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COMPARISON OF DEEP LEARNING METHODS IN BRAIN TUMOR DIAGNOSIS: HIGH-PERFORMANCE CLASSIFICATION WITH MRI DATA

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Abstract. Brain tumors are serious health problems that must be diagnosed accurately and in a timely manner in order to provide effective treatment. Magnetic resonance imaging (MRI) is widely used in the detection of brain tumors. The accuracy of MRI results depends on the expertise of the physician and usually requires confirmation with biopsy. In recent years, revolutionary developments in image processing and deep learning technologies have provided significant improvements in the diagnosis and classification of brain tumors using MRI. In this study, it is aimed to classify brain tumors accurately and effectively for four different classes (glioma, meningioma, pituitary, and no tumor) previously created using MRI image data. Four different transfer learning-based deep learning methods for classification; ResNet-18, EfficientNet-B0, DenseNet-121, and ConvNeXt-Tiny, are compared using the Fastai library. Accurate diagnosis of brain tumors is of critical importance in the treatment of patients, and the aim of the study is to achieve high accuracy and speed. Our proposed Fastai library-based EfficientNet-B0 model has achieved both fast and highly successful results in the diagnosis of brain tumors with a 99% accuracy rate and 73 minutes of training performance. In addition, the DenseNet-121 model has achieved highly successful results with 99% accuracy rates, and the ResNet-18 and ConvNeXt-Tiny models have achieved 98% accuracy rates. Our results provide fast and effective insights into the possible uses of deep learning frameworks in the field of medical imaging. In addition, these results provide significant improvements compared to studies in the literature.

Keywords. Deep learning, brain tumors, Fastai, magnetic resonance imaging.

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1. Introduction

Abnormal growth and mass formation of brain cells is called brain tumor. The death rate due to brain tumor corresponds to approximately 2.17% of all cancer deaths [1]. Detection of brain tumors, especially gliomas, plays a critical role in the patient's treatment planning [2]. Today, brain tumors can be detected using various imaging methods such as X-ray scanning, Computed Tomography (CT) scanning, Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI) [3]. However, the accuracy of the images depends on the interpretation of the specialist physicians and usually results in procedures requiring biopsy.

With the increase in technological developments in recent years, the use of deep learning (DL) methods in the diagnosis of brain tumors provides important insight to specialist physicians. DL is advanced machine learning that involves training multilayered artificial neural networks and aims to perform different operations such as classification and recognition of data based on the data on which the artificial neural network is trained [4,5]. The use of DL approaches in diagnosing brain tumors is important in terms of reliable and rapid classification of large amounts of data. In recent years, DL models have been run on different libraries in order to gain speed and performance. Among these libraries, the Fastai library [6], which is increasingly effective recently, is increasing the number of users every day. The Fastai library is an important deep learning library and offers significant improvements such as optimizing hyperparameters, faster training time and achieving higher performance results. When recent studies are examined, it is determined that this library is almost never used on MRI images. Table 1 shows the deep learning methods and achievements used for diagnosing and classifying brain tumors.

As seen in Table 1, different deep learning models and approaches are used in the classification of brain tumors. However, none of the studies have utilized the speed and performance power of the Fastai library. In particular, it is observed that the hybrid models used are not effective enough to meet the speed in clinical applications. In addition, in studies comparing four different classes, the accuracy rate remained low. The main motivation of this study is to develop a model with a high success rate in multiple tumor classification that can provide fast and accurate results in clinical applications. By using the advantages offered by the Fastai library, it is aimed to exceed the current success rates in the literature, especially in the classification of complex tumor types such as glioma. Our study reveals the advantages of increasing the efficiency of important neural networks with the Fastai library and transfer learning for health imaging. Thanks to our proposed method comparing four different classes, the accuracy rates have almost approached 100 percent. A very significant performance is achieved, especially in the classification of gliomas. And the efficiency and performance obtained from deep learning models are increased with the proposed method.

In the following sections of the study, the materials and methods used are explained in detail in Section 2. In Section 3, the results of the study are discussed under the title Results and Discussion. Finally, the general evaluation of the study and the conclusions are presented in the Conclusion section.

TABLE 1. Deep learning methods used in the diagnosis and classification of brain tumors in past studies and their successes.

