

Convolutional Neural Network Based on Brain Tumor Identification and Classification

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Abstract. The human brain is one of the body's most major organs. If there are problems within the human brain, they may cause serious consequences, and even endangers the human life. One of the most fatal diseases for humans is a brain tumor. In the old days, tumor detection was done manually by doctors through reading magnetic resonance images, which might not be time efficient, and sometimes may even produce inaccurate results. Nowadays, with the development of science and technology, Artificial Intelligence (AI) is present in many fields in human life, including medical field. Tumor detection with AI is one of the applications that technology changes human life. The Convolution Neural Network (CNN), a prominent algorithm in deep learning, is widely employed in tumor identification. In this study, a CNN model is proposed. Over 7000 brain tumor magnetic resonance images, including glioma, meningioma, no tumor and pituitary are used in this study. The images are also preprocessed to improve the accuracy of the proposed models. In this study, the well-known VGG16 model, which is a pretrained deep learning model, is utilized to compare with the proposed model. The proposed model and the VGG16 model are trained and evaluated using both the original (uncropped) images and preprocessed (cropped) images. The results of the experiment indicate that the suggested model exceeds the VGG16 model in the light of loss and accuracy.

Keywords: Brain tumor, CNN, Magnetic reasoning imaging.

1. Introduction

Brain tumor is a possibly deadly disease for humans. They are caused by cancer cells that grow uncontrolled and attack brain tissue. To detect brain tumor, a type of scan called Magnetic Resonance Imaging (MRI) is required. There are many kinds of tumors, including glioma, meningioma and pituitary, which will be discussed in this study. Glioma is among the most prevalent brain tumors derived from adult glial cells. Gliomas make for 80% of all malignant tumors and 30% of all major brain tumors [1]. Symptoms of glioma include vomiting, illnesses, headaches and irritation. Meningioma is also among the most prevalent forms of brain tumors [1]. Meningiomas originate from the brain's dural covering. They represent 13–26% of all primary intracranial tumors and are the most prevalent benign intracranial tumor [2]. Pituitary tumor is in the pituitary gland which affects the working of the pituitary gland. Pituitary tumor mostly appears in the third and fourth decade of human life and counts for about 10% of the adult intracranial tumors [3].

MR imaging enables noninvasive evaluation of mesoscopic brain tumor characteristics and is a crucial tool for early tumor identification, monitoring, and diagnosis [4].

There are three main reasons for why magnetic resonance imaging is such a crucial component in the patients who have glioblastoma. To begin, MRI has a fantastic capability for the identification of contrast in soft tissues because it offers the greater anatomical information. Second, the different MR imaging sequences have the potential to be sensitive to the important aspects of tumor features, such as cellular density and blood flow, and have the ability to differentiate between tumor regions that contain distinct environments which are likely to influence the genotypes and phenotypes of local cells. Lastly, MRI can be used repeatedly to evaluate the tumor's response to treatment in a nondestructive and noninvasive manner, and it can be incorporated into therapeutic plans [5].

2. Related works

In recent years, as a result of the advancement of science and technology, an increasing number of algorithms, especially CNN, are capable of accurate image classification. A significant number of people have attempted to classify brain tumors using CNN models.

RamdasVankdothuet al. [2] suggested a CNN-LSTM based deep learning model. LSTM, which is the abbreviation for Long-Short-Term-Memory, can give an extra help to CNN to extract features performs better than pure CNN layer. Theuseddatasethas 2870 magnetic resonance images for training and 394 images for testing, includes glioma, meningioma, pituitary and no tumor. The CNN-LSTM model is able to get an accuracy of 0.92, which outperforms CNN and RNN models in the light of accuracy, precision and recall.

Kai Roman Laukampet al. [6] suggested a multiparametric deeplearning modelwhich is based on the DeepMedic architecture. The model was trained using a separate dataset made up of 249 glioma cases, and it segmented several tumor classifications according to the benchmark for brain tumor image segmentation (BraTS benchmark) and it was able to predict 55 out of 56 meningioma cases.

Sidra Sajid et al. [7] suggested aCNN model which is based on different modalities of MR images.The images first undergo a preprocessing process. This process will eliminate the noises such as bias field distortions or motion heterogeneity by using N4ITK method, which normalizes the input images and will increase the quality of the input images. The images then undergo a hybrid CNN architecture which is built by combining two-path and three-path CNNs. This hybrid CNN classifies individual patch's central pixel valueby a patch-based approach. Based on the pixel value, local and global features, the model then predicts labels for the images. The images then undergo a post-processing process to remove some false positives. TheBraTS 2013 dataset is used to validate the model, which gives score of 0.86 in dice score, 0.86 in sensitivity and 0.91 inspecificity.

Nilesh BhaskarraoBahadure et al. [8] suggested aSupport Vector Machine (SVM) and Berkeley wavelet transformation (BWT) based model. The model removes black edges surrounding the images using morphological operations before extracting details about the image, for example, contrast and color. The accuracy, specificity, and sensitivity of the model's output were 0.9651, 0.942, and 0.9772, respectively.

