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Automated Classification of Brain Tumor Disease with a Novel CNN Relief and SVM-Based Deep Hybrid Model

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ABSTRACT

The brain tumor is a very dangerous type of cancer that can be seen in people of almost any age and usually results in the patient's death. Early detection of these tumors, which have many varieties, is extremely important in terms of the patient's survival, affecting the planning of treatment, just as with other types of cancer. Early diagnosis of the disease is usually performed by means of imaging devices. It takes a lot of expertise to analyze the MRI images and diagnose the brain tumor. In this study, a hybrid deep model is recommended that can be used effectively in the classification of the brain tumor. The proposed hybrid model is a Convolutional Neural Network (CNN)-based method that automatically classifies Magnetic Resonance (MR) images of three different types of brain tumors, Glioma, Meningioma and Pituitary successfully. Our model is basically going through these stages. First of all, the features from the two models that show the highest performance from pre-trained deep models are combined. The most effective features of the specification map obtained in the next phase were selected using the Relief method. At the last stage, classification was carried out with Support Vector Machine (SVM), one of the most known machine learning techniques. As a result of the experiments, the hybrid deep model we proposed obtained 93.2% accuracy. It seems that proposed hybrid method has very competitive results and is thought to be efficiently used to classify the brain tumor.

1. INTRODUCTION

The brain generates approximately 2% of the human body weight. This ranges from approximately 1.2 to 1.4 kg in adult individuals. It is an organ that, along with the spinal cord, forms the central nervous system, with approximately 1260 cm^3 women and 1130 cm^3 in men [1]. The brain tumor is a common name for cells and tissues that grow inside the skull without any control mechanism. Over time, the volume of these tumors increases and creates pressure on the skull. For this reason, symptoms such as walking disorders, speech disorders, memory loss, hearing and loss of vision, numbness in the body can also occur, especially in patients with headaches and nausea. It is still being investigated around the world, despite the fact that it is not known exactly what caused the brain tumor. Brain tumors can sometimes progress in metastases. This is often seen in individuals with lung, colon, and breast cancer [2]. The declining number of neurons in the brain, and consequently the symptoms of the patient, determine the severity of the brain tumors. Brain tumors can be determined by experts in benign and malignant ways. But those identified as benign from brain tumors can become malignant at a later time. Therefore, this tumor can cause the patient's death [3, 4]. If brain tumors are diagnosed early and treatment is started without any time, the patient may survive. Early diagnosis of brain tumors is extremely important for the patient's survival [5]. Computerized tomography (CT) or magnetic Resonance (MR) images are often used in the diagnosis of brain tumors. This is because the MRI images are scanned at regular intervals and the changes in the images are analyzed, allowing early diagnosis of many cancer diseases. However, the ability to diagnose the tumor correctly depends on the expert's experience and knowledge. The fault finding situation is difficult because the tumor can be in different shapes and sizes anywhere in the brain. This situation makes the decision-making process of the expert complicated. This process takes a lot of time for experts and can result in incorrect diagnosis. In addition, manual detection of the tumor is not appropriate in health institutions where there are more patients, but not enough experts. For all these reasons, the need to automatically classify the brain tumor.

Recently, artificial intelligence software has been frequently used to help diagnose diseases correctly in the field of health [6-8]. In this article, deep learning techniques used in the classification of brain tumor in MR images are actually a subbranch of artificial intelligence. The deep learning models in which many layers have systematically combined work quickly and effectively by their structure [9]. It can achieve very high accuracy values when performing classification operations. Deep learning owes its popularity to this success. Figure 1 illustrates the technologies covered by artificial intelligence.

In our study, the effect of computer-aided systems is quite high in order to increase the ability of specialists to diagnose, reduce their workload and serve more patients. In this study, different CNN architectures were used as the basis to increase the performance of the proposed model and different features of the same image in different architectures were obtained.