Reference Number	**Method Name**	**Findings**	**Advantages**	**Limitations**
[1]	Improvement of Brain Tumor Categorization using Deep Learning: A Comprehensive Investigation and Comparative Analysis	The main aim of the study is to improve the performance of deep learning models in brain tumor classification using MRI images.	The proposed CNN model achieved higher success than existing methods with 96.63% accuracy in brain tumor classification.	Some models have high computational costs.
[3]	Brain tumor detection using proper orthogonal decomposition integrated with deep learning networks	Integration of POD with CNN (Convolutional Neural Networks) is achieved to detect brain tumors with minimal MRI data.	The integration of POD with CNN has reduced the computational costs and achieved a 95.88% accuracy rate.	The model has difficulty detecting tumors when there are large pixel intensity changes in MRI images.
[7]	RU-Net2+: A Deep Learning Algorithm for Accurate Brain Tumor Segmentation and Survival Rate Prediction	RU-Net2+ model is proposed for the detection and segmentation of brain tumors on the glioma dataset.	An accuracy rate of 99% is achieved.	Since the deep structure of the model requires high computational power, it needs to be optimized for real-time use in clinical settings.
[8]	Brain Tumor Detection and Multi-Grade Segmentation Through Hybrid Caps-VGGNet Model	Caps-VGGNet hybrid model is used to perform feature extraction and classification from MRI brain images.	The presented hybrid model is achieved accuracy of 99% on the Brats20 dataset.	Since the deep structure of the model requires high computational power, it needs to be optimized for real-time use in clinical settings.

[9]	Classification of brain tumor using deep learning at early stage	The study aims to use deep learning methods for the early detection and classification of brain tumors.	The proposed model gave better results than existing models with an accuracy rate of 92.3%.	The model requires high computational power and data storage, which poses a hurdle for resource-limited environments.
[10]	Introducing a deep learning method for brain tumor classification using MRI data towards better performance	By comparing different deep learning models and optimization methods, a Nesterov Momentum based model that provides the best performance is proposed.	The model optimized with Nesterov Momentum showed the best performance with 95% accuracy.	None
[11]	Brain tumors recognition based on deep learning	The main aim of the study is to develop deep learning-based approaches to enable accurate and rapid recognition of brain tumors.	The model achieved an accuracy rate of 97.28%, demonstrating the effectiveness of deep learning in brain tumor detection.	High computational power is required in training deep learning models.
[12]	Brain tumors classification with deep learning using data augmentation	The main purpose of the study is to examine the increase in classifier performance resulting from data increase in medical images on the Figshare dataset.	After data augmentation, the R values of the CNN architecture increased from 88% to 96.7% and the accuracy values increased from 94.6% to 98.6%.	None
[13]	Tumor detection in MR images of regional convolutional neural networks	The aim is to realize an automatic computer-aided tumor detection system to help physicians detect tumors in MRI images.	The best average performance of 98.66% is obtained with RCNN4 and is recommended for use by physicians.	The high computational power requirement in training CNNs is an important problem.

2. Material and methods

In this paper, it is aimed to classify brain tumors obtained from MRI images in the fastest and most accurate way. For this purpose, optimization algorithms that provide the fastest, most efficient, and most optimum determination of the parameters of the Fastai library are used. The study is conducted on a laptop with a 13th generation i9 central processor and RTX 4060 graphics processor, 32 GB of RAM, and the Windows 11 Pro operating system. The codes are compiled on the Jupyter notebook running on the Anaconda platform. The work steps are given in the flow chart in Figure 1.

As seen in Figure 1, firstly the dataset is obtained. MRI images for Brain Tumor with Bounding Boxes [14] on Kaggle are used as the dataset. This dataset developed for Yolo is edited and made suitable for the Fastai library. A small part of the normalized images for the Fastai library are given in Figure 2.

