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Classification of Brain Tumor Images using Deep Learning Methods

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Abstract: Big data refer to all of the information and documents in the form of videos, photographs, text, created by gathering from different sources about a subject. Deep learning architectures are often used to reveal hidden information in the big data environment. Brain tumor is a fatal disease that negatively affects human life. Early diagnosis of the disease greatly increases the patient's chance of survival. For this reason, this study was conducted so that doctors could diagnose patients early. In this paper, deep learning architectures Alexnet, Googlenet, and Resnet50 architectures were used to detect brain tumor images. The highest accuracy rate was achieved in the Resnet50 architecture. The accuracy value of 85.71 percent obtained as a result of the experiments will be improved in our future studies. We will try to develop a new method based on convolutional neural network in the near future. With this model, we will try to achieve higher accuracy than any known deep learning method.

Key words: Brain tumor, deep learning, Alexnet, Resnet50, Googlenet.

Derin Öğrenme Yöntemleri Kullanılarak Beyin Tümörü Görüntülerinin Sınıflandırılması

Öz: Büyük veri bir konu hakkında farklı kaynaklardan toplanarak oluşturulan video, fotoğraf, metin formatındaki bilgi ve belgelerin tümünü ifade etmektedir. Büyük veri ortamında gizli bilgiyi ortaya çıkarmak için genellikle derin öğrenme mimarileri kullanılmaktadır. Beyin tümörü insan hayatını olumsuz etkileyen, ölümcül bir hastalıktır. Hastalığın erken teşhisi, hastanın yaşama şansını büyük oranda arttırmaktadır. Bu nedenle doktorların hasta olan kişileri erken teşhis edebilmesi için bu çalışma gerçekleştirilmiştir. Bu çalışmada beyin tümörü görüntülerini tespit etmek için derin öğrenme mimarilerinden olan Alexnet, Googlenet ve Resnet50 mimarileri kullanılmıştır. En yüksek doğruluk oranı Resnet50 mimarisinde elde edilmiştir. Deneyler sonucu elde edilen yüzde 85.71'lik doğruluk değeri, gelecek çalışmalarımızda iyileştirilecektir. Yakın zamanda evrişimli sinir ağı tabanlı yeni bir metot geliştirmeye çalışacağız. Bu model ile bilinen tüm derin öğrenme tabanlı modellerden daha yüksek doğruluk elde etmeyi deneyeceğiz.

Anahtar kelimeler: Beyin tümörü, derin öğrenme, Alexnet, Resnet50, Googlenet.

1. Introduction

Big data generally have a complex structure. Its complexity is due to the enormous amount of data they contain. [1]. Today, people generate huge amounts of data. Taking pictures of everything or videotaping everything is among the habits of people these days. The massive data produced by humans reach astronomical numbers and increase steadily. These data are not only produced by people using social media, but every professional person produces data about their expertise. Although medical science is very advanced today, it is still a problem that doctors cannot diagnose some diseases early. Doctors use brain tomography images and magnetic resonance images (MRI) to diagnose a brain tumor. These images from many patients are collected. Developing a system to diagnose the disease at an early stage is vital for patients. Brain tumor is a very dangerous, even fatal form of cancer. There are two known types of the disease, these are LGG (Low Grade Glioma) and HGG (High Grade Glioma). HGG patients usually die within 14 months of diagnosis. Treatment methods of the disease such as Radiotherapy and Chemotherapy are available [2]. Generally, this disease is tried to be treated with surgical intervention. The reason for this is that the tumor puts pressure on the brain.