After combining the feature maps obtained using different CNN architectures, the Relief method was used to make the proposed model work faster. The feature map optimized by the Relief method is classified in the SVM classifier. The basic structure of the proposed model is shown in Figure 2.

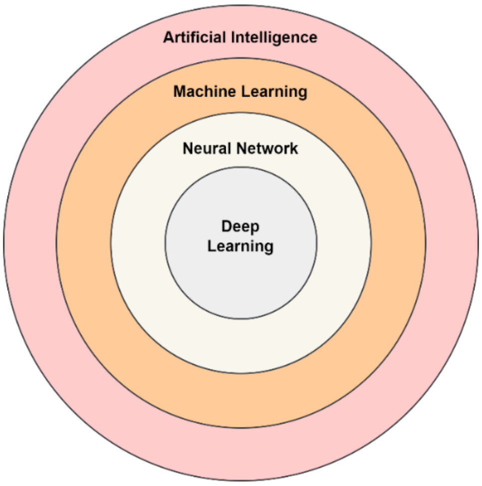

Figure 1. Artificial intelligence technologies

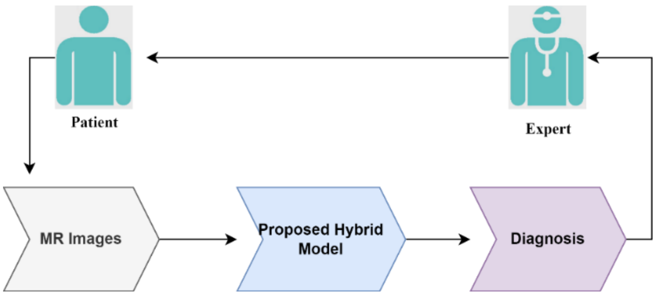

Figure 2. Basic structure of the proposed model

1.1 Related works

Some of the scientific studies that use artificial intelligence techniques in the diagnosis and classification of the brain tumor are as follows:

Cheng and his friends have proposed a model to classify 3 different brain tumors. They stated that they used a dataset with a total of 3064 MR images collected from 233 patients to demonstrate the performance of this model. In the model they recommend, not only the tumor region, but the tumor environment should be classified by inclusion in the image. Because they thought the tissue around the tumor contained information about the tumor. They also examined this enlarged tumor site in the next step by splitting it into rings. They classified the features obtained from three different feature extraction methods; Bag of Words (BoW), Intensity Histogram (IH) and Gray Level Co-occurrence Matrix (GLCM). With the model they proposed and stated that they achieved the highest accuracy rate of 91.28 percent [10].

Bingol and Alatas used three different CNN models to detect and classify the brain tumor. During the experiment, they used a 2-class dataset with a total of 253 MR images. With Resnet50 architecture, they achieved the highest accuracy of 85.71 percent. In the study, the authors stated that they used a two-class data set. A two-class dataset cannot produce fully accurate results regarding the diagnosis of the disease. The number of classes and the number of samples should be increased in order for the study to be carried out more soundly [4].

Paul and his friends used the CNN model to classify the images of the brain tumor. To prove the confidentiality of the study, they used a dataset as they saw 989 MR images within 3064 MR images obtained from 191 patients during the experiments. They obtained 91.48% accuracy with the model they proposed. They stated that the model they proposed showed higher performance than the image expansion or split the image into rings methods. The number of data used in this study and the low number of classes can be shown among the limitations of the study [11].

Çinar and Yildirim suggested a deep model based on CNN to classify the brain tumor in a 2-class dataset containing 253 MR images. They used the Resnet50 architecture as a base on the model they proposed. They removed the last five layers of this model and replaced them with eight new layers. They stated that the model they proposed obtained 97.2% accuracy. The number of data used by researchers in experiments is very few for deep learning techniques to produce healthy results. In the study, it is understood that high accuracy values are achieved by using data multiplexing methods. Data multiplexing methods have a positive effect on increasing the performance of the models [5].

