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Categorical and Binary Brain Tumor Classification Using Transfer Learning Techniques

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ABSTRACT

The quality and length of life may be affected by brain tumors, which are created when cells in the head region proliferate out of control. Patients with misdiagnosed or late-diagnosed brain tumors and untreated patients have a lower chance of survival. Images obtained from MR imaging equipment are typically used to diagnose brain cancers. Given the rising number of patients and the high doctor density, computer-assisted techniques are particularly helpful in the diagnosis and categorization of brain tumors. In this study, transfer learning techniques were used to classify brain tumors from MRI data. In the study, a 4-class dataset made up of glioma, meningioma, pituitary, and no-tumor was used in addition to a binary data set of tumor and no-tumor. Repetitive and unneeded regions in the images were eliminated by applying image preprocessing techniques to the datasets. Following that, classification was performed using the EfficientNet, XceptionNet, and CoAtNet models, which modified the last layer and used the weight values of the models trained on very large datasets (imagenet). As a result, show that CoAtNet performed best in multiclassification validation accuracy (98.26) and EfficientNet in binary classification (99.98). When compared to high-success studies with similar datasets, it was observed that the success metrics were quite close to those of these studies

Keywords: transfer learning, coatnet, efficientnet, xceptionnet, brain tumor, classification, medical image

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Introduction

The brain is a massive, intricate structure that governs the whole nervous system in humans and comprises about 100 billion nerve cells [1]. This vital organ is formed in the brainstem, the core of the neurological system. Therefore, any type of irregularity in the brain could be dangerous for people's health. The most severe of these anomalies are brain tumors.

Brain tumors are defined as abnormally growing cells in the skull region. Typically, abnormal and uncontrolled cell division is what causes a brain tumor. Both the brain and the skull can develop these tumors; they can also start in the tissues surrounding the brain.

According to the World Health Organization, brain tumors account for less than 2% of all human cancers, but because of their high morbidity and comorbidities, early diagnosis is a critical idea in contemporary medicine [2].

The World Health Organization (WHO) has categorized brain tumors into four classes [1]. Meningiomas are an example of grade 1 and grade 2 tumors, while grade 3 and grade 4 tumors are more serious ones (e.g., glioma). Meningioma, pituitary, and glioma tumor incidence rates in clinical practice are roughly 15%, 15%, and 45%, respectively.

Meningiomas, pituitary adenomas, and schwannomas are the most commonly seen benign tumors, while gliomas, which account for 78% of all malignant brain tumors, are included in the category of malignant tumors. Most benign intracranial tumors, or 10 to 15% of all neoplasms, are meningiomas, which are the most frequent type. After meningiomas, gliomas, and schwannomas, pituitary adenomas are the most frequent intracranial tumors, commonly affecting patients in their 30s and 40s. Schwannomas, which form along nerves and are made up of cells that normally provide the nerve cell's electrical insulation, also affect patients frequently in these age groups. Glia, the brain's supporting cells, give birth to gliomas, which include ependymomas, medulloblastomas, astrocytomas, and Glioblastoma multiforme (GBM), the most aggressive kind of glial tumor [3].

Depending on the location, size, and kind of tumor, there are many treatment options for brain tumors. Surgery is currently the most popular method of treating brain tumors because it has no negative consequences on the brain [4].

The inside state of the human body can be observed using a variety of medical imaging technologies, including computed tomography (CT), positron emission tomography (PET), and magnetic resonance imaging (MRI). Since MRI is the only non-invasive, non-ionizing imaging technique that provides useful information in 2D and 3D formats regarding the kind, size, shape, and location of brain tumors, it is regarded as being the most advantageous among all imaging modalities [5].

There are many artificial intelligence applications for brain tumors such as automatic brain tumor classification, brain tumor segmentation, and finding optimal routes to the tumor as we developed before, and it is a very important field [6].

Brain tumor classification is a multidomain problem that requires designing the data collection, pre-processing, denoising, segmenting, feature extraction, feature selection, classification, and post-processing procedures.

In this study, multiple brain tumor classification was performed with two datasets from Kaggle. The Kaggle BR35H dataset [7] was used for binary classification (normal/tumor), and the Kaggle Brain Tumor Classification dataset [8] was used for multi-class classification (normal, glioma tumor, meningioma tumor, and pituitary tumor).

The work is organized as follows. In Section 2, the most recent studies in the literature that perform automatic brain tumor classification images datasets are presented. Methods are explained in Section 3. Information about the dataset used, architectures of transfer learning models, and the deep learning model is given. And explains how the experimental study was carried out. The preprocessing applied to the images and the hyperparameters of the models are presented. In Section 4, the experimental results and the success of the models are presented. In Section 5, the conclusion and discussion are presented and future work is mentioned.