Since brain tumors are tumors located in the skull, they can show distinct symptoms depending on the pressure increase. Severe headache, nausea and vomiting are among the most important symptoms. The disease can sometimes cause circulatory system disorders in patients and even paralyze these patients. Furthermore, different symptoms occur depending on the affected area of the brain. These are weakness, numbness, gait disturbance, vision loss, hearing loss, memory impairment, and difficulty speaking. It is not known exactly what causes brain tumors. However, it is known for certain that brain tumors can be seen in all age groups. As the world's population ages, more and more people will get this disease [3]. Since the disease is very dangerous, brain tumor diagnosis studies are a very active field of study [4]. In this study, a method was developed to help doctors diagnose the disease using a data set containing MRI images that are publicly available [5]. Also, with this study, it is aimed to

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help early diagnosis of brain tumor disease in people living in rural areas where there are no specialist doctors. Another benefit of this study is to ease the workload of doctors. Again, with this study, it is aimed to prevent the doctors who are exhausted under excessive workload from making wrong diagnoses.

There are some studies in the literature for the detection of brain tumor. Dong et al. proposed a reliable segmentation method for automatic segmentation of brain tumor. They used the BRATS2015 data set in their experiments. They stated that the method they proposed gave promising results [6].

Amin et al. proposed an automatic system that detects whether the brain has a tumor or not from MRI images. Harvard, Rider, and Local datasets were used during the experiments and the highest accuracy rate obtained was 97.1 percent [7].

Wu et al. proposed a color-based segmentation to detect brain tumor. This method uses the k-means clustering method. They stated that the method could successfully achieve segmentation for MRI brain tumor images to help pathologists distinguish exactly lesion size and region [8].

Chandra et al. proposed a model for detection of brain tumor. This model was based on genetic algorithm. Tumor pixels on MRI images are detected with the help of a genetic algorithm [9].

The overall article organization is as follows: Section 2 defines materials and methods. Experimental results are demonstrated in Section 3. Conclusion of this paper is illustrated in Section 4. Again, in this section, information is given about the future studies.

2. Materials and Methods

The structure of the brain, the region where the tumor is located, the type of the tumor, and how much the brain and nerves are damaged are very important data for treatment. Revealing the information hidden in the MRI images is vital for early detection of the tumor.

2.1. Data Set

The data set used during the experiments was obtained from Kaggle [5]. This data set consists of two classes. There is no tumor in first-class data. The data in the second class are images of the patient with tumor. Figure 1 shows MRI images of a healthy individual on the left. Again, Figure 1 shows MRI images of a person with a brain tumor on the right.

Brain Tumor (NO)	**Brain Tumor (YES)**

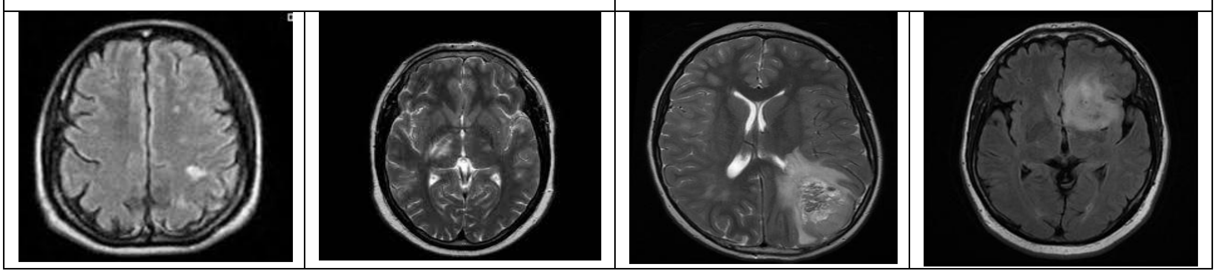

Figure 1. Brain MRI images.

2.2. Deep Learning Architectures

Deep learning is based on the concept of artificial neural networks and computational systems that mimic the functions of the human brain. Deep learning is based machine learning methods. Deep learning uses many layers for feature extraction and conversion. Each layer takes the output of the previous layer as input [10]. There are many deep learning architectures.

2.2.1. Alexnet

Alexnet is a convolutional neural network (CNN) architecture proposed by Alex Krizhevsky [11]. Basically it is similar to the LeNet model. The main reason for this similarity is that there are convolution and pooling layers that follow each other. Approximately 60 million parameters are calculated in this architecture. Alexnet architecture is shown in Figure 2.