Shahzadi et al. [12] used the Alexnet, Resnet, VGG16 architects and the Long Short Term Memory (LSTM) method to classify the lower types of glioma brain tumor, High Grade (HG) and Low Grade (LG). The researchers set the data set they use as half HG, and the other half as LG. For 60 cases selected in the experiments, dataset containing a total of 240 MR images, four MR images per case were used. They stated that they achieved the highest performance from the VGG16 architecture with an accuracy of 84%. The number of data used in the study is very small for CNN architectures to operate in a healthy way.

Seetha et al. [13] tried to classify the brain tumor using CNN and SVM classifiers. Because the collection is a dataset, the number of data it contains is not shared in the study. However, they indicated that the dataset consists of two classes. They stated that the accuracy they obtained was 97.5%.

Vani et al. [14] considered the brain tumor as an object, and classified it with machine learning methods to identify it. They conducted experiments on a dataset containing two classes using the SVM classification. They correctly classified 44 of the 54 test images and expressed their accuracy at 81.48%.

Zulpe et al. [15] used a dataset of four classes containing 80 MR images to classify the brain tumor in the experiments. They stated the accuracy of the 2-layer model created by the forward-fed Neural Network (NN) architecture as 97.5%. The study was performed by classifying with a very small number of images. In this study, the authors conducted a study with very limited data. Increasing the number of data will increase the performance of the model proposed by the authors [15].

Afshar et al. [16] used the CapsNets architecture to classify brain tumor from MR images. It was stated that the accuracy of the researchers was 90.89 as a result of their experiments with a 3-class dataset with 3064 MR images of data.

1.2 Contributions and novelty

The literature contribution of the study is briefly:

- A hybrid method that can be used effectively in the automated classification of the brain tumor is proposed in this study.

- A comprehensive literature study was conducted using deep models and machine learning techniques related to the diagnosis and classification of brain tumor.
- In the proposed architecture, Inceptionv3 and Resnet50 architectures, which are deep architectures that have been accepted all over the world, are used as the base. The image features obtained from these architectures that process the MR images in the dataset are combined. In other words, the image feature size has been doubled by revealing the classification power of both architectures. Since the feature map growing in size will extend the training time of the proposed model, the Relief method was used as an optimization method in order to select the best among the features. The feature map consisting of these selected features is classified in the SVM Cubic classifier.
- The hybrid method we have proposed has achieved very competitive results.

1.3 Organization of paper

In the first section of the article, some information about brain tumor disease is presented. In the second section, detailed information is given about the data set, deep models, classifier, optimization method and architectural structure of the proposed model. In the third section, the results of the experiments are presented. The discussion is given in the fourth section. The paper is concluded along with the possible future research directions in the fifth section.

2. MATERIAL AND METHODS

2.1 Dataset description

A publicly available dataset in which brain tumors were labeled by experts in four different classes (glioma, meningioma, pituitary, and normal) was used in this study. This dataset contains a total of 3264 MR images. The brain tumor dataset used in the experiments was accessed from https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri. The number of images for each class in the data set is listed in Table 1. Example MR images of each class in the data set are demonstrated in Figure 3.

Table 1. Number of images of brain tumor types in the dataset

Brain Tumor Classes	Glioma	Meningioma	Pituitary	Normal	Total
Number of Images	926	937	901	500	3264

