and loss during the training process for each model are shown in Figure 3 and Figure 4, respectively. In addition, to further evaluate the classification performance of the models, the confusion matrix for each model is also presented in Figure 5.

According to the results obtained, the model with the highest success rate was realized with MobileNetV2. When the success graph of this model is examined, a success and loss graph is generally observed that is directly proportional to the increase in the number of epochs. At the end of the training, the success rate is 90% according to the test data. In this study, a multi-class confusion matrix was used to evaluate the performance of the model; accuracy, precision, recall, and F1 score were preferred as evaluation metrics. The calculation equations for these metrics are given below, respectively:

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

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

$$f1 - score = \frac{2*Precision*Recall}{Precision+Recall} \tag{3}$$

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{4}$$

Table 2. Numerical results obtained from each deep learning model structure based on the test dataset

Model	Accuracy	Precision		Recall		F1-Score		Support
		Macro Avg	Weighted Avg	Macro Avg	Weighted Avg	Macro Avg	Weighted Avg	
VGG16	0.83	0.83	0.84	0.82	0.83	0.82	0.82	1311
ResNet-50	0.87	0.86	0.86	0.86	0.87	0.86	0.86	
InceptionV3	0.82	0.82	0.82	0.81	0.82	0.80	0.81	
Xception	0.86	0.86	0.86	0.85	0.86	0.86	0.86	
MobileNetV2	0.90	0.90	0.90	0.89	0.90	0.89	0.90	
EfficientNet-B0	0.86	0.86	0.87	0.85	0.86	0.85	0.86	