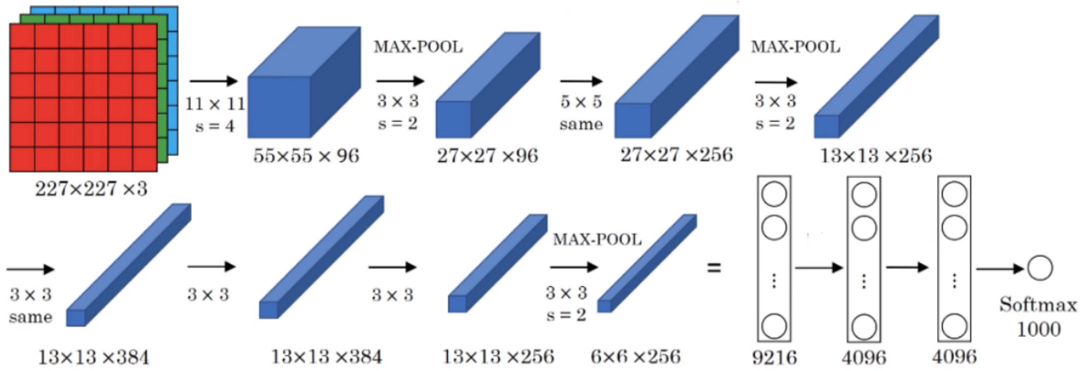

Figure 2. Alexnet architecture.

2.2.2. Resnet50

Residual network (ResNet) architecture was proposed by He Kaiming in 2015. ResNet consists of adding residual values and residual blocks to the architectural model. ResNet architecture kept the performance of the model while increasing depth. In addition, the number of parameters, which is an important factor in computational complexity, was reduced in this model. [12]. ResNet50 architecture is shown in Figure 3.

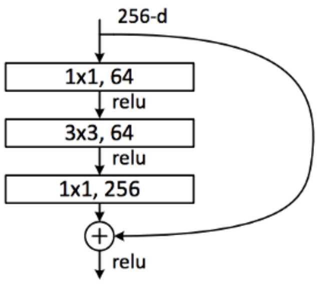

Figure 3. ResNet50 architecture.

2.2.3. GoogleNet

GoogleNet architecture was proposed by Christian Szegedy in 2015. GoogleNet is a deep learning architecture with hyperparameters optimized [13]. This model consists of 22 layers. Approximately 5 million parameters are calculated in this architecture. GoogleNet architecture is shown in Figure 4.

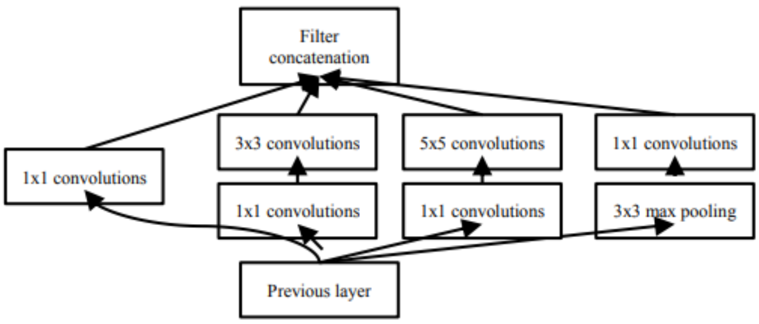

Figure 4. GoogleNet architecture.

3. Experimental Results

Deep learning architectures were used for the classification of brain tumor images. There are certain criteria that express the performance of the models in deep learning [14, 15]. All these performance metrics were calculated using Confusion Matrix [16]. A simple example of a Confusion matrix is given in Table 1. PC used in the present work has Core i7-10510U CPU, 1.80 GHz processor, 8 GB RAM, and 2 TB HDD.