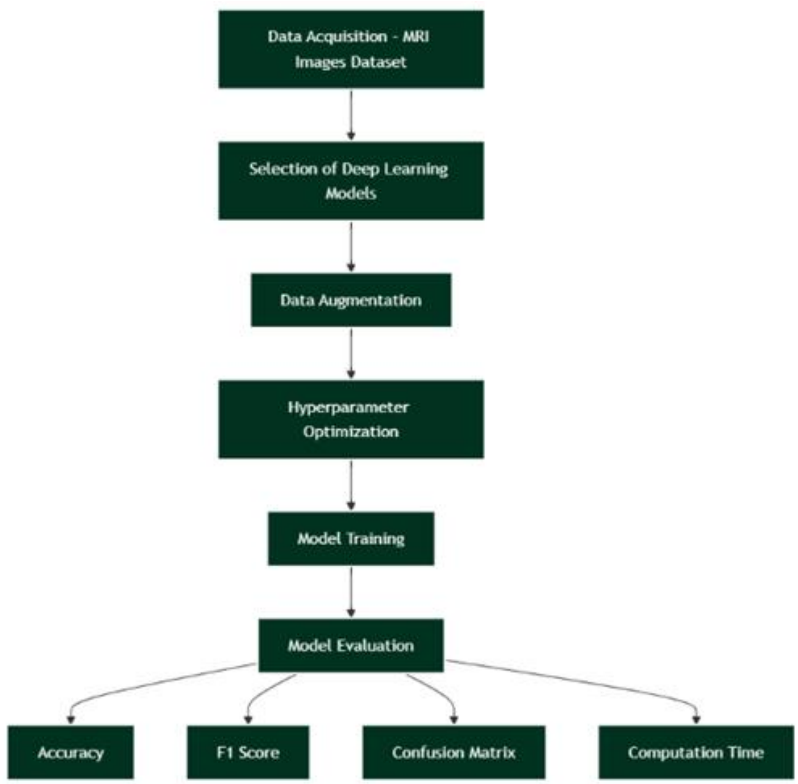

FIGURE 1. Flow diagram of the study.

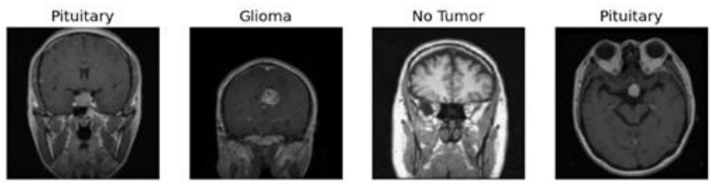

FIGURE 2. Data images used in deep learning application with Fastai.

MRI images are created in a total of 4737 images containing 4 different classes. The images are normalized to have an input image size of 224*224. The dataset is divided into training, test, and validation sets in a 7:2:1 ratio, which is frequently used in deep learning applications. In this way, the data is randomly divided into 3316 training, 947 test, and 474 validation data.

Considering the size and complexity of the dataset, four different transfer learning based deep learning models; ResNet-18, EfficientNet-B0, DenseNet-121, and ConvNeXt-Tiny are used to train the data in the fastest way and to obtain optimum results. ResNet-18 is a widely used architecture for image classification. ResNeT use of "residual connections" in deep learning models increases the trainability of deeper networks and reduces the overfitting problem. EfficientNet-B0 is quite successful in model scaling. It offers a good balance in terms of both performance and efficiency. EfficientNet-B0 has the potential to achieve high accuracy while requiring fewer parameters and less computation. DenseNet-121 increases the information flow and prevents the gradient decay problem since each layer is connected to all previous layers. ConvNeXt-Tiny can be considered a modern ResNet variant and has a deeper and wider network structure than ResNet. ConvNeXt-Tiny is a version that requires less computation. This model, which can perform efficient calculations with high performance, is suitable for medical image processing tasks. Considering all these advantages, it has been decided to use these models. In order to further increase the performance of the selected models, the data is augmented with the data augmentation method. Data augmentation is an important technique that increases the data by applying various transformations such as rotation, scaling, translation, cropping, or even adding noise to the original data, thus reducing overfitting and increasing performance in the DL model. Figure 3 shows some images obtained after data augmentation.

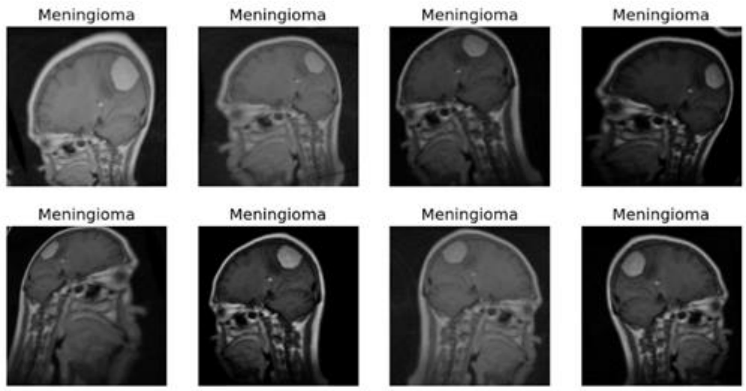

FIGURE 3. As a result of data augmentation, a piece of the data.