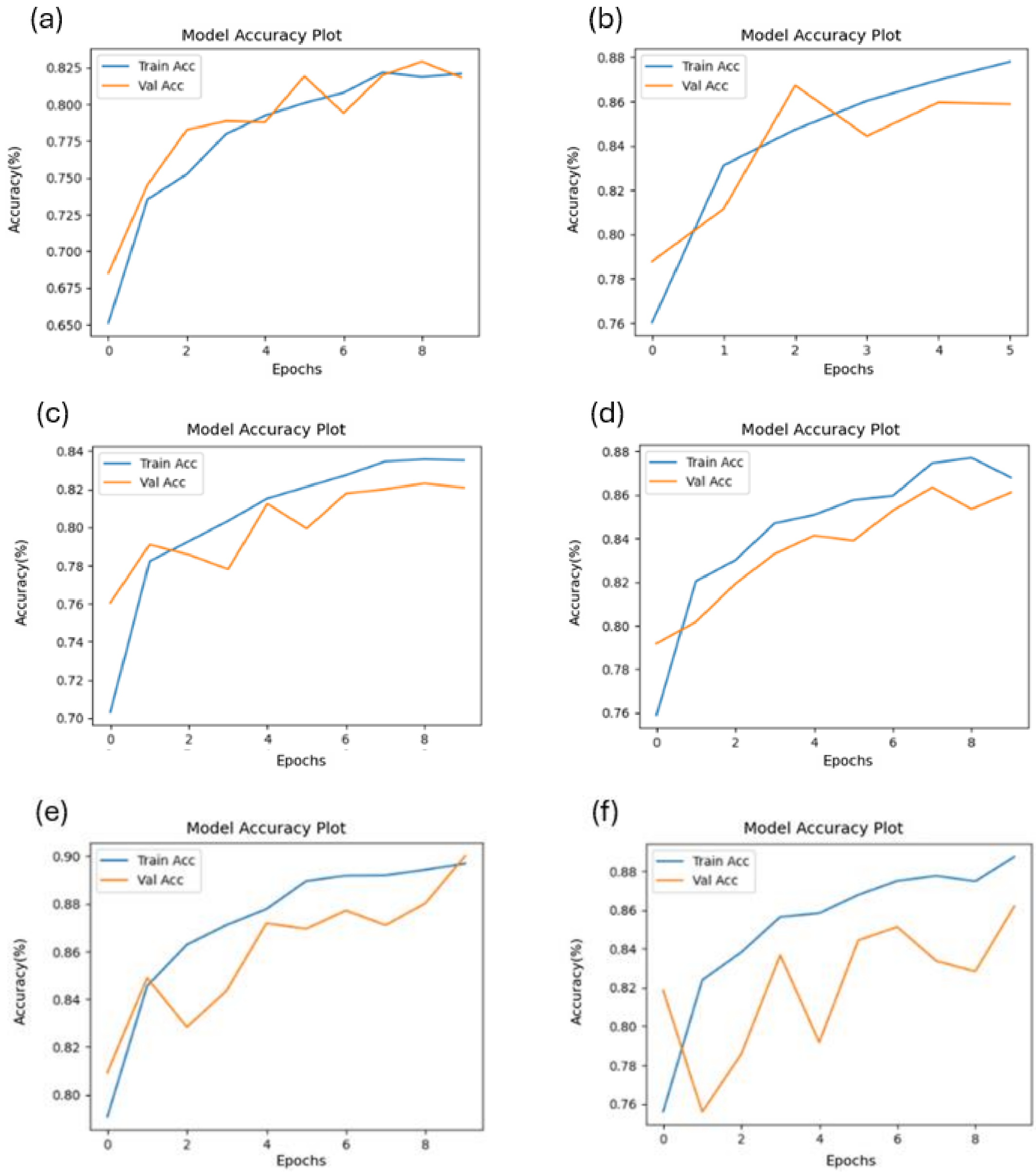
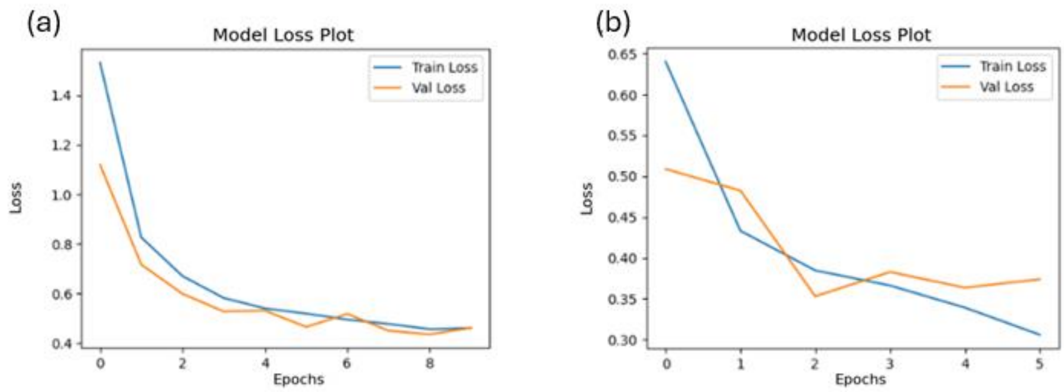


Figure 3. Test-training accuracy graphs of the deep learning methods used (a) VGG16 (b) ResNet-50 (c) InceptionV3 (d) Xception (e) MobileNetV2 (f) EfficientNet-B0



