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MULTIPLE CLASSIFICATION OF BRAIN TUMORS FOR EARLY DETECTION USING A NOVEL CONVOLUTIONAL NEURAL NETWORK MODEL

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Keywords
Deep learning, CNN models, pre-trained models, brain MRI images, classification.

Abstract
Brain tumors can be dangerous and fatal if not diagnosed early. These are diagnosed by specialized doctors using biopsy samples obtained from the brain. This process is exhausting and wastes the doctors' time. Researchers have been working to develop a quick and accurate way to identify and classify brain tumors to overcome these drawbacks. Computer-assisted technologies are used to support doctors and specialists in making more efficient and accurate decisions. Deep learning-based methods are one of these technologies that have been used extensively in recent years. However, there is still a need to explore architectures with higher accuracies. For this purpose, in this paper, we propose a novel convolutional neural network (CNN) which has twenty-four layers to multi-classify brain tumors from brain MRI images for early diagnosis. Various comparisons and tests were performed to demonstrate the effectiveness of the proposed model. Three different state-of-the-art CNN models were used for the comparison: AlexNet, ShuffleNet, and SqueezeNet. At the end of training, the proposed model achieved the highest accuracy of 92.82% and the lowest loss of 0.2481. In addition, ShufleNet achieved the second highest accuracy of 90.17%. AlexNet had the lowest accuracy at 80.5%, with a loss of 0.4679. These results demonstrate that the proposed CNN model provides greater precision and accuracy than state-of-the-art CNN models.

YENİ BİR EVRİŞİMLİ SİNİR AĞI MODELİ KULLANILARAK ERKEN TEŞHİS İÇİN BEYİN TÜMÖRLERİNİN ÇOKLU SINIFLANDIRMASI

Anahtar Kelimeler
Derin öğrenme, ESA modelleri, önceden eğitilmiş modeller, Beyin MR görüntüleri, sınıflandırma.

Öz
Beyin tümörleri erken teşhis edilmezse çok tehlikeli ve ölümcül etkilere sahip olabilir. Beyin tümörleri, uzman doktorlar tarafından beyinden alınan biyopsi örnekleri kullanılarak teşhis edilir. Bu süreç yorucudur ve doktorların çok fazla zamanını harcar. Araştırmacılar, bu dezavantajların üstesinden gelmek amacıyla beyin tümörlerini tanımlamak ve sınıflandırmak için hızlı ve doğru bir yol geliştirmeye çalışmaktadırlar. Doktorların ve uzmanların daha verimli ve doğru kararlar vermelerini desteklemek için bilgisayar destekli teknolojiler kullanılmaktadır. Derin öğrenme tabanlı yöntemler de bu teknolojilerden biridir ve son yıllarda yoğun olarak kullanılmaya başlanmıştır. Bununla birlikte, daha yüksek doğruluk performansına sahip mimarileri keşfetmeye hala ihtiyaç vardır. Bu amaçla, bu çalışmada erken teşhis için beyin MR görüntülerinden beyin tümörlerini çoklu sınıflandırmak için yirmi dört katmana sahip yeni bir evrişimli sinir ağı (ESA) önerilmiştir. Önerilen modelin etkinliğini göstermek için çeşitli karşılaştırmalar ve testler yapılmıştır. Karşılaştırmada üç farklı son teknoloji CNN modeli kullanılmıştır: AlexNet, ShuffleNet ve SqueezeNet. Eğitim sonunda önerilen model %92.82 ile en yüksek doğruluk ve 0.2481 ile en düşük kayıp elde edilmiştir. Ek olarak, ShufleNet %90.17 ile ikinci en yüksek doğruluk değerine ulaşmıştır. AlexNet, 0.4679 kayıpla %80.5 ile en düşük doğruluğa sahiptir. Bu Sonuçlar, önerilen CNN modelinin, son teknoloji CNN modellerinden daha fazla kesinlik ve doğruluk sağladığını göstermektedir.