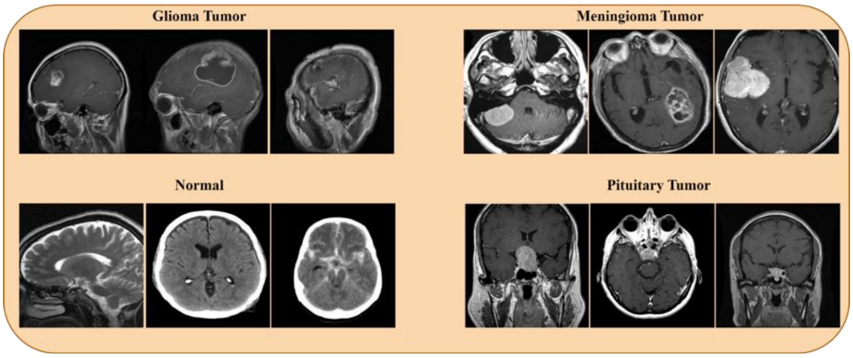

Figure 3. Example MR images of brain tumor classes

2.2 Deep models, relief, and support vector machine

In this section, six different CNN architectures, which were used during the experiments and whose performances were accepted all over the world, were examined. These architectures are Alexnet, Resnet50, Googlenet, Inceptionv3, Efficientnetb0, and Shufflenet. The Alexnet architecture is an architecture proposed by Krizhevsky et al. and first appeared in the ImageNet LSVRC-2012 competition. This architecture, consisting of 25 layers, has 60 million parameters and 650 thousand neurons [17]. The Resnet50 model developed by He et al. won the ImageNet LSVRC-2015 competition held in 2015. Although the increase in the depth of the network has a positive effect on the performance of the network up to a certain level, after a certain level there is a serious decrease in the performance of the network. Namely, as the number of layers in the network increases, the gradient values decrease and approach to zero. This situation is undesirable. In order to get rid of this, instead of calculating gradient, Resnet50, which consists of residual blocks, has eliminated the problem of zeroing gradient by adding x value to f(x) function. Other architectures could not reach the 3.6% error rate achieved by this architecture. It is one of the first architectures to use batch normalization [18]. Googlenet, which is very similar to the Inception architecture, was developed by Szegedy et al. The difference of Googlenet, which consists of 22 layers and 5 million parameters, from the Inception architecture is that it is deeper than it [19]. Inceptionv3 architecture is the development of Inceptionv1 and Inceptionv2, which were developed before it. This architecture was developed by Szegedy et al., just like Googlenet. This model is defined as a convolutional neural network model consisting of three blocks: initial, convolution, and classifier [20]. The Efficientnet architecture is based on the principle of scaling different dimensions of the network simultaneously, such as depth, width, and image resolution; evenly, using a fixed composite coefficient. There are eight versions from Efficientnetb0 to Efficientnetb7. The image size accepted by this model, which has 11 million parameters, in the input layer is 224×224 [21]. The Shufflenet architecture is a convolutional neural network architecture that can effectively deliver results even on devices with low hardware capabilities developed for mobile devices [22].

The Relief method tries to determine the features from the most important to the least important, while giving each feature a weight value. This optimization method randomly selects samples. It changes the feature weights of these selected samples by calculating them according to their nearest neighbors. During the experiments, 374 features among 2000 features were adjusted according to the selection of the features that have the most impact on the performance of the model [23].

Support Vector Machine (SVM) is a machine learning method developed by Vapnik that is often used in regression and classification applications [24]. In order to classify data belonging to different classes, SVM aims to find an optimum separator that acts as a boundary between these classes. The data points closest to the optimum separator form the support vectors [25].

2.3 Proposed model

Inceptionv3 and Resnet50 deep architectures, whose performances have been proven all over the world and which have been very popular in recent years, have been used as the basis for our proposed method to classify brain tumor images. The main reason we chose these two architectures is because they achieve the highest accuracy among the pre-trained deep models. Thanks to these architectures, different features of the images in the data set consisting of brain tumor MR images have been extracted. The size of the feature map obtained in each architecture is 3264×1000. Features were obtained from the "predictions" layer of the Inceptionv3 architecture and the "fc1000" layer of the Resnet50 architecture. By concatenating the feature maps obtained from both Inceptionv3 and Resnet50 architectures, a new 3264×2000 feature map was obtained. This fusion process, it is aimed to combine different features of the same image. Thanks to this combining process, the performance of the proposed model has increased. The Relief dimension reduction method is used to reduce the size of this feature map. The size of the feature map obtained after applying the Relief size reduction method was 3264×374. Finally, the optimized feature map is classified in SVM, a classical machine learning classifier. Since the best results were obtained in the cubic version of the SVM classifier in the proposed model, cubic SVM was used in the study. The block diagram of our proposed method is shown in Figure 4.