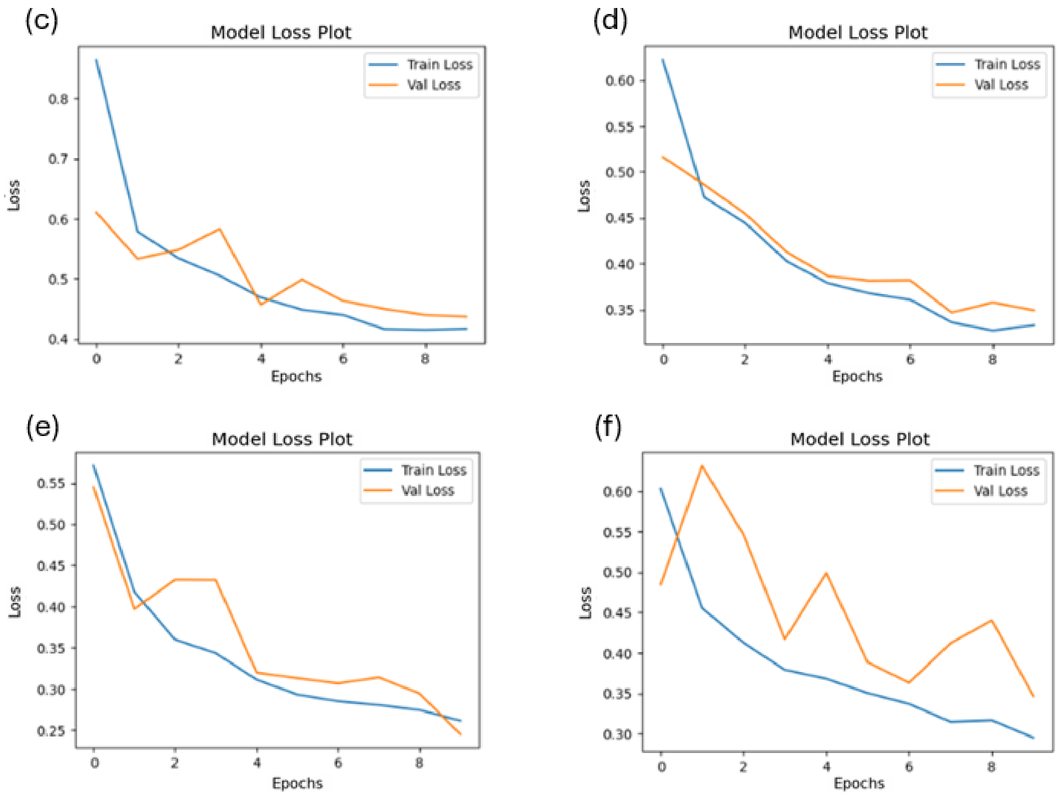
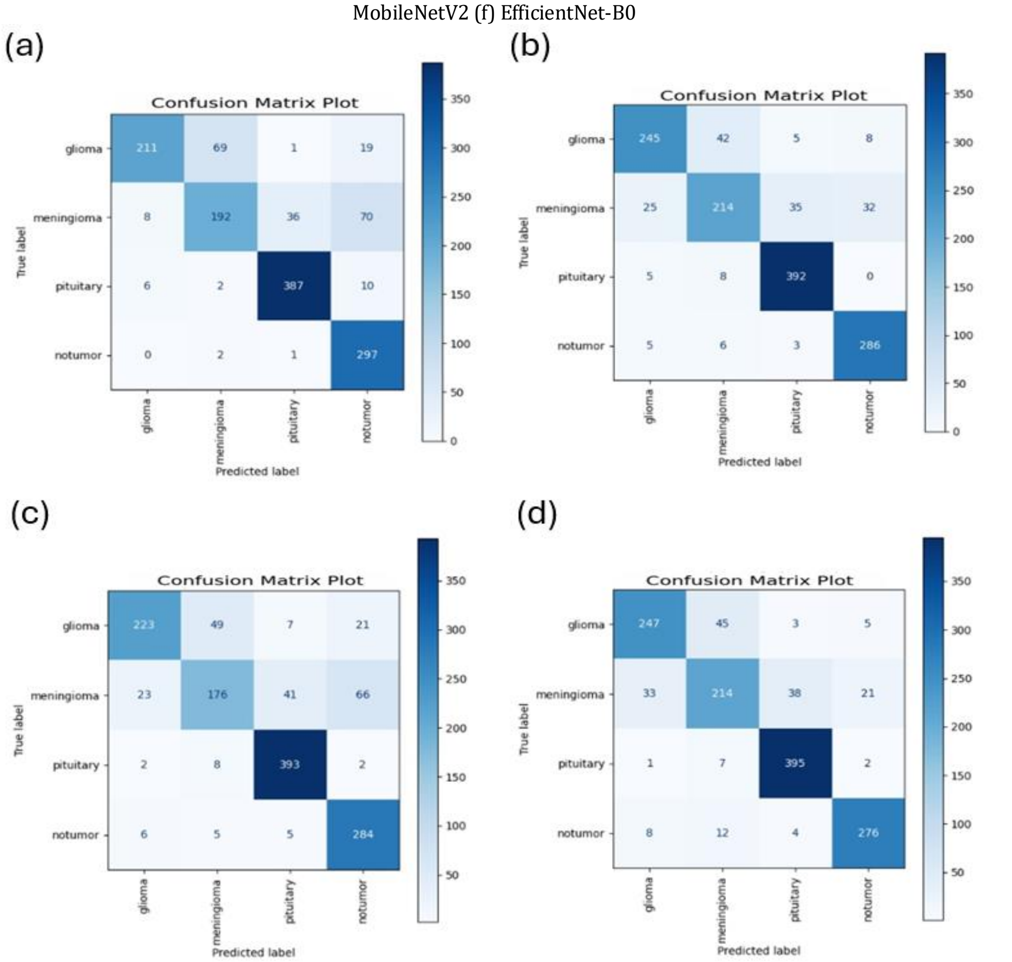