Literature Review

For automatic brain MRI classification using machine learning and deep learning approaches, many different methods have been presented. Numerous studies using cutting-edge deep convolutional neural networks have been written to address binary and multiclass brain tumor diagnosis difficulties.

For quick and accurate tumor classification performance, Kushwaha and Maidamwar [9] suggest a model that combines the Saliency map with VGGNet, AlexNet, Inception Net, and Xception Net models. The model's 95% accuracy, 94.1% precision, and 95.6% recall make it suitable for low-error applications for brain tumor classification. Kang et al. [10] used many pre-trained deep Convolutional neural networks (CNNs) to extract important features from the MRI scans and ML algorithms to classify the MRI scans of three freely available datasets. According to the results, the Support Vector Machines (SVM) with radial basis function kernel outperforms other machine learning classifiers.

Deep tumor networks, as defined by Amran et al. [11], were proposed by Google Net and CNN model hybrids for the detection of CTs. The proposed model was built on top of the GoogleNet model. The final five layers of GoogleNet were removed, and 14 layers—each one deeper than the previous—of the CNN model were replaced. Although the fundamental CNN architecture was left unmodified, the ReLU AFs were converted to a leaky Re-AF. After the modifications were made, the layers increased from 22 to 33 in total. The hybrid model that is advised acquired the maximum level of classification accuracy, 99.10%.

In another study, Four real-world data sets were successfully used to test and suggest a novel method for the diagnosis of brain cancers based on genetic algorithm-based deep learning. According to experiments on the Gazi Brain Data Set 2020 dataset, this inference was supported by four separate metrics outcomes. The proposed model achieved %85 accuracy. While the conventional CNN model had a success rate of 78%, the proposed CNN+GA model had a success rate of 85% [12].

Papageorgiou [13] proposed a model to follow while creating an automated and cost-effective categorization tool that will help medical professionals everywhere identify brain tumors from MRI scans. The proposed model provides 99.62% testing accuracy utilizing a cross-entropy loss function and was trained and verified using MRI images.

Sert et al. [14] and Özyurt et al. [15] propose ResNet for the first component of the CNN-SVM architecture, whereas resolution improvement and entropy segmentation approaches were used for image preprocessing. On the same dataset, Özyurt et al. [15] compare their model to a CNN-KNN with a 90.62% accuracy. The research in these articles is based on MRI image segments that simply show the tumor tissue. Sajja and Kalluri's [16] use of a CNN on a BRATS dataset of 577 photos yields an accuracy of 96.15% when tested on 182 images, showing another successful attempt to identify images with and without brain tumors.

Using a CNN to combine five separate models into one, Mittal and Kumar [17] identify MRI images in relation to three tumor classifications and a class for the negative diagnoses, achieving a testing accuracy of 98.8%. On two databases comprising three kinds of malignancies (meningiomas, pituitary adenomas, and gliomas), Sultan et al. [18] confirm their CNN model with overall accuracies of 96.13% and 98.7%.

Using pre-trained CNNs [19] is another strategy. On two datasets with three and four tumor types, respectively, accuracy rates of 97.64% and 98% were achieved. In order to segment the image regions containing the tumor and categorize these parts into five groups with an accuracy of 81%, Zhao and Jia [20] use a deep convolutional neural network.

Methods

In this section, firstly, the datasets will be introduced. Then, the preprocessing steps applied on the datasets will be explained. Then, the used transfer learning models will be introduced and the parameters and model structure used will be mentioned.

Datasets

In the study, two different data sets were used for binary and multiple classifications. The BR35H for a binary dataset is also shared as open source on Kaggle. In this dataset, there are a total of 3000 MR images in 2D format, consisting of 1500 tumor images and 1500 healthy images. These images are in JPEG format [21]. For multi-classification, a data set shared as open source on Kaggle was used. This dataset contains 2870 data for 4 classes for training; glioma, meningioma, pituitary, and no-tumor MR images in 2D jpeg format[22].

Image PreProcessing

In both brain MRI datasets, nearly all of the images have unwanted gaps and areas, resulting in below-average classification performance. Therefore, it is very important to cut photos to eliminate unnecessary parts and use only relevant information.

First, the image dimensions are set to 224*224 pixels. It is necessary to calculate the size of the unwanted black areas in the images. Thresholds are applied to images. However, before that, Blurring is performed on the images so that the Threshold process can be applied more successfully. For this, the GaussianBlur method of the OpenCV library is used. The 'otsu' threshold is an OpenCV technique where pixel values are assigned according to the threshold value provided. Each pixel value is compared with the threshold value, if the pixel value is less than the threshold value, it is set to 0. Otherwise, it is set to the maximum value. As a result of this process, the outside of the region we are interested in is masked. Then we contour with the coordinates of the top, bottom, right and left endpoints of the region of interest. The area inside this contour is considered the area we are interested in and the crop is done according to these coordinates. By re-sizing, the images are prepared to be given to the model.