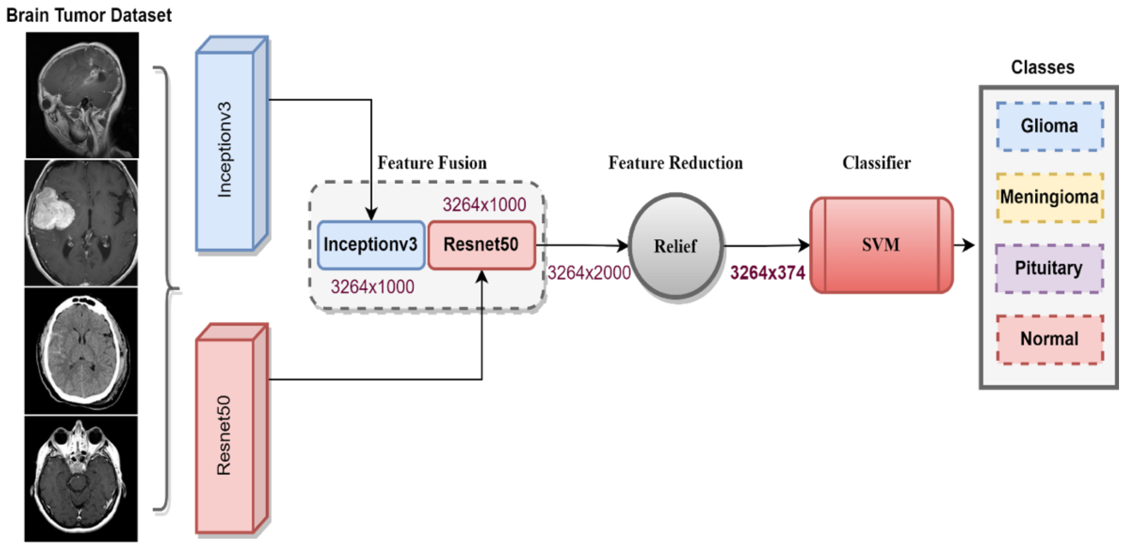

Figure 4. Block diagram of the proposed hybrid method

3. EXPERIMENTAL RESULTS

The use of fixed parameters and coefficients in this study is the common side of all experiments. The cross validation value was set to five. Experiments were carried out on a Windows 11 operating system computer with i5 processor, 16 GB ram and Geforce GTX1650 4GB graphics card in Matlab 2021b application. Performance metrics of deep models were computed by using TP (True Positive), FP (False Positive), FN (False Negative), and TN (True Negative) values in the confusion matrix. The performances of the algorithms were checked according to the metrics F-score (F1), Sensitivity (Sens.), Accuracy (Acc.), Specificity (Spc.), False Discovery Rate (FDR), False Positive Rate (FPR), and False Negative Rate (FNR) [26]. An example of the confusion matrix is given in Figure 5. Glioma, meningioma, normal, and pituitary classes in the confusion matrix are represented as 1, 2, 3, and 4 respectively.