Figure 4. Test-training loss graphs of the deep learning method (a) VGG16 (b) ResNet-50 (c) InceptionV3 (d) Xception (e) MobileNetV2 (f) EfficientNet-B0



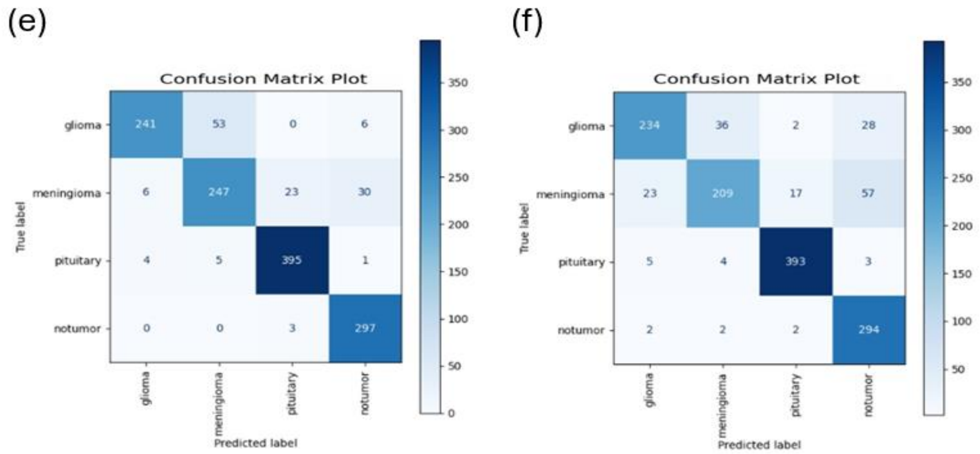


Figure 5. Confusion matrix plot of each deep learning method according to the test dataset (a) VGG16 (b) ResNet-50 (c) InceptionV3 (d) Xception (e) MobileNetV2 (f) EfficientNet-B0

In this section, we trained and tested the VGG16, ResNet-50, InceptionV3, Xception, MobileNetV2, and EfficientNet-B0 deep learning models to successfully detect brain tumors from MRI images. The MRI brain tumor images in Figure 1 were divided into training and test data as shown in Table 1. Figure 3 shows the performance graphs of the training and test data. Figure 4 shows the training and test losses. The numerical results of the model performance are shown in Table 2. The graphical equivalents of the numerical results are given in Figure 5.

With the VGG16 model structure, one of the deep learning models used for the study, 82% training, 83% testing and 1.1 loss success rates were achieved. The Resnet-50 model achieved a success rate of 88% training, 87% testing, and 0.51 loss. The InceptionV3 model achieved a success rate of 84% training, 82% testing, and 0.6 loss. The Xception model achieved a success rate of 88% training, 86% testing, and 0.52 loss. The MobileNetV2 model achieved a success rate of 90% training, 90% testing, and 0.55 loss. The EfficientNet-B0 model achieved a success rate of 89% training, 86% testing, and 0.65 loss.

According to the results obtained, MRI image brain tumor data were classified with MobileNetV2, Resnet-50, Xception, EfficientNet-B0, Vgg16, InceptionV3 model structures with success rates of 90%, 87%, 86%, 86%, 83%, 82%, respectively.