After the data augmentation, the optimization of the selected hyperparameters is performed. In particular, the learning rate is a very important hyperparameter and can be optimized thanks to the optimization methods provided by the Fastai library. Here, the learning rate is determined as a range of values, not a number. The learning rates obtained by the optimization method of the models are given in Figure 4 for ResNet-18, EfficientNet-B0, DenseNet-121, and ConvNeXt-Tiny, respectively.

After determining the learning rates, the determination of the optimizers of the algorithms is carried out. Adam Optimizer provides fast and stable training thanks to the moment estimates that correct the gradient deviations. In addition, it works efficiently even on small data sets because it optimizes using a different learning rate for each parameter. This allows you to get better results without overfitting on small data sets. Considering these advantages, it has been decided to use Adam Optimizer. The epoch number is determined as 20 as a result of several trials to prevent overfitting. Hyperparameter values determined for all algorithms are given in Table 2. All hyperparameter values given in Table 2 are optimized to allow the algorithms to work optimally.

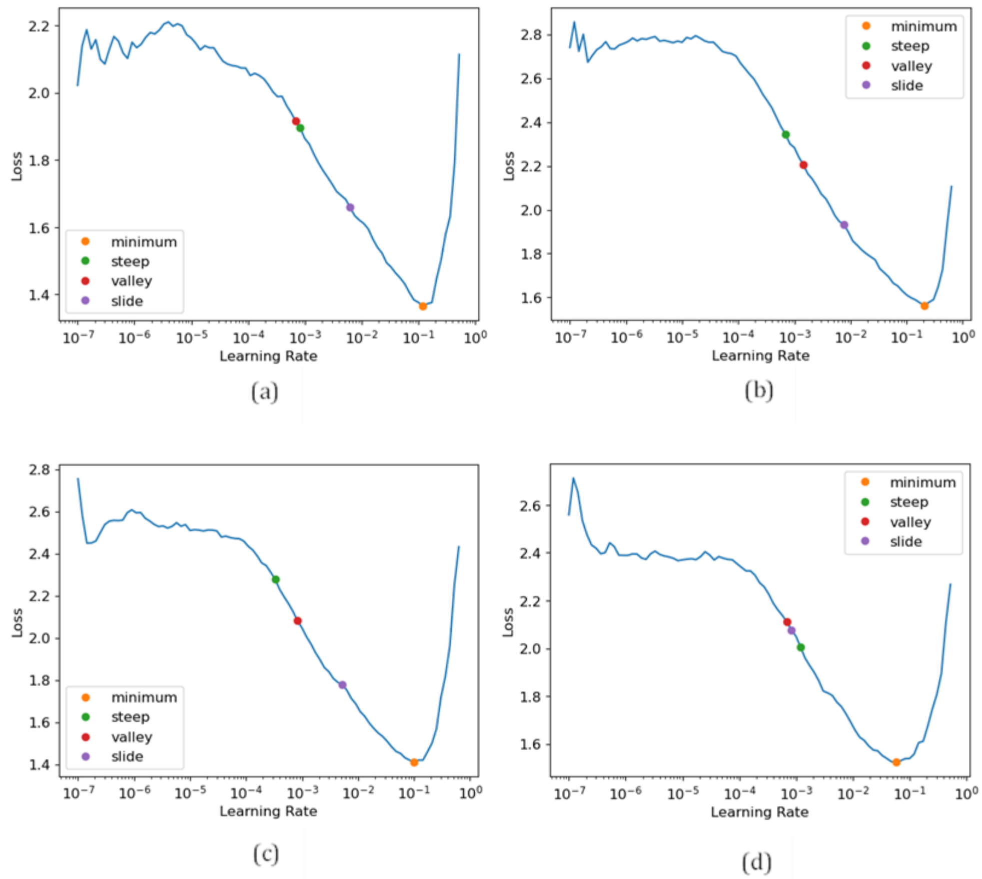

FIGURE 4. Learning rates of the algorithms: (a) ResNet-18, (b) EfficientNet-B0, (c) DenseNet-121, (d) ConvNeXt-Tiny.