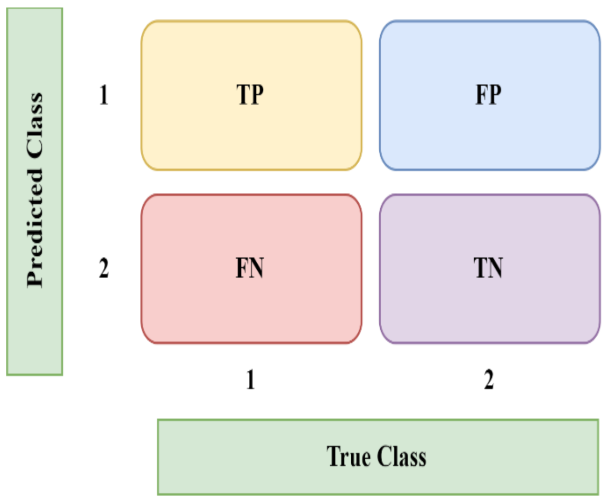

Figure 5. Confusion matrix

3.1 Results of pre-trained deep models

Table 2. Parameters for the deep models

Language	MaxIteration	MaxEpochs	MiniBatchSize	LearnRate	Optimization
Matlab 2021b	2608	8	16	1e-4	Sgdm

Table 3. Accuracy values obtained from deep models

Efficientnetb0	Inceptionv3	Alexnet	Resnet50	Googlenet	Shufflenet
70.40%	**80.52%**	75.15%	78.07%	75.77%	75.31%