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1.Introduction

In recent years, convolutional neural network (CNN) has been used effectively in many applications. These are classification (Fu, Zang, He, Cao, Guo & Wang, 2022; Inik, Uyar, & Ülker, 2019; Mao, Yin, Zhang, Chen, Chang, Chen, Yu & Wang, 2022; Zhou, Wang, & Wan, 2022), detection (Gonçalves, Souza & Fernandes, 2022; Inik & Ulker 2022; Kaya, Kurt, Isik, Koca & Cicek, 2022; Li, Dong, Wen, Hu, Zhou & Zeng, 2019; Zhao, Liu, Yin &Wang, 2022), and segmentation (Fradi, Zahzah & Machhout, 2022; Inik & Ulker 2022; Kang, Zhou, Huang & Han 2022; Karthik, Menaka & Won 2022; Niyas, Pawan, Kumar & Rajan, 2022). CNN-based methods have started to be used extensively in the diagnosis of brain tumors due to their high success in solving different problems.

Brain tumors are anomalies that occur when brain cells proliferate at an abnormal rate. The most common types of brain tumors include meningiomas, gliomas, and pituitary tumors. Radiologists use their skills to identify and categorize brain tumors, which is a complex and time-consuming procedure. Computer-assisted technologies are used to help doctors and experts to operate more efficiently and make more accurate decisions. Artificial intelligence is becoming increasingly useful in identifying and classifying brain tissues as contemporary medical standards evolve. To categorize MRI images, several machine learning and deep learning approaches such as Support-Vector Machine (SVM), K-Nearest Neighbors (KNN), and Convolutional Neural Network (CNN) are being developed.

To increase the multiple classification accuracy of brain tumor MRI images, Srikanth and Venkata Suryanarayana (2021) developed a Deep Neural Network (DNN)-based VGG-16 (2014) network. As a result of the training, a 98% accuracy in producing results that were close to reality was achieved. Deepak and Ameer (2019) developed a method for categorizing three different forms of brain tumors. The transfer learning method was used to extract features from MRI images. The pre-trained GoogLeNet (2014) CNN network was used. For classification after the fully connected layer in the GoogLeNet network, the SVM and KNN classifiers were applied instead of the Softmax classifier. As a result of the experiments, 98% accuracy was obtained. Jia and Chen (2020) proposed the Fully Automatic Heterogeneous Segmentation (FAHS-SVM) approach for brain tumor detection and segmentation using SVM based on deep learning techniques. An extreme learning machine (ELM) method was used to categorize MRI images and extract features. The proposed method detected between healthy and unhealthy tissues with 98.51% accuracy.

Irmak (2021) presented three different CNN architectures for multi-classification in the early diagnosis of brain cancer. To adjust the hyperparameters of the suggested CNN architectures, they were automatically calculated using the grid search optimization technique. The first proposed CNN model detected brain tumors with 99.33% accuracy. The second model had 92.66% accuracy in classifying brain cancers into five types: normal, glioma, meningioma, pituitary, and metastatic. In contrast, the third CNN model had 98.14% accuracy in classifying brain tumors as grade II, grade III, or grade IV.

MRI is used in the diagnosis of multiple sclerosis (MS) and brain tumors. Siar and Teshnehlab (2019) proposed a CNN for diagnosing brain tumors and MS simultaneously. The researchers used MRI images of 200 patients and healthy individuals. A total of 1286 images were used for training, and 384 images were used for testing. As a result of the training, they achieved a 96% accuracy rate in the diagnosis of MS and brain tumor patients. Hashemzehi et al. (2020) suggested a hybrid technique combining CNN and neural autoregressive distribution estimation (NADE). The most essential characteristic of this method is its ability to extract features and estimate data distribution rapidly and automatically. The approach examined 3064 CE-MRI images from 233 patients, including 1426 images of gliomas, 708 images of meningiomas, and 930 images of pituitary tumors. The proposed method was shown to have a classification accuracy of 95%.