TABLE 2. Hyperparameter values determined for all algorithms.

	ResNet-18	EfficientNet-B0	DenseNet-121	ConvNeXt-Tiny
Learning Rate	0.01-0.001	0.001-0.003	0.001-0.003	0.01-0.001
Batch Size	64	64	64	64
Weight Decay	0.01	0.01	0.01	0.01
Optimizer	Adam	Adam	Adam	Adam
Epochs	20	20	20	20

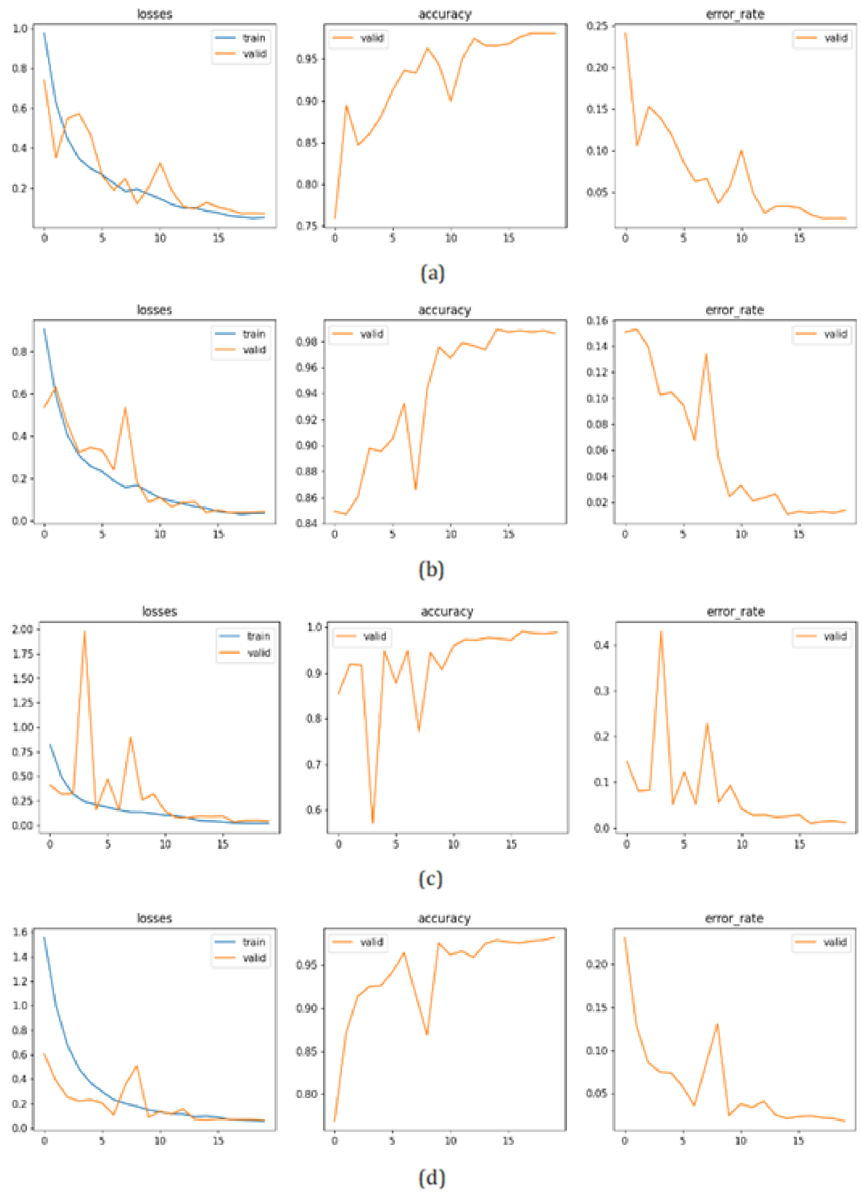

FIGURE 5. Loss, accuracy and error rates of the algorithms: (a) ResNet-18, (b) EfficientNet-B0, (c) DenseNet-121, (d) ConvNeXt-Tiny.