Transfer Learning

It is a machine learning approach in which a deep learning network (usually convolutional networks) previously trained for a task is taken with weights and used as a starting point for a different task [23]. Transfer learning has been successfully used in several fields recently, including the segmentation and classifications of medical images. In this study, preprocessed images for brain tumor classification were classified with EfficientNet, XceptionNet, and CoAtNet.

EfficientNet; It is considered a group of convolutional network models. The ImageNet classification problem consisting of more than 14 million images, reaches 84.4% accuracy with 66 M parameters and is among the state-of-the-art models [24]. EfficientNet; It consists of 8 different models between B0 and B7. The B0 model was used in this study. In EfficientNet, an activation function called Swish is used instead of Rectifier Linear Unit- ReLU. Google Brain Team: They noted that the Swish activation function tended to work better than ReLU when applied in deeper models on a group of datasets. XceptionNet; It is a 71-layer convolutional neural network model trained on the ImageNet classification problem and achieved 79% accuracy in ImageNet. It was basically developed by adding on the InceptionV3 network. In the convolution section, in addition to InceptionNet, smart depth convolution and smart point convolution sections have been added [25]. In this way, it is aimed to prevent over-learning by using fewer parameters.

For large-scale image identification and classification, CoAtNet offers a special mix of depthwise convolutions (1) and self-attention (2) that enables quick and precise progress. The suggested design is based on the finding that self-attention models typically demonstrate higher capacity whereas CNN's typically show better generalization. If the model hyperparameters are mentioned; Weight values for all models are from 'imagenet'. Validation split is =0.2. Training is 30 epochs. optimizer is Adam (lr= 1e-4). Other parameters are given in Table 1.

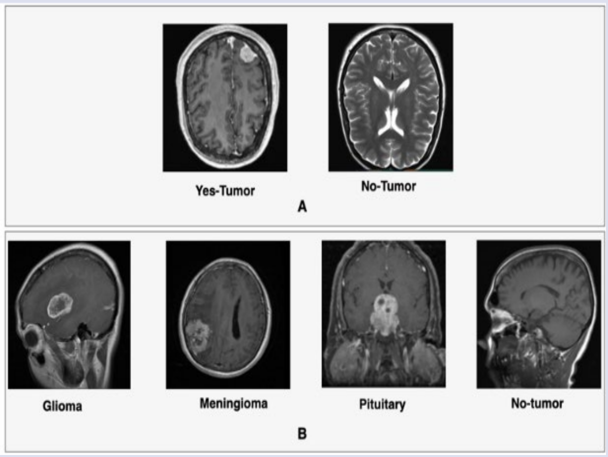

Figure 1. A- Example image from dataset for binary classification, B- Example image from dataset for multiclassification

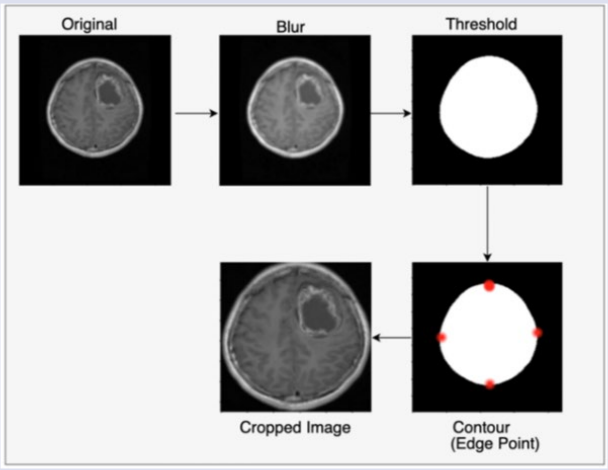

Figure 2. Image preprocessing steps

Table 1. Hyperparameters

Model	Hyperparameters	
	Binary	Multi-class
EfficientNet	Last_activation=sigmoid,loss=binary_ _crossentopy	Last_activation=softmax,loss=categorical_crossentopy
	Version=EfficientNetB0,	
XceptionNet	Last_activation=sigmoid,loss=binary_ _crossentopy	Last_activation=softmax,loss=categorical_crossentopy
	Version='XceptionNet',	
CoatNet	Last_activation=sigmoid,loss=binary_ _crossentopy	Last_activation=softmax,loss=categorical_crossentopy
	Version='CoatNetv0',	