Aziz et al. (2021) proposed an ensemble framework for brain tumor categorization. The CNN architecture was built using pre-trained ResNet-50 (2015) and Densenet-201 (2016) networks. These networks were retrained using transfer learning after they were updated. For the best feature selection, an efficient ant colony optimization (EACO) algorithm was proposed. The BRATS 2019 dataset was used in the experiments, and the classification accuracy was 87.7% for high-grade glioma (HGG) and 84.6% for low-grade glioma (LGG). Using a CNN's two-stage feature set, Aurna et al. (2022) suggested a new method for the exact and automatic categorization of brain tumors. An ensemble learning-based architecture was developed by merging the pre-trained VGG-19, EfficientB0 (2019), ResNet-50, Inception-V3 (2015), and Xception (2016) models and the proposed CNN model to find the best features in the proposed method. The best extracted features were chosen using the PCA algorithm. The proposed model was able to classify correctly with an accuracy of 99.13 %. Noreen et al. (2021) developed an ensemble learning-based method to classify brain tumors. For feature extraction, the proposed method uses the pre-trained Inception-V3 and Xception models. The characteristics extracted from the CNN model outputs were categorized using a variety of machine-learning techniques, including softmax, random forest (RF), SVM, and K-NN, with 94% accuracy. Sajid et al. (2019) proposed a deep learning-based method for brain tumor segmentation using MRI images. They used a patch-based hybrid CNN architecture for this. If the output label could not be predicted while analyzing the network output, labeling was performed using both local and contextual information. The images were normalized using a preprocessing step and then post-processed to reduce minor positive errors in the proposed method, thus skipping the CNN network feed-forward. The BRATS 2013 dataset was used to train the network, and sensitivity and specificity values of 0.86 were obtained according to the membrane score.

In this study, we proposed a novel CNN model for brain tumor multi-classification using brain MRI images. Three different state-of-the-art CNN models were used for the comparison: AlexNet, ShuffleNet, and SqueezeNet. According to the results obtained in the experimental studies, the proposed model outperformed other models.

This paper is organized as follows: section 2 presents material and method. Section 3 presents experimental results and section 4 presents discussions. in the section 5, results are given.

2. Material and Method

This section contains details of the proposed method and the dataset used. In addition, in this study, article research and publication ethics were complied with.

2.1. The Dataset

In this study, the dataset from Kaggle (2020) includes brain MRI images that are divided into four classes: meningioma, pituitary, glioma, and no tumor. This dataset contains 3264 images. Different numbers of images are included in each class. There are 500 images in the no tumor class, 937 images in the meningioma class, 901 images in the pituitary class, and 926 images in the glioma class. Table 1 lists the number of classes in the dataset and the number of images used for testing and training in each class. The dataset was split into training and testing datasets. Some examples of the training and test images are shown in Figure 1 and Figure 2.

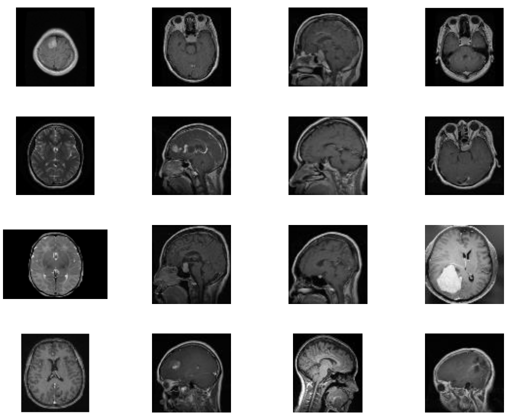

Figure 1. Train Images

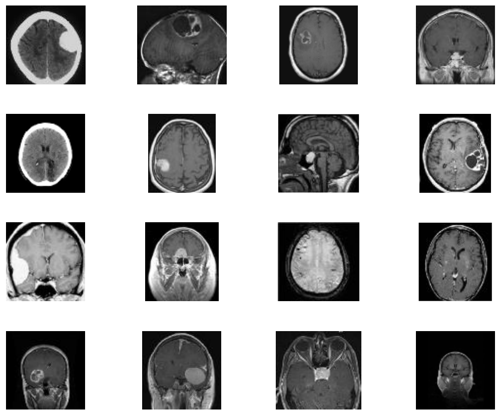

Figure 2. Test Images

Table 1

Classes in Data Set and the Number of Images Used for Training and Testing in Each Class.

