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Multiclass Classification of Brain Tumors with Various Deep Learning Models †

Fatih Uysal [1,*] and Metehan Erkan [2]

[1] Department of Electrical and Electronics Engineering, Faculty of Engineering and Architecture, Kafkas University, Kars TR 36100, Turkey
[2] Department of Electrical and Electronics Engineering, Faculty of Engineering, Gazi University, Ankara TR 06570, Turkey; metehan.erkan@gazi.edu.tr
* Correspondence: fatih.uysal@kafkas.edu.tr; Tel.: +90-534-022-6128
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Abstract: Brain cancer is one of the most dangerous cancer types in the world, and thousands of people are suffering from malignant brain tumors. Depending on the level of cancer, early diagnosis can be a lifesaver. However, thousands of scans must be studied in order to classify tumor types with high accuracy. Deep learning models can handle that amount of data and they can present results with high accuracy. It's already known that deep learning models can give different results depending on dataset. In this paper, the effectiveness of some of the deep learning models on 2 different publicly available MRI (Magnetic Resonance Imaging) brain tumor datasets is examined. The reason for choosing this topic is that we are trying to find the best solution to classify tumors in the datasets. Different deep learning models are used separately on preprocessed datasets with the CLAHE preprocessing variable to extract features from images and classify them. Datasets are shuffled randomly for 80% training, 10% validation, and 10% testing. For finetuning, models are modified so that the output channel of the classifier is equal to the number of classes in the datasets. Results show that pre-trained and fine-tuned ResNet, RegNet, and Vision Transformer (ViT) deep learning models can achieve accuracies higher than 90% and they can be used as classifiers when diagnosis is required.

Keywords: brain tumors; classification; deep learning; transfer learning

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1. Introduction

Brain is the most complex organ in vertebrates and it locates in the center of the nervous system [1]. Tumor types in brain can be mainly classified as benign and malignant tumors. Also, brain tumors can be classified as primary and secondary. Tumors that start to grow in the tissue of the brain are named as primary brain tumors and if neoplasm has grown in another organ and then affected the brain, that type of tumors are called as secondary brain tumors [2]. The most common primary brain tumors are meningiomas (referred as meningioma tumor), pituitary adenomas (referred as pituitary tumor) and astroglial neoplasms (including glioblastoma and referred as glioma tumor) [3]. Treatments are dependent to patient but common treatment techniques for primary brain tumors are multimodality treatments, radiation and chemotherapy [4].

Although there are many types of benign and malignant tumors, the most common ones are meningioma, glioma, and pituitary. Meningioma tumor forms in the thin layers of tissue which cover the spinal cord and brain [5]. Gliomas are tumors that are thought to derive from neuroglial stem or progenitor cells [6]. They comprise 80% of all malignant brain tumors [7]. Pituitary adenomas are tumors of the anterior pituitary and most of them are benign and slow-growing [8].

In this study, classification of MR images into 4 different tumor classes, normal and 3 different abnormal brain tumor classes, was carried out. Meningioma, glioma and pituitary are the abnormal classes.

2. Related Works

There are many studies have done on brain tumor images with deep learning models in literature. Rajat et. al. have obtained 99.04% binary classification accuracy with their pretrained AlexNet model on a public dataset obtained from The Cancer Imaging Archive (TCIA). The F1-scores of their model for benign and malignant tumors are 0.985075 and 0.992958, respectively [9]. Jianfeng et. al. have obtained 94.82% accuracy and 89.52% precision on multiclass malignant tumor classification of randomly divided CE-MRI dataset with VGG19 model [10]. Javed et. al. used Inceptionresnet V2 model and acquired 98.91% accuracy and 98.28% precision. Their study on a publicly available Kaggle dataset consists of malignant tumor classification [11]. Arshia et. al. studied on publicly available Figshare dataset which consists meningioma, pituitary, and glioma tumor classes. They obtained 98.69% test accuracy with fine-tune VGG16 model, data augmentation, and SGDM optimizer [12]. In another study, Mohamed et. al. used a custom dataset which has 155 tumor and 98 non-tumor brain images. They augmented the dataset to 1516 images and acquired the best accuracy of 98.24% with MobileNet V2 [13].

In the literature, it is seen that especially ResNet50, VGG16, and Inception v3 deep learning models are used to classify obtained MR brain tumor images from different hospitals. In this study, classification processes were done with 3 different deep learning models and preprocessing variable on open-access randomly distributed train, validation, and test datasets, which are different from the literature.

3. Materials and Methods

2 different datasets which are available open-access on the Kaggle platform are used for multiclass classification of MR brain images. Classes, percentages and quantities of datasets can be seen in the table below.

Table 1. Information about DS-1 (Dataset-1).

Classes	Train Split	Validation Split	Test Split	Total
Normal	328	28	40	396
Meningioma	733	98	106	937
Glioma	752	95	79	926
Pituitary	715	95	91	901
Total	2528 (80%)	316 (10%)	316 (10%)	3160

Table 2. Information about DS-2 (Dataset-2).

Classes	Train Split	Validation Split	Test Split	Total
Normal	1587	215	198	2000
Meningioma	1297	174	174	1645
Glioma	1334	143	144	1621
Pituitary	1401	170	186	1757
Total	5619 (80%)	702 (10%)	702 (10%)	7023

In this study, ResNet50, RegNetY_16GF and VisionTransformer_L_16 deep learning based models have been used for the classification process. All information about models and customizations is given below.