3. Results

In this section, the performances of deep learning models used in the classification of brain tumors of different classes with high accuracy are compared. A series of performance evaluation metrics such as loss, accuracy, error rate, confusion matrix, precision, recall, and F-score are used in the test dataset in order to classify the brain tumor data correctly and to compare the performances of the models. Loss, accuracy, and error rates are given for each algorithm used in Figure 5, respectively. In Figure 6, the confusion matrix of the algorithms used is given, respectively, in order to better understand the performance of the algorithms. In Table 3, the computational complexity, computational time, accuracy, recall, precision, and F-score values required for the proposed methods are presented in detail.

As seen in Figure 5, ResNet-18 and ConvNeXt-Tiny have shown a very stable and successful performance in terms of accuracy, error rate and loss. EfficientNet-B0 model is seen to be quite successful in terms of accuracy and error rate, however, there are fluctuations in the loss rate and accuracy in the DenseNet-121 model. Although some precautions are taken to prevent overfitting, it is thought from these graphs that overfitting occurs from time to time. Although all models appear successful, it is understood that EfficientNet-B0 model performs better.

As seen in Figure 6, ResNet-18 performed very successfully in classification, especially in the Pituitary class. However, confusions are observed in the Meningioma and No Tumor classes. In addition, while EfficientNet-B0 showed almost perfect performance in the Glioma and Pituitary classes, it was observed that the Meningioma class is confused with the Pituitary class. While DenseNet-121 is quite successful in the Glioma and Pituitary classes, the ConvNeXt-Tiny model gave more successful results, especially in the Pituitary class. When evaluated in general, the Pituitary class is classified quite well in all four models. Similarly, the models generally performed successfully in the Glioma class. The Meningioma class and the No Tumor class are the classes where confusion occurs. In terms of model performances, EfficientNet-B0 and DenseNet-121 models showed the best performance.

When the main reasons for these performance differences are examined, it is seen that the architectural structures of the models have a significant effect on the classification success. The main reasons why EfficientNet-B0 and DenseNet-121 models show superior performance in the Glioma and Pituitary classes are as follows: EfficientNet-B0 can better detect the characteristic features of Gliomas (irregular borders, heterogeneous structure) thanks to the compound scaling method, DenseNet-121 can better use feature maps with its dense connection structure and thus learn the distinct visual features of Pituitary tumors (size, location), Both models can effectively combine information at different scales from low-level features

(texture, edge information) to high-level features (tumor structure, shape). ResNet-18's success in the Pituitary class is due to the model's ability to better learn the characteristic features of this tumor type thanks to its residual connections. The modern architectural design of the ConvNeXt-Tiny model has enabled it to detect location-based features of Pituitary tumors more effectively.
Performance comparisons of all models are given in Table 3.