Class	Train (80%)	Test (20%)	Total
Meningioma	750	187	937
Pituitary	721	180	901
Glioma	741	185	926
No Tumor	400	100	500
Total	2612	652	3264

2.2. Data Pre-preparation

In this study, several parameters were adjusted to obtain a unique CNN model. Among these parameters, the dataset must be resized to adjust the model input image size. For this purpose, the original dataset was transformed into different sizes in the flow diagram shown in Figure 3, and the best result was obtained with an input image size of 224×224×3.

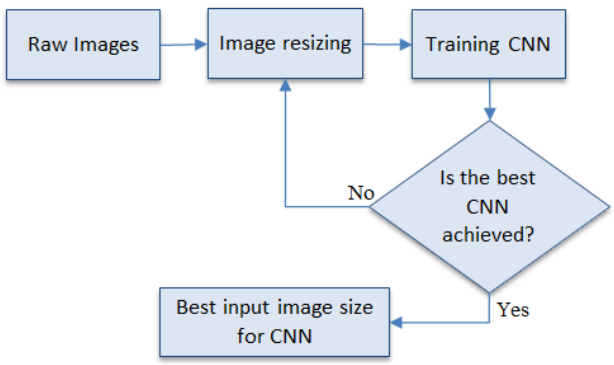

Figure 3. Flow Diagram Finding the Best Input Image Size

2.3. Proposed CNN Architecture

CNNs have been widely used in many other fields where the input data can be any signal, such as audio and video, despite the fact that they now focus on image classification and accept images as input data. Feature extraction and classification are the two components of a standard CNN model. The five primary layers of the CNN architecture are the input, convolution, pooling, fully connected, and classification layers. Through successive trainable layers arranged sequentially, the CNN conducts feature extraction and classification. Convolutional and pooling layers are often included in the feature extraction phase of a CNN, whereas fully connected and classification layers are typically included in the classification phase.

The architecture of the proposed method is shown in Figure 4. First, the images in the dataset were resized. Following the resizing procedure, the dataset was split into training (80%) and test (20%) sets. During the training process, more than one CNN model was designed and trained. The layer architecture of the CNN model that provides the highest accuracy rate among the models is shown in Figure 6. As seen in the figure, The CNN model has 24 layers that are 1 input, 7 convolutions, 7 ReLu, 3 batch normalization, 3 max pooling, 1 fully connected, 1 softmax and 1 classification layers. The parameter values for each layer of the model are listed in Table 2.

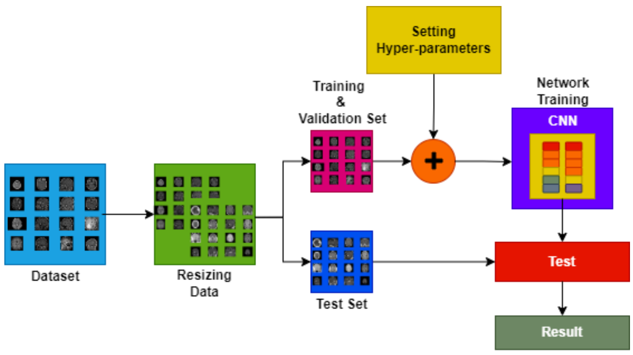

Figure 4. Flowchart of the Proposed Method

3. Experimental Studies

The technical details of the computer used for the experimental studies and the experimental results are presented in this section.

3.1. Technical Specification of the Computer

In the experimental tests, the deep learning library was implemented using the MATLAB 2021b software. The computer's technical specifications for use in experiments are as follows: Intel(R) Core (TM) i5-8400 CPU @ 2.80GHz (6 CPUs), 2.8GHz, 16 GB RAM, and NVIDIA GeForce GTX 1080 Ti with 11 GB memory.