Table 4. Confusion matrices obtained from deep models

Efficientnetb0	1	2	3	4
1	100	46	35	4
2	58	100		29
3	1	4	92	3
4		13		167

InceptionV3	1	2	3	4
1	110	44	29	2
2	31	141	2	13
3		1	99	
4		5		175

Alexnet	1	2	3	4
1	107	46	32	
2	52	114	3	18
3		2	97	1
4	1	5	2	172

Resnet50	1	2	3	4
1	110	31	42	2
2	44	122	1	20
3			99	1
4		2		178

Googlenet	1	2	3	4
1	120	52	13	
2	52	120	1	14
3	2	4	91	3
4	8	9		163

Shufflenet	1	2	3	4
1	109	43	31	2
2	48	119	3	17
3		2	96	2
4	1	11	1	167

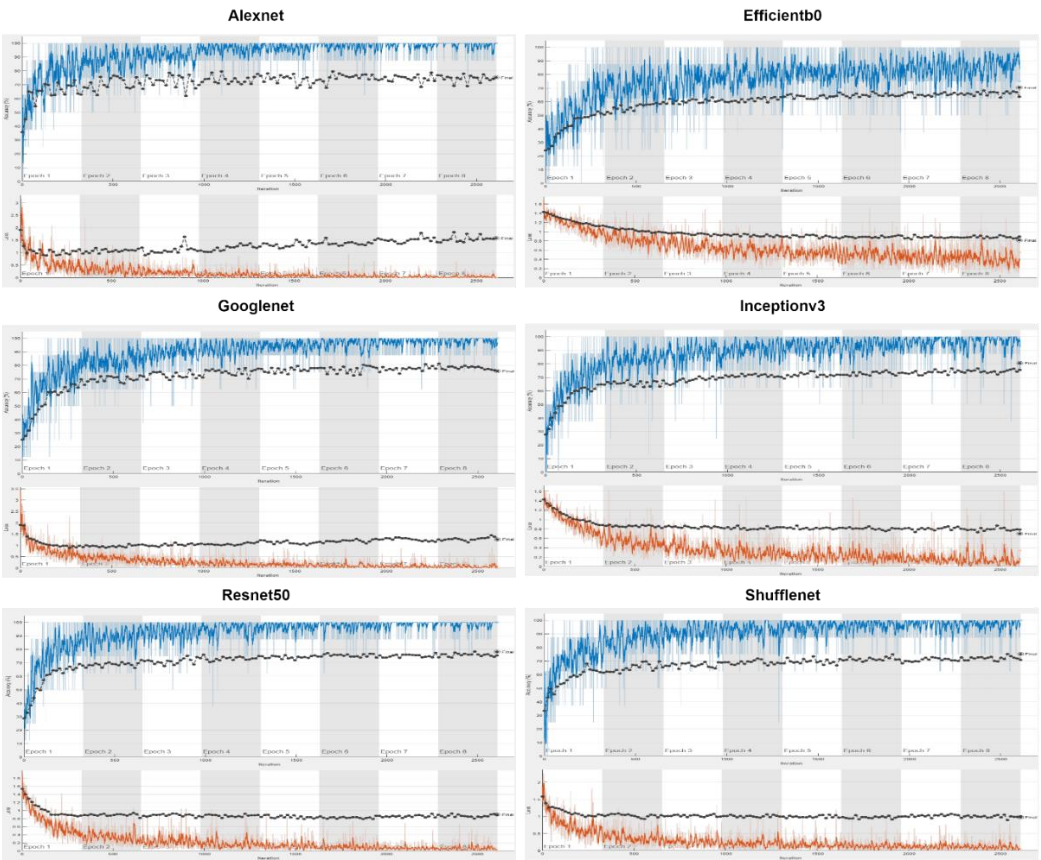

Figure 6. Accuracy and loss curves of deep models

The programming language and parameters used during the experiments are shown in Table 2. These training parameters are common to all deep models. In addition, while 80% of the data set was used in order to train the deep architectures, the remaining 20% of the data set was used to test the trained model.

The accuracies obtained from the pre-trained deep models are given in Table 3. In Table 3, the Inceptionv3 deep model, which achieved the highest accuracy with 80.52 percent, is shown in bold. This architecture was followed by Resnet50 78.07%, Googlenet 75.77%, Shufflenet 75.31%, Alexnet 75.15%, and finally Efficientnetb0 70.40% accuracy.

When Table 4 is examined, it is seen that while the Inceptionv3 architecture succeeds in correctly classifying 525 of 652 MR test images, it misclassifies 127 MR images. It can be stated that Resnet50 architecture performs close to Inceptionv3 architecture. In Resnet50 architecture, it is seen that while 509 of 652 MR test images were able to be classified correctly, it misclassified 143 MR images. In the Efficientb0 architecture, which has the lowest performance, it is seen that while it is able to correctly classify 459 of 652 MR test images, it misclassifies 193 MR images. The Accuracy and Loss curves of the deep models are shown in Figure 6. When Figure 6 is examined, it is seen from the training and validation curves that the number of epochs used is sufficient. This shows that the models have completed their training.

3.2 Proposed model

In the last part of the study, the Relief optimization method, which is the feature map obtained by concatenating the features obtained from the two highest performing deep models (Inceptionv3 and Resnet50), was applied. Thus, the size of the feature map has been reduced from 3264×2000 to 3264×374. In this way, the accuracy of the model is preserved, the features that are useful for the training of the model are selected and the training period is shortened. Then, the obtained reduced feature map was classified with the SVM (Cubic Version) classifier.

When Table 5 is examined, the proposed hybrid model classified 3042 of 3264 brain tumor MR images correctly, while it misclassified 222 brain tumor MR images.

Class-based performances of our proposed model in terms of seven different performance metrics are shown in Table 6.

Although the accuracy metric is the most important parameter when comparing the performances of the models, examining the performance of the model in terms of other metrics provides more in-depth information. In other words, the accuracy parameter alone cannot guarantee the performance of a model. When Table 6 is examined, the lowest performance in the class-based accuracy parameter was obtained in the Glioma class, while the lowest performance in the sensitivity parameter was obtained in the Meningioma class. Similarly, it is seen in Table 6 that the lowest performance in terms of F1 parameter was obtained in the Meningioma class.

Table 5. Confusion matrix obtained in the proposed model

	Proposed Model			
1	833	82	9	2
2	48	854	9	26
3	4	20	472	4
4	1	16	1	883
	1	**2**	**3**	**4**

Table 6. Performance values of the proposed hybrid model

	Acc. (%)	Sens. (%)	Spc. (%)	F1 (%)	FPR (%)	FDR (%)	FNR (%)
Glioma	89.96	94.02	96.09	91.94	3.91	10.04	5.98
Meningioma	91.14	87.86	96.38	89.47	3.62	8.86	1.21
Normal	94.40	96.13	98.99	95.26	1.01	5.60	3.87
Pituitary	98.00	96.50	99.23	97.25	0.77	2.00	3.50