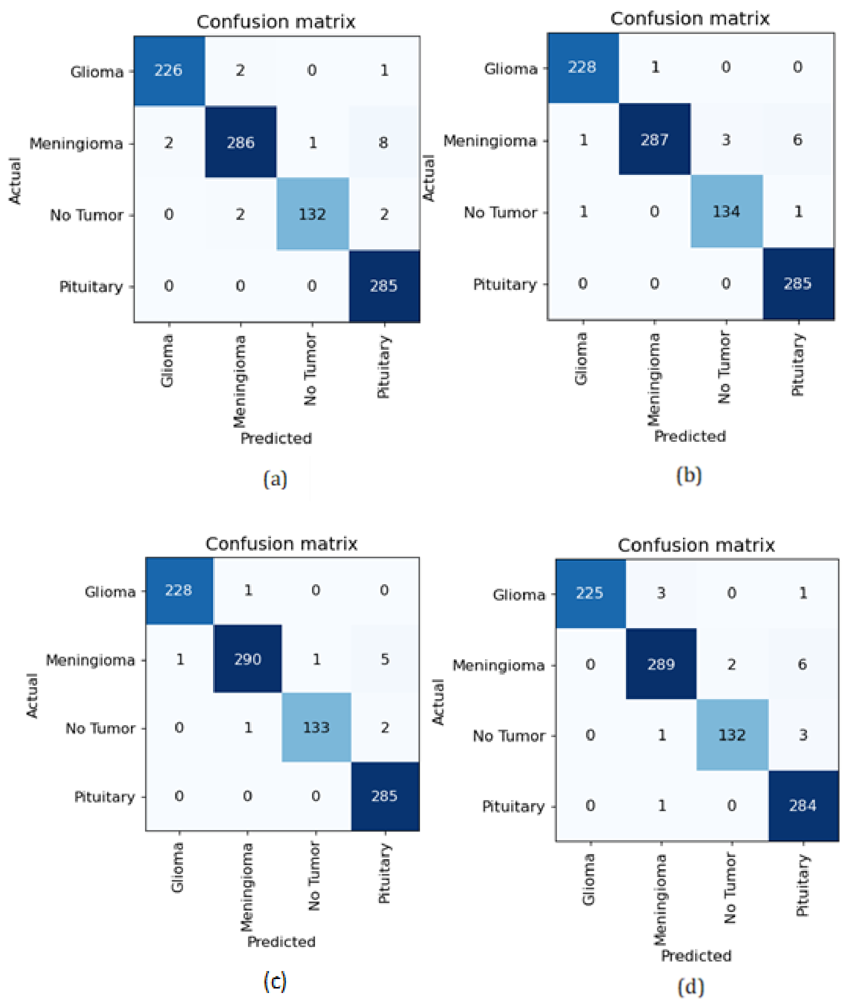

FIGURE 6. Confusion matrix of the algorithms: (a) ResNet-18, (b) EfficientNet-B0, (c) DenseNet-121, (d) ConvNeXt-Tiny.

TABLE 3. Performance comparison of all models.

	Metrics	Glioma	Meningioma	Pituitary	No_Tumor
ResNet-18	Computational Complexity FLOPs	1.824			
	Computational Time (minute)	40.43			
	Accuracy	0.98			
	Recall	0.99	0.96	1.00	0.97
	Precision	0.99	0.99	0.96	0.99
	F1-Score	0.99	0.97	0.98	0.98
EfficientNet-B0	Computational Complexity FLOPs	3.90			
	Computational Time (minute)	73.04			
	Accuracy	0.99			
	Recall	1.00	0.97	1.00	0.99
	Precision	0.99	1.00	0.98	0.98
	F1-Score	0.99	0.98	0.99	0.98
DenseNet-121	Computational Complexity FLOPs	2.897			
	Computational Time (minute)	125.40			
	Accuracy	0.99			
	Recall	1.00	0.98	1.00	0.98
	Precision	1.00	0.99	0.98	0.99
	F1-Score	1.00	0.98	0.99	0.99

ConvNeXt-Tiny	Computational Complexity FLOPs	4.464			
	Computational Time (minute)	103.20			
	Accuracy	0.98			
	Recall	0.98	0.97	1.00	0.97
	Precision	1.00	0.98	0.97	0.99
	F1-Score	0.99	0.98	0.98	0.98

Table 3 comprehensively discusses the performance of all models. According to the table, ResNet-18 appears to be a highly efficient model with the lowest FLOPs and shortest training time. However, its accuracy rate is not as close to perfect as EfficientNet-B0 and DenseNet-121. DenseNet-121 requires the longest training time, while ConvNeXt-Tiny also has the highest FLOPs and training time. Although EfficientNet-B0 is more complex and provides longer training than ResNet-18, when the table in Figure 5 is considered, it has become the recommended model as a result of this study in terms of both training quality and accuracy.

4. Conclusions

Our study focuses on the use and comparison of pre-trained deep learning models in the identification and classification of brain tumors of different classes using MRI images. Four different pre-trained deep learning algorithms; ResNet-18, EfficientNet-B0, DenseNet-121, and ConvNeXt-Tiny are used to predict the classes with high accuracy for data divided into four different classes; Glioma, Meningioma, Pituitary, and No tumor. The accuracy rates of the models are 98% for ResNet-18 and ConvNeXt-Tiny models, and 99% for EfficientNet-B0 and DenseNet-121 models. All models performed very close to each other, providing a very successful result. However, considering both the graphs formed during model training and the classification parameters, the EfficientNet-B0 model, which has a high accuracy and performance rate, is recommended for the classification of brain tumors as a result of this study. In future studies, the performance of the EfficientNet-B0 hybrid model created for the classification of brain tumors will be compared with the EfficientNet-B0 model. Our expectation is to provide more effective detection of brain tumors with higher performance and faster training time.

Declaration of Competing Interests There is no conflict of interest with any person/institution in the article prepared.

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