3.2. Experimental Results

Three different pre-trained CNN models: AlexNet, ShuffleNet, and SqueezeNet, as well as the proposed CNN model, were used in the experiments. These pre-trained models were trained on millions of labeled data. Our model was trained only on the dataset used in this study. The hyperparameters are crucial for model training. Therefore, they should be carefully chosen. Table 3 lists the hyperparameters selected for this study. Optimizers such as SGD, Adam, Adagrad, AdaDelta, and RMSProp are algorithms or methods used to change the attributes of a neural network, such as weights and learning rate, to reduce losses. The learning rate controls the weight update in the optimization algorithm. It can use a fixed learning rate, gradually decreasing learning rate, momentum-based methods, or adaptive learning rates, depending on the choice of optimizer. The number of epochs is the number of times that the entire training set passes through the neural network. The batch size is typically preferable in the learning process of a CNN. A range of 16–128 is a good choice for testing. SGDM was selected as an optimizer because it showed better performance during the training phase than the other optimizers. The learning rate is usually chosen as 0.001 for classification problems. The accuracy of the models did not change after the 17th epoch. Therefore, 17 was selected to reduce the computational cost. The GPU memory of the computer confines the amount of data that will be processed simultaneously. Therefore, in this study, we used a batch size of 64. This value is the upper limit for GPU memory used in the study.

In the first experiment, AlexNet was used; however, the size of the image input layer was 227×227×3. To train the model, we replaced the image input layer with a 224x224x3 dimensional input. Additionally, AlexNet's fully connected layer includes 1000 classes. It has been replaced with a new fully connected layer with four classes. After 17 epochs, a classification accuracy of 80.5% and a loss of 0.47 are obtained in the training phase. It is seen in Figure 5. The confusion matrix obtained by AlexNet during the test process after the training phase is shown in Figure 10.

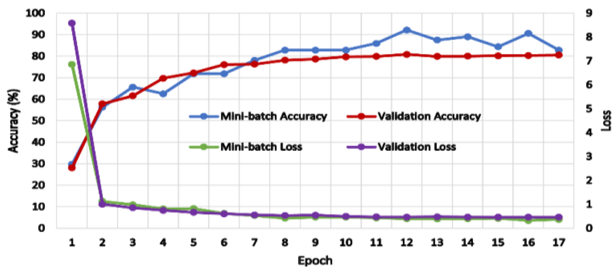

Figure 5. Accuracy and Loss Curves for AlexNet

Figure 6. Proposed CNN Model

Table 2

Classes in Data Set and the Number of Images Used for Training and Testing in Each Class

Layer Name	Activation Maps	Learnable Parameters	Total Learnable Parameters
Input	224x224x3	-	0
Conv2D-1	224x224x32	Weights:1x1x3x32, Bias:1x1x32	128
ReLu-1	224x224x32	-	0
Conv2D-2	224x224x64	Weights:1x1x32x64, Bias:1x1x64	2112
ReLu-2	224x224x64	-	0
MaxPool2D-1	111x111x64	-	0
BatchNorm-1	111x111x64	Offset: 1x1x64,	128
Conv2d-3	110x110x64	Scale: 1x1x64	16448
ReLu-3	110x110x64	Weights:2x2x64x64, Bias:1x1x64	0
Conv2D-4	108x108x64	-	36928
ReLu-4	108x108x64	Weights:3x3x64x64, Bias:1x1x64	0
Conv2d-5	106x106x128	-	73856
ReLu-5	106x106x128	Weights: 3x3x64x128, Bias:1x1x128	0
MaxPool2D-2	51x51x128	-	0
BatchNorm-2	51x51x128	-	256
Conv2D-6	49x49x128	Offset: 1x1x128,	147584
ReLu-6	49x49x128	Scale: 1x1x128	0
Conv2D-7	46x46x128	Weights: 3x3x128x128, Bias:1x1x128	262272
ReLu-7	46x46x128	-	0
MaxPool2D-3	9x9x128	Weights: 4x4x128x128, Bias:1x1x128	0
BatchNorm-3	9x9x128	-	256
FC	1x1x4	-	41476
Softmax	1x1x4	Offset: 1x1x128,	0
Classification Output	1x1x4	Scale: 1x1x128	0
		Number of total learnable parameters	581444