4. DISCUSSION

The fact that brain tumor disease occurs in individuals of almost all ages today, and the parallel progression of the increase in the number of brain tumor cases with the aging of the world population makes this disease more important. The lack of sufficient number of specialists worldwide and the diagnosis of the disease in advanced stages negatively affect the patient's life. Manual examination of brain tumor images requires a lot of expertise [27, 28]. Sometimes, specialists can make erroneous diagnoses while examining MR images. One of these cases is the confusion of tumor-like but non-tumor tissue in any part of the brain with a brain tumor. Another problem is the mistakes of the specialist in diagnosing the type of tumor, even in cases where there is a tumor. The type of tumor directly affects the treatment method and planning of the disease. In order to prevent all these negative situations, the fully automatic diagnosis and classification of brain tumors by computer-aided systems will not only alleviate the workload of the specialists, but also save the specialists extra time and allow them to deal with more patients. In addition to these, early diagnosis of the disease will increase the chance of treatment of the patient and perhaps ensure his survival.

Today, artificial intelligence techniques are used for the diagnosis and classification of brain tumors. In this way, classification processes are carried out in a shorter time and with very high accuracy. Some studies using artificial intelligence and machine learning techniques related to brain tumors are given in Table 7.

When the literature given in Table 7 is examined, it is seen that there are other brain tumor classification studies that achieved approximately 4% higher accuracy than the hybrid model we proposed. However, when these studies are examined, it is seen that there are generally accuracy values obtained on a 2-class data set. In 2-class datasets, AI models are only concerned with whether or not the tumor is present. However, there are 4 different classes in the hybrid model we have proposed. In other words, besides whether the brain tumor is in the MR image, if there is a tumor, it is a much more sensitive study that determines what type of tumor it is. This is one of the main elements that distinguishes our work from other studies. Another factor is that studies in the literature have generally been carried out on data sets containing a small number of MR images. This is an undesirable situation that prevents deep learning techniques from producing healthy results. Our study differs from other studies in the literature in these aspects.

Table 7. Scientific studies in the literature on the classification of brain tumors

Paper	Methodology	Number of Images/Number of Class	Acc. (%)
Cheng et al. [10]	BOW-IH-GLCM	3064/3	91.28
Bingol and Alatas [4]	Resnet50	253/2	85.71
Paul et al. [11]	CNN	989/3	91.48
Cinar and Yildirim [5]	Enhanced Resnet50	253/2	97.20
Shahzadi et al. [12]	CNN-LSTM	240/2	84.00
Seetha et al. [13]	CNN-SVM	-/2	97.50
Vani et al. [14]	SVM	54/2	81.48
Zulpe et al. [15]	NN	80/4	97.50
Afshar et al. [16]	CapsNets	3064/3	90.89
Proposed Method	Resnet50-Inceptionv3-Relief-SVM	3264/4	**93.20**

5. CONCLUSIONS

Deep learning methods, a sub-branch of artificial intelligence, are frequently used in image processing and pattern recognition and object classification problems. The increasing number of brain tumor cases all over the world in recent years and the fact that this disease is a very deadly disease increases the interest of the scientific world in this field. In this study, a brain tumor classification application was carried out together with deep learning methods and feature selection methods, using a publicly available data set consisting of four classes containing 3264 MR images. The accuracy of the proposed model is 93.20%.

CNN architectures, Relief size reduction method and SVM classifier used in this study showed very effective results on brain tumor MR images. The deep architectures and technologies that we used in the experiments can also be used in the detection and diagnosis of other diseases.

This study has shown that instead of using all the features of an image, the classification process with better performance can be performed by selecting a much smaller number of qualified features. The use of a public dataset in the study is one of the limitations of the study. In future studies, both deep learning methods and feature selection methods that will enable us to achieve more successful results will be investigated. In addition, it is among our aims to collect new brain tumor data from different regions and conduct promising multi-disciplinary studies.

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