Table 2. Success Values For Multiple Classification

Model	Accuracy	AUC	Precision	Recall
EfficientNetB0	98.12	98.99	98.12	98.12
XceptionNet	95.63	99.40	95.63	95.63
CoAtNetv0	98.26	99.39	98.26	98.26

Table 3. Success Values For Bınary Classification

Model	Accuracy	AUC	Precision	Recall
EfficientNetB0	99.98	1	99.90	1
XceptionNet	97.50	99.30	1	94.67
CoAtNetv0	99.38	99.18	99.6	99.2

Table 4. Success Values for Similar Datasets

References	Model	Dataset	Classification	Accuracy
Kushwaha and Maidamwar [9]	VGGNet, AlexNet, InceptionNet, XceptionNet	Kaggle BR35H Brain Tumor Dataset, IEEE Data Port Dataset	Multi	95
Kang et al. [10]	CNN	BT-small-2c, BT-large-2c, BT-large-4c	Binary and Multi	98.17
Amran et al. [11]	GoogleNet, CNN	Kaggle BR35H Brain Tumor Dataset	Binary	99.10
Özdem et al. [12]	CNN+GA (Genetic Algorithm)	Gazi Brain Data Set 2020	Binary	85
Papageorgiou [13]	CNN	Kaggle BR35H Brain Tumor Dataset, Kaggle Brain MRI Images for Brain Tumor Detection	Binary	99.62
Sert et al. [14]	ResNet	TCGA-GBM	Binary	95
Özyurt et al. [15]	NS-CNN	TCGA-GBM	Binary	95.62
Sajja and Kalluri [16]	CNN	BRATS	Binary	96.15
Mittal and Kumar [17]	AiCNN	Two private datasets	Multi	98.8
Sultan et al. [18]	CNN	Dataset from Tianjing Medical University, REMBRANDT	Multi	98.7
Ari et al. [19]	CNN	RIDER, Figshare, REMBRANDT	Multi	99
Zhao and Jia [20]	DCNN	BRATS	Multi	81
Our Study	CoAtNetv0	Kaggle Brain Tumor Classification (MRI)	Multi	98.26
Our Study	EfficientNetB0	Kaggle BR35H Brain Tumor Dataset	Binary	99.98

Experimental Results

The results obtained in this section will be presented in tables. First, the validation success values for transfer learning in multiple classification are given in Table 2.

Accordingly, the highest accuracy values for multiple classifications were obtained with the CoatNetv0 model.

In Table 3, validation success values for transfer learning in binary classification are presented.

Accordingly, the highest accuracy values for binary classification were obtained with the EfficientNetB0 model.

In Table 4, the comparisons of studies with similar datasets and the achievements obtained with the transfer learning model are presented. It is observed in the table that many methods are used for brain tumor binary and multiple classifications and the most successful models are CNN-based.

Conclusions

Brain tumors, which are formed by the uncontrolled proliferation of cells in the head region, can cause a decrease in the quality and duration of life. Patients with misdiagnosed or late-diagnosed brain tumors and untreated patients have a lower chance of survival. Diagnosis of brain tumors is usually provided by images taken from MR imaging systems. It is very useful to use computer-aided systems in the detection and classification of brain tumors due to the increasing number of cases and the high density of doctors. The development of artificial intelligence and deep learning models and automatic classification of brain tumors are very common areas of study in recent years.

In this study, brain tumor classification from MRI images was performed by transfer learning methods. In the study, a binary dataset of tumor and no-tumor, as well as a 4-class dataset consisting of glioma, meningioma, pituitary, and no-tumor, was used. By applying image preprocessing steps to the datasets, redundant and unnecessary areas in the images were removed. Then, classification was carried out with EfficientNet, XceptionNet, and CoAtNet models, which used the weight values of the models trained with very large datasets (imagenet) and changed the last layer.

According to the results of the study, while EfficientNet gave the highest success values in binary classification (validation accuracy is 99.98), CoAtNet gave more successful results in multi-classification (validation accuracy is 98.26)., which is a more challenging task. EfficientNet is a model that uses a compound scaling method to increase the depth, width, and resolution of the network in a coordinated way. This allows EfficientNet to be a more efficient and scalable network with improved performance. The CoAtNet model, based on both CNN and Vision Transformer (ViT) architectures, is one of the most successful models developed in recent years. CoAtNet takes advantage of both of these strengths by using a hybrid architecture that combines CNNs and transformers. When compared to high-success studies with similar datasets, it was observed that the success metrics were quite close to those of these studies. In future studies, it is aimed to achieve the highest success values by performing different transfer learning studies with more datasets for brain tumor classification.

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