Table 3

Hyperparameters

Parameters	Value
Optimizer	SGDM (stochastic gradient descent with momentum)
Learning Rate	0.001
Epoch	17
Batch Size	64

In the second experiment, ShuffleNet pre-trained model was used. The input size of the ShuffleNet was 224×224×3. Similar to AlexNet, ShuffleNet's fully connected layer includes 1000 classes. It has been replaced with a new fully connected layer that also has four classes. The convergence graphs obtained using ShuffleNet are presented in Figure 7. ShuffleNet achieved a classification accuracy of 90.17% and loss of 0.28 after 17 epochs. The confusion matrix obtained by ShuffleNet for the test images is shown in Figure 11.

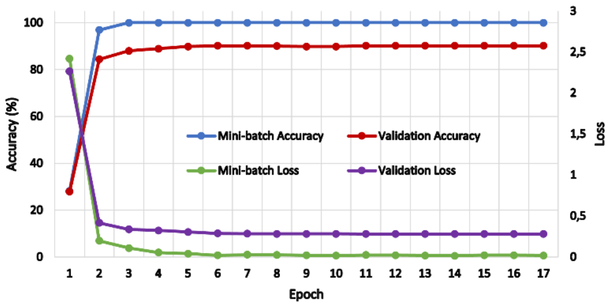

Figure 7. Accuracy and Loss Curves for ShuffleNet

In the third experiment, SqueezeNet was used. However, the size of the image input layer of SqueezeNet was 227×227×3. For training the model, we replaced the image input layer with a 224x224x3 dimensional input. In addition, SqueezeNet's fully connected layer includes 1000 classes. It has been replaced with a new fully connected layer that has four classes. As shown in Figure 8, after 17 epochs, a classification accuracy of 89.95% and a loss of 0.34 are obtained after the training process. The confusion matrix obtained by SqueezeNet for the test images is shown in Figure 12.

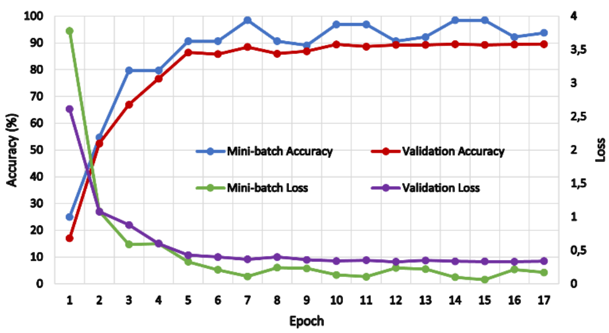

Figure 8. Accuracy and Loss Curves for SqueezeNet

Finally, experimental studies are conducted using the proposed CNN model. Convergence graphs of the proposed model are shown in Figure 9. After the 17th epoch, the accuracy rate was 92.82% and the loss value was 0.25. The confusion matrix obtained by the proposed CNN model on the test images is given in Figure 13.