Table 1. Confusion matrix

	Prediction No	**Prediction Yes**
Actual No	TN	FP
Actual Yes	FN	TP

The performance metrics of deep learning networks are given as Accuracy in Equation 1, Sensitivity in Equation 2, Specificity in Equation 3, Precision in Equation 4, Recall in Equation 5, and F-measure in Equation 6.

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

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

$$Specificity = \frac{TN}{TN+FP} \tag{3}$$

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

$$Negative\ Predictive\ Value(NPV) = TN\ /\ (TN + FN) \tag{5}$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6}$$

Accuracy and Loss plots obtained with AlexNet architecture are demonstrated in Figure 5. The confusion matrix and performance parameters of the AlexNet architecture are shown in Table 2 and Table 3, respectively.

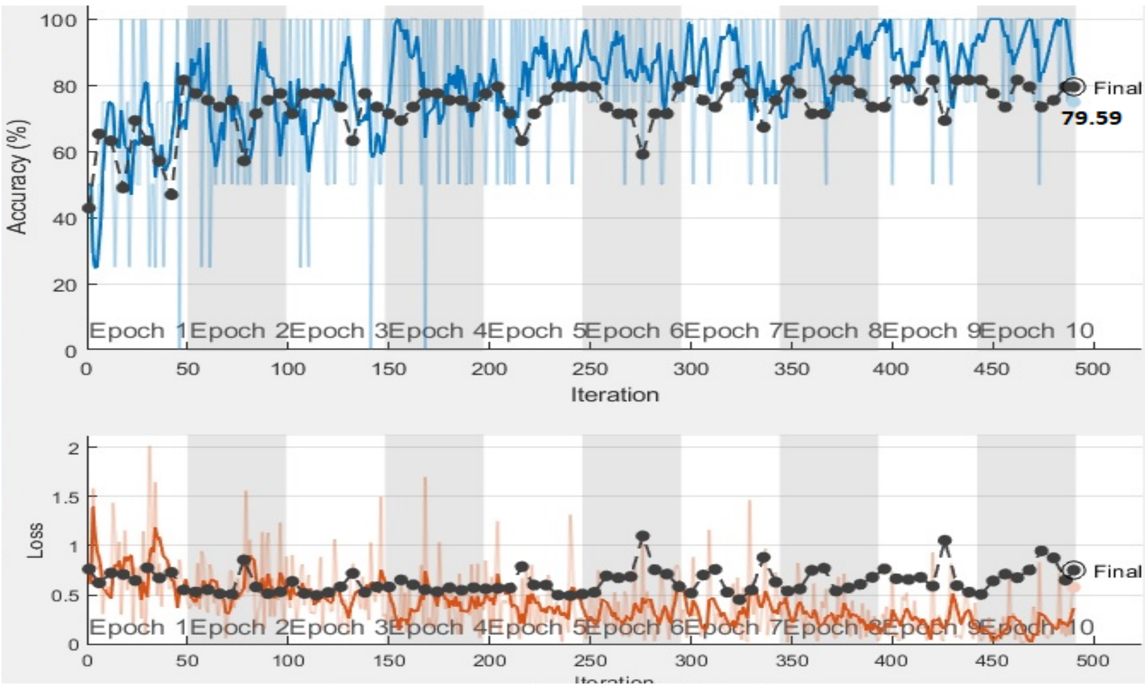

Figure 5. The accuracy and loss curve of AlexNet.

Table 2. Confusion matrix of AlexNet

	No	**Yes**
No	14	4
Yes	6	25

Table 3. Performance parameters of the AlexNet architecture

Accuracy	Sensitivity	Specificity	Precision	NPV	F1-Score
0.7959	0.70	0.8621	0.7778	0.8065	0.7368

Alexnet architecture has been tested with test data containing 49 images. 39 of these data were classified correctly. The remaining test data were classified incorrectly.