ResNet50 used as first model in this study. Residual Networks can be used as image classifiers. Architecture consists of sequential layers, and these layers contain bottleneck blocks [14]. In Torchvision Library, the bottleneck blocks assigned the downsampling strides to the second 3 × 3 convolution, whereas the original paper assigned it to the first 1 × 1 convolution [15]. Last fully connected (FC) layer originally working to classify images into 1000 categories, but datasets have 4 categories (normal, meningioma, glioma, and pituitary). Therefore, the last FC layer's output features are customized to number of classes.

RegNetY_16GF used as second model in this study. RegNet is a product of design spaces [16]. All RegNet models have stem, layer, and head blocks. These blocks can be customized with parameters. Stem layer is a Convolution + Batch Normalization + ReLU block. For this layer stride and filter size are 2 and 3, respectively. Layer block consists of chains of residual blocks. Residual blocks contain of bottleneck blocks as in ResNet but RegNetY model has squeeze and excitation attention module. Finally, head block contains AveragePool2D and FC layer. Similarly, output features customized to number of classes.

VisionTransformer_L_16 (ViT) used as third and the last model. ViT uses different deep learning method called transformer [17]. Encoders are the main blocks and they have multiple layers. Each block consists of three elements: Layer Norm, Multi-head Attention, and Multi-Layer Perceptrons. Like other 2 model, head of model customized as the output features equal to the number of classes.

In the training part, datasets are fed into models where preprocessing is variable. Figure 1 shows the major processes of the training part.

Figure 1. Training Diagram of the Models.

For training and testing, Pytorch implementations of models are used. Training is partially done by HPC sources. Information about hardware can be seen in Table 3.

Table 3. Information about hardware.

CPU	GPU	Memory	OS
Intel Xeon Scalable Gold 6148 (20 cores used)	2 X Nvidia Tesla V100 16 GB	170 GB	CentOS 7.3

Contrast Limited Adaptive Histogram Equalization (CLAHE) preprocess has been applied to RGB images by converting the color format from BGR to LAB and then applying CLAHE on the L channel with a custom clip limit and tile grid size. An example of the CLAHE process can be seen in Figure 2.

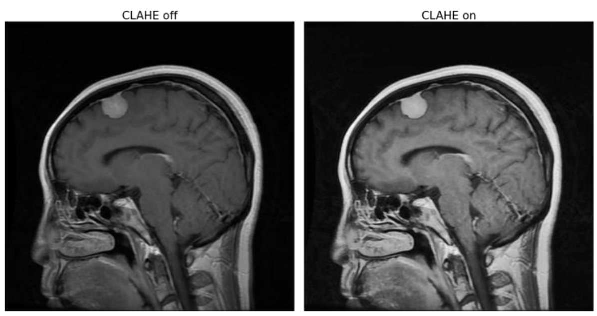

Figure 2. An example of CLAHE process.

4. Results

The obtained results are presented in the tables below. In Table 4, it is seen that the highest accuracy on DS-1 has been acquired with the RegNet model with preprocessing. In Table 5, it can be seen that both VisionTransformer (ViT) and ResNet models have acquired the same accuracy, and preprocessing has not been applied to DS-1. Similarly, Table 6 shows that the best accuracy has been acquired with ResNet and RegNet models on DS-2 with preprocessing. Lastly, Table 7 shows that ResNet 50 has the best accuracy on DS-2 without preprocessing.

Table 4. Results for Various Models on *DS-1 with CLAHE preprocess.*

Model	Accuracy	Precision	Recall	F1 Score
ResNet50	0.94937	0.94	0.94	0.94
RegNetY_16GF	0.96519	0.96	0.96	0.96
VisionTransformer_L_16	0.9557	0.95	0.95	0.95

Table 5. Results for Various Models on *DS-1 without CLAHE preprocess.*

Model	Accuracy	Precision	Recall	F1 Score
ResNet50	0.95253	0.95	0.94	0.95
RegNetY_16GF	0.93354	0.93	0.93	0.93
VisionTransformer_L_16	0.95253	0.95	0.94	0.95

Table 6. Results for Various Models on *DS-2 with CLAHE preprocess.*

Model	Accuracy	Precision	Recall	F1 Score
ResNet50	0.99288	0.99	0.99	0.99
RegNetY_16GF	0.99288	0.99	0.99	0.99
VisionTransformer_L_16	0.9886	0.99	0.99	0.99

Table 7. Results for Various Models on *DS-2 without CLAHE preprocess.*

Model	Accuracy	Precision	Recall	F1 Score
ResNet50	0.9943	0.99	0.99	0.99
RegNetY_16GF	0.99145	0.99	0.99	0.99
VisionTransformer_L_16	0.99003	0.99	0.99	0.99

5. Conclusions and Future Work

In the scope of this work, MR brain images are classified with various deep learning models, and it is observed that the Contrast Limited Adaptive Histogram Equalization (CLAHE) preprocess has positive effects on some of the models and datasets. Classification results are highly dependent on used dataset and deep learning model. As a result of multiclass classification study, the highest accuracy and recall on DS-1 have been 96.519% and 96%, respectively, and these results have been achieved with the RegNetY_16GF model. For DS-2, the best model has been ResNet50. Furthermore, accuracy and recall have been 99.43% and 99%, respectively. The best results on DS-1 have been achieved with the CLAHE preprocess. In contrast, the CLAHE did not improve results on DS-2.

In future work, a hybrid system can be developed to assist physicists who are working in this field. Machine learning (ML) algorithms can be an addition to deep learning models in this system.

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