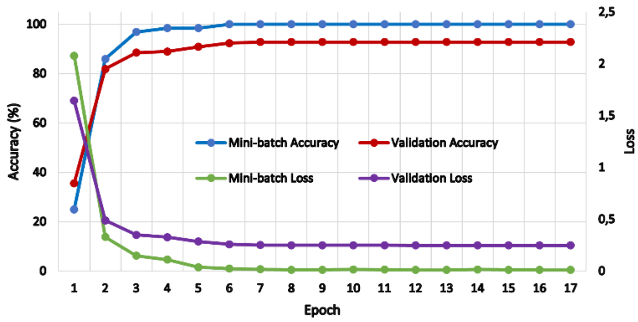

Figure 9. Accuracy and Loss Curves for Proposed CNN Model

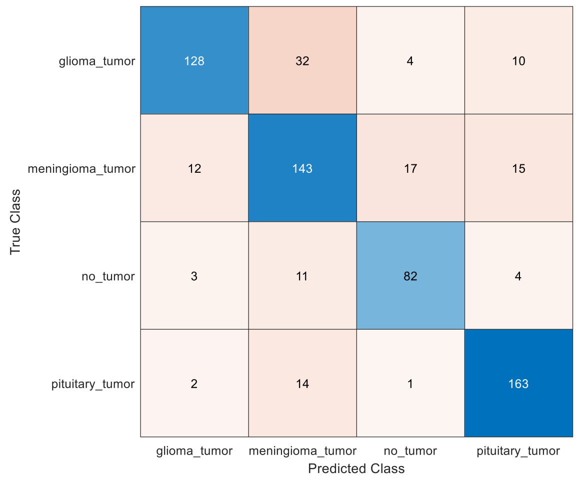

Figure 10. Confusion Matrix for AlexNet

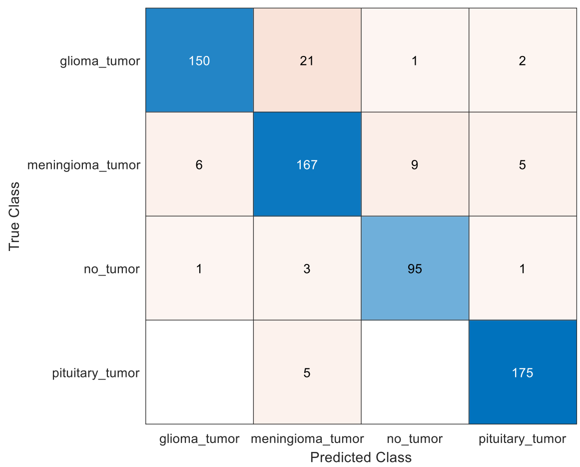

Figure 11. Confusion Matrix for ShuffleNet

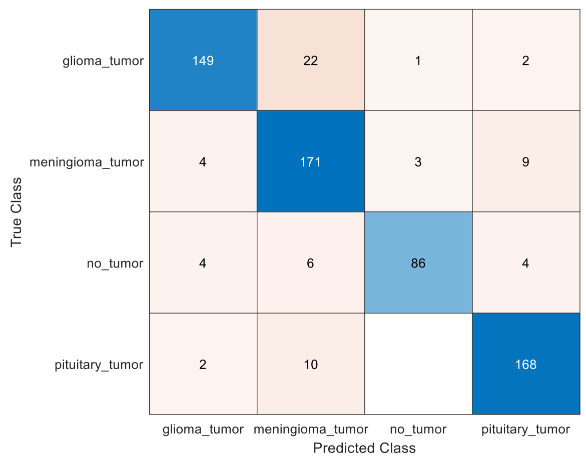

Figure 12. Confusion Matrix for SqueezeNet

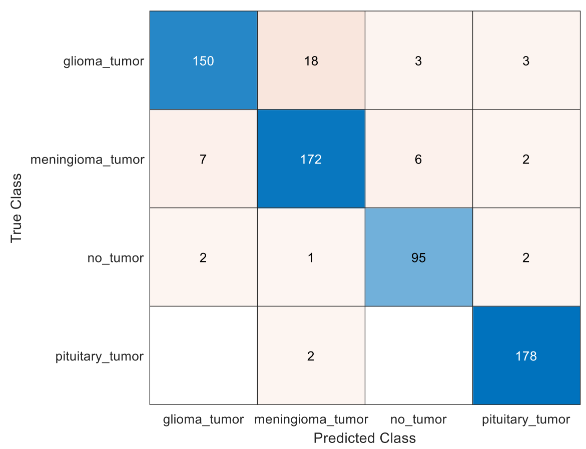

Figure 13. Confusion Matrix for Proposed CNN

The comparison between the proposed CNN model and other state-of-the-art models is presented in Table 4. Table 4 shows that the highest accuracy rate is obtained using the proposed CNN. The other models are ShuffleNet, SqueezeNet, and AlexNet in descending order.