The Confusion Matrix results for the MobileNetV2 model, which achieved the highest F1-Score metric, are presented in Figure 5 (e). These results were obtained from evaluations performed on the test dataset. In the Figure 5, the actual classes are shown on the left vertical axis, and the classes predicted by the model are shown on the lower horizontal axis. As can be seen in Figure 5, while 241 images were correctly predicted for the glioma class, 53 of them were meningioma, 0 were pituitary, and 6 were no tumor. In the meningioma class prediction, 247 images were correctly predicted, 6 were glioma, 23 were pituitary, and 30 were no tumor. In the pituitary class prediction, 395 images were correctly predicted, 4 were glioma, 5 were meningioma, and 1 was no tumor. In the no tumor class prediction, 297 images were correctly predicted, 0 were glioma, 0 were meningioma, and 3 were pituitary.

The study achieved successful results with the current dataset and limited resources. However, further studies can improve the model's performance. For example, using larger datasets with higher resolution and a variety of images can improve the model's overall performance. Furthermore, applying more advanced data preprocessing techniques can positively impact accuracy rates. The simple preprocessing steps used in this study were chosen considering existing hardware limitations. In the future, implementing comprehensive data processing processes with the support of more powerful hardware will further increase success rates.

5. CONCLUSIONS

In this study, classification was conducted using six deep learning models for the early diagnosis of brain tumors. The tumor models included in the study were Glioma, Pituitary, Meningioma, and No

Tumor, and 7023 MRI brain tumor images were used. VGG16, ResNet-50, InceptionV3, Xception, MobileNetV2, and EfficientNet-B0 deep learning methods were used for classification. Based on the experimental results obtained from the training and testing processes of each method, MobileNetV2 was found to be the deep learning method that provided the best success in classifying brain tumors from MRI images. The goal of this study is to achieve the fastest and highest accuracy classification with low-cost hardware. The study concludes that this success has been achieved. Considering the image quality, data preprocessing, and model structure used, a good success rate has been achieved. In future studies, the performance of the proposed models can be enhanced by using larger datasets with higher image resolution. Moreover, the use of more advanced preprocessing and hybrid model structures may further improve the robustness of the system.

Author Contribution

The authors' contribution rates in the study are equal.

Conflict of Interest Statement

The authors declare that there is no conflict of interest.

References

[1] Beşkirli, M. (2019). Performance Analysis of Tree Seed Algorithm in High Dimensional Test Functions. European Journal of Science and Technology 93-101. https://doi.org/10.31590/ejosat.636416

[2] Dörterler, S., Dumlu, H., Özdemir, D., & Temurtaş, H. (2022). Melezlenmiş K-means ve Diferansiyel Gelişim Algoritmaları ile Kalp Hastalığının Teşhisi. In International Conference on Engineering and Applied Natural Sciences içinde (pp. 1840-1844). Konya.

[3] F. Atlan and İ. Pençe, "An Overview of Artificial Intelligence and Medical Imaging Technologies", ACIN , v. 5, no. 1, pp. 207–230, 2021.

[4] F. Bulut, I. Kilic, and I. F. Ince, "COMPARISON AND ANALYSIS OF IMAGE SEGMENTATION METHODS' PERFORMANCE IN BRAIN TUMOR DETECTION", DEUFMD , v. 20, no. 58, pp. 173–186, 2018.

[5] Dörterler, S., Dumlu, H., Özdemir, D., & Temurtaş, H. (2024). Hybridization of meta-heuristic algorithms with k-means for clustering analysis: Case of medical datasets. Gazi Mühendislik Bilimleri Dergisi, 10(1), 1-11.

[6] Abbas, Shafaq & Jalil, Zunera & Javed, Abdul Rehman & Batool, Iqra & Khan, Mohammad & Noorwali, Abdulfattah & Gadekallu, Thippa & Akbar, Aqsa. (2021). BCD-WERT: a novel approach for breast cancer detection using whale optimization based efficient features and extremely randomized tree algorithm. PeerJ Computer Science. 7. e390. 10.7717/peerj-cs.390.