Accuracy and Loss plots obtained with ResNet architecture are demonstrated in Figure 6. The confusion matrix and performance parameters of the ResNet architecture are shown in Table 4 and Table 5, respectively.

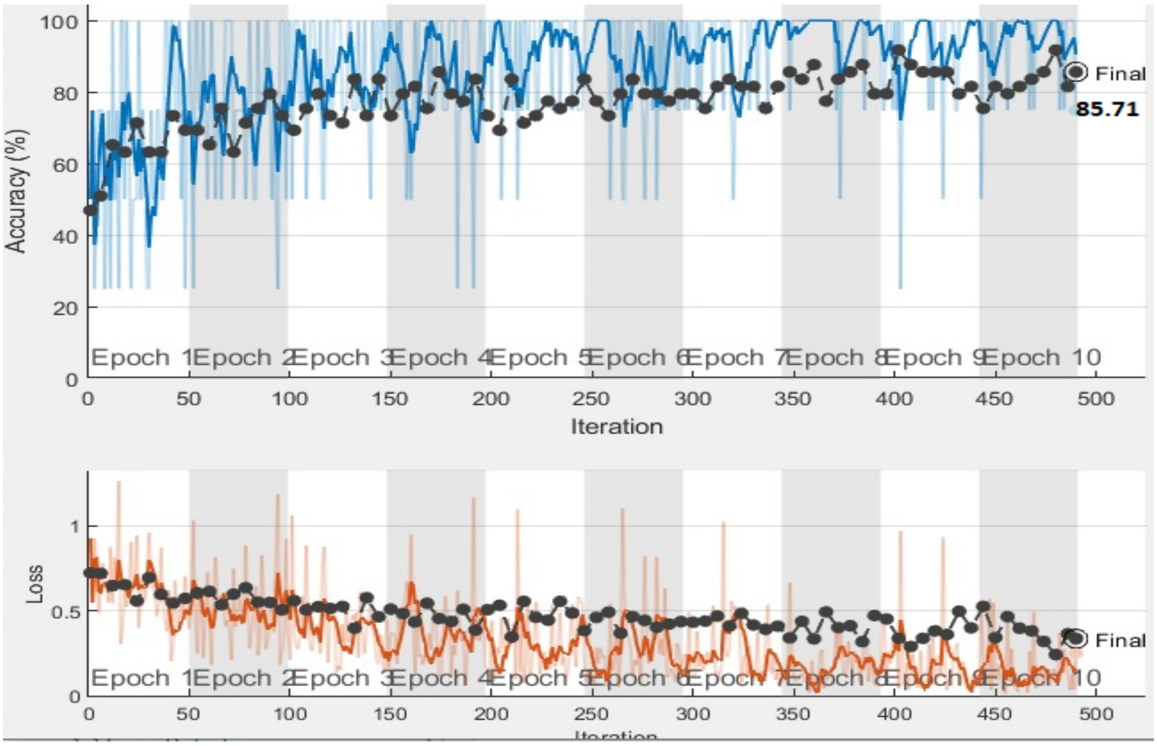

Figure 6. The accuracy and loss curve of ResNet.

Table 4. Confusion matrix of ResNet

	No	**Yes**
No	14	4
Yes	3	28

Table 5. Performance parameters of the ResNet architecture

Accuracy	Sensitivity	Specificity	Precision	NPV	F1-Score
0.8571	0.8235	0.8750	0.7778	0.9032	0.80

ResNet50 architecture has been tested with test data containing 49 images. 42 of these data were classified correctly. The remaining test data were classified incorrectly.