Table 4

Comparison Validation Accuracy and Loss Values with the Other Studies

Model	Validation accuracy (%)	Loss
AlexNet	80.5	0.47
ShuffleNet	90.17	0.28
SqueezeNet	89.95	0.34
Proposed CNN	**92.82**	**0.25**

The accuracy values obtained using the models for the test data are listed in Table 5. In the table, the proposed model achieved the highest accuracy rate with 92.82%, recall rate with 92.5%, precision rate with 93% and F1-score with 93%. The other models are ShuffleNet, SqueezeNet, and AlexNet in descending order.

Table 5

Comparison Performance Metrics with the Other Studies (%)

Model	Accuracy	Recall	Precision	F1-Score
AlexNet	80.19	80.5	80.5	80.25
ShuffleNet	91.58	91.75	91.75	91.75
SqueezeNet	89.55	91	89	89.75
Proposed CNN	**92.82**	**92.5**	**93**	**93**

4. Discussion

It is known that CNN-based methods used in the early diagnosis of brain tumors are widely used. However, studies are still being conducted to determine the model with the best performance among these methods. The biggest difference between these studies is in the parameter values used in the design of the models. Therefore, researchers are developing CNN-based architectures with different parameters for tumor classification in brain MRI images. In this study, a CNN model was designed to classify brain tumors using brain MRI. To show the efficiency of our model, we compared it with 3 different pre-trained CNN models.

The confusion matrix for AlexNet is shown in Fig .10. It is obvious that no_tumor class is the best estimated class with 82 correct and 40 incorrect estimations. meningioma_tumor class is the worst estimated class with 143 correct and 101 incorrect estimations. Confusion matrix in Figure 11 shows ShuffleNet's estimation performance. pituitary_tumor class is the best estimated class with 175 correct and 13 incorrect estimations. meningioma_tumor class is the worst estimated class with 167 correct and 52 incorrect estimations. For SqueezeNet in Fig 12, the no_tumor class is the best estimated class, with 171 correct and 54 incorrect estimations. Meningioma_tumor class is the worst estimated class with 167 correct and 52 incorrect estimations.

The confusion matrix in Figure 13 shows the estimation performance of the proposed model. The pituitary_tumor class is the best estimated class, with 178 correct and nine incorrect estimations. The no-tumor class has 95 correct estimations and 14 incorrect estimations. Glioma _tumor has 150 correct and 33 incorrect estimations, respectively. Finally, the worst estimated class for proposed model is meningioma_tumor class with 172 correct and 36 incorrect estimations.

It was observed that the proposed CNN model performed better than the other models. These performance values were achieved without pretraining. Other pre-trained models performed poorly despite being used with thousands of data. This indicates that better models can be designed without transfer learning on fewer datasets.

5. Conclusions

Brain tumors are among the most harmful anomalies to human health. Precisely classifying brain tumors is difficult and relies on the experience of doctors and experts. With the advancement of computer science, computers have begun to implement classification issues using machine learning and deep learning approaches. In this study we proposed a CNN model to classify brain tumors using brain MRI images. In the proposed model there are 24 weighted layers that was explained in section 2.

The experiments were conducted on a dataset of four classes. To demonstrate the efficiency of the proposed CNN model, it was compared with three pre-trained CNN models: AlexNet, ShuffleNet, and SqueezeNet. In comparison, the proposed CNN model had the highest classification accuracy of 92.82% and the lowest loss of 0.2481. ShuffleNet has the second highest classification accuracy of 90.17% and a loss of 0.28. SqueezeNet has higher classification accuracy than AlexNet. AlexNet has the worst accuracy and loss values.

In the next studies, we are planning to merge a couple of pre-trained models to increase classification accuracy on MRI images.

Author Contribution Statements

The first author (Muhammed CELIK) is responsible for data curation, writing- original draft, software, investigation, visualization, and resources. The second author (Ozkan INIK) is responsible for supervision, conceptualization, validation, methodology, formal analysis, writing- reviewing and editing.

Conflict of Interest

The authors (Muhammed CELIK and Ozkan INIK) have no conflicts of interest to disclose. This study complies with scientific research and publication ethics and principles.

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