[7] Gadekallu, T. R., Iwendi, C., Wei, C., & Xin, Q. (2021). Identification of malnutrition and prediction of BMI from facial images using real-time image processing and machine learning. IET Image Process, 16, 647-658

[8] Beskirli, A., Beskirli, M., Hakli, H., & Uguz, H. (2018). Comparing energy demand estimation using artificial algae algorithm: The case of Turkey. Journal of Clean Energy Technologies, 6(4), 349-352

[9] Kotia, J., Kotwal, A., & Bharti, R. (2020). Risk susceptibility of brain tumor classification to adversarial attacks. In Man-Machine Interactions 6: 6th International Conference on Man-Machine Interactions, ICMMI 2019, Cracow, Poland, October 2-3, 2019 (pp. 181-187). Springer International Publishing

[10] H. Çetiner, "MULTI-LABEL TEXT ANALYSIS WITH A CNN AND LSTM BASED HYBRID DEEP LEARNING MODEL", Adıyaman Üniversitesi Mühendislik Bilimleri Dergisi, c. 9, sy. 17, ss. 447–457, 2022, doi: 10.54365/adyumbd.1106981.

[11] Dörterler, S. (2023). KANSER HASTALIĞI TEŞHİSİNDE ÖLÜM OYUNU OPTİMİZASYON ALGORİTMASININ ETKİSİ. Mühendislik Alanında Uluslararası Araştırmalar VIII, 15.

[12] Hashemzehi, R., Mahdavi, S. J. S., Kheirabadi, M., & Kamel, S. R. (2020). Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE. Biocybernetics and biomedical engineering, 40(3), 1225-1232.

[13] Al-Rumaihi, G., Khan, M. M., Saleh, A., Ali, A., Al-Romaihi, L., Al-Jaber, N., Al-Suliaiti, G., Chowdhury, M. E., Rathnaiah Babu, G., & Pedersen, S. (2025). Performance Evaluation of Artificial Intelligence Techniques in the Diagnosis of Brain Tumors: A Systematic Review and Meta-Analysis. Cureus, 17(7).

[14] Gao, P., Shan, W., Guo, Y., Wang, Y., Sun, R., Cai, J., Li, H., Chan, W. S., Liu, P., Yi, L., Zhang, S., Li, W., Jiang, T., He, K., & Wu, Z. (2022). Development and Validation of a Deep Learning Model for Brain Tumor Diagnosis and Classification Using Magnetic Resonance Imaging. JAMA network open, 5(8), e2225608.

[15] Halimeh, S., & Teshnehab, M. (2019, January). Diagnosing and classifications tumor and MS simultaneous of magnetics resonances image using convolutions neural networks. In Proceedings of the 7th Iranian Joint Congress on Fuzzy and Intelligent System.

[16] Wong, Y., Su, E. L. M., Yeong, C. F., Holderbaum, W., & Yang, C. (2025). Brain tumor classification using MRI images and deep learning techniques. PloS one, 20(5), e0322624.

[17] Srinivasan, S., Francis, D., Mathivanan, S.K. et al. A hybrid deep CNN model for brain tumor image multi-classification. BMC Med Imaging 24, 21 (2024).

[18] A. Şener and B. Ergen, "Enhancing Brain Tumor Detection on MRI Images Using an Innovative VGG-19 Model-Based Approach", SAUJS, vol. 27, no. 5, pp. 1128–1140, 2023, doi: 10.16984/saufenbilder.1302803.

[19] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556

[20] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

[21] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the inception architecture for computer vision. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2818-2826).

[22] Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1251-1258).

[23] Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. C. (2018). Mobilenetv2: Inverted residuals and linear bottlenecks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4510-4520).

[24] Tan, M., & Le, Q. (2019, May). Efficientnet: Rethinking model scaling for convolutional neural networks. In International conference on machine learning (pp. 6105-6114). PMLR

[25] Kaggle, (2021). Nickparvar. https://www.kaggle.com/datasets/masoudnickparvar/ brain-tumor-mri-dataset

[26] Google Colaboratory, (2025). Colab research. https://colab.research.google.com (Accessed June 20, 2025)