Accuracy and Loss plots obtained with GoogleNet architecture are demonstrated in Figure 7. The confusion matrix and performance parameters of the GoogleNet architecture are shown in Table 6 and Table 7, respectively

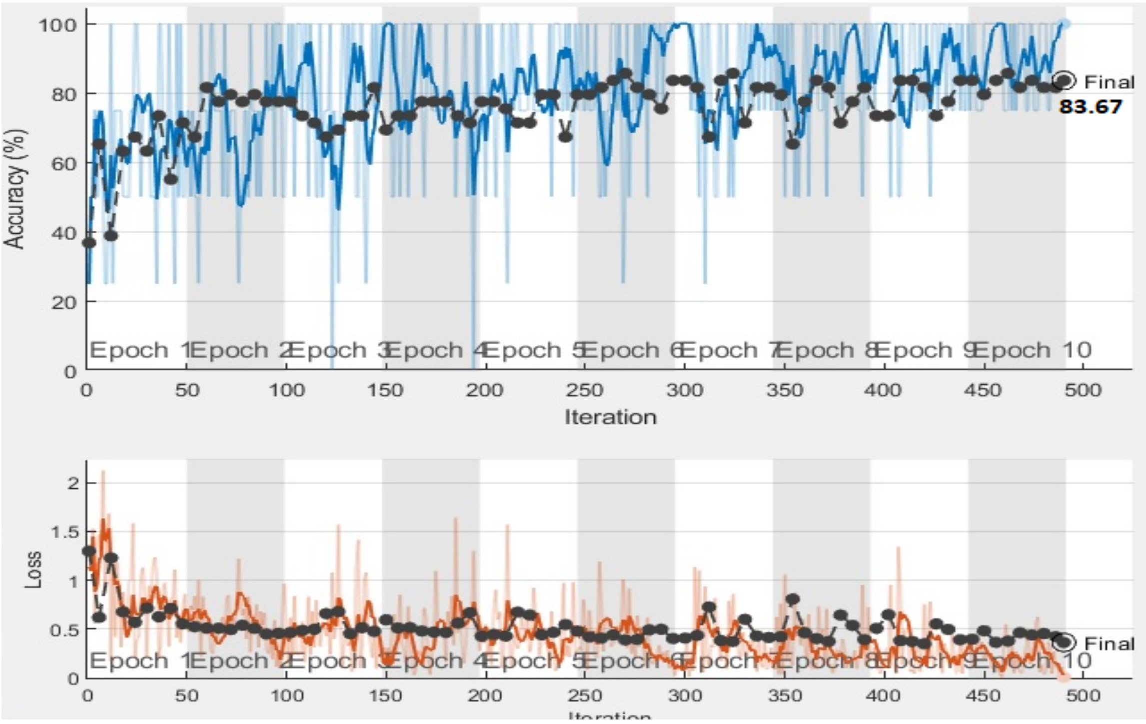

Figure 7. The accuracy and loss curve of GoogleNet.

Table 6. Confusion matrix of GoogleNet

	No	**Yes**
No	15	3
Yes	5	26

Table 7. Performance parameters of the GoogleNet architecture

Accuracy	Sensitivity	Specificity	Precision	NPV	F1-Score
0.8367	0.7500	0.8966	0.8333	0.8387	0.7895

GoogleNet architecture has been tested with test data containing 49 images. 41 of these data were classified correctly. The remaining test data were classified incorrectly.

4. Conclusions

In this paper, it was aimed to develop a method to diagnose a disease that changes human life completely negatively. The sooner the disease is diagnosed, the sooner the treatment process begins. In this study, deep learning methods were used to detect brain tumor from MRI images. The purpose of this classification process is to assist the doctor. Among the deep learning architectures, Alexnet, Resnet50, and Googlenet architectures were used during the experiments. The Resnet50 architecture achieved the highest accuracy rate during the experiments. The accuracy rate of the Resnet50 architecture is 85.71 percent. Googlenet architecture has the second highest accuracy rate after Resnet50 architecture. The architecture with the lowest accuracy is Alexnet. The scientific world continues to work on both diagnosing and treating brain tumors. In the future, architectures that will give higher accuracy can be developed for brain tumor diagnosis. We will try to develop a new method based on convolutional neural network in the near future. With this model, we will try to achieve higher accuracy than any known deep learning method.

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