Javeria Amin et al. [9] suggested a model for the detection of brain tumor using Deep Neural Networks (DNN). There are 7 layers in this model, which are 3 convolutional layers, 3 ReLU layers and 1 softmax layer. The model first divides the MR images into numerous patches and provides each patch's center pixel value to DNN. The DNN can assign labels based on center pixel value and perform segmentation. The used datasets in this study are from BraTS and ISLES. There are five different MR forms in this dataset, including spin-spin relaxation, fluid attenuation inversion recovery, diffusion weighted image, T1, and T1-contrast. The results for the different forms of MR images are 0.98, 1, 0.998, 0.974 and 0.954, respectively.

3. Methodology

3.1. Dataset description

The dataset that is utilized in this project is known as the Brain Tumor MRI Dataset [10], and it is acquired from Kaggle. The images are divided into training and testing folders, with each folder containing the categories "glioma," "meningioma," "notumor," and "pituitary." Following this step, one half of the images in the testing folder are copied into a new validation folder in order to complete the model validation process while the model is being executed. Over the course of all the folders, there are a total of 7022 images. The distribution of the images is depicted as follows in Figure 1.

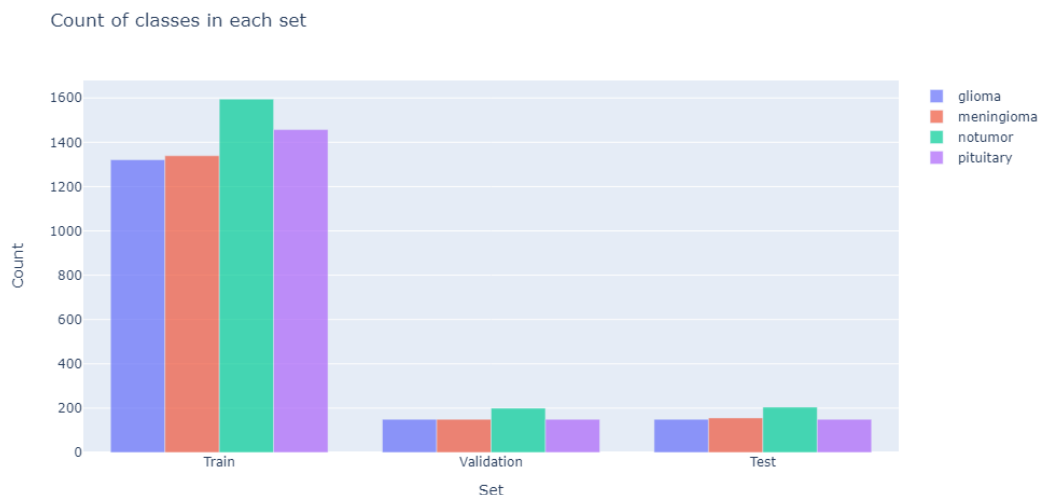


Figure 1. Distribution of images

3.2. Data Augmentation

Figure 2 displays a selection of the dataset's original images:

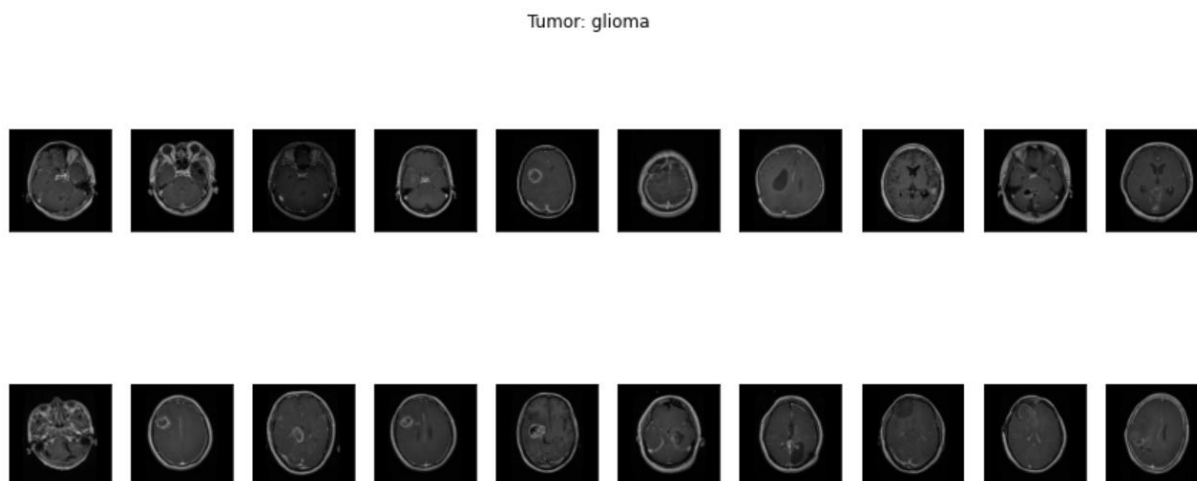


Figure 2. Visualization of original glioma images

In Figure 2, one potential problem of these images is that there are black areas around the main portion of the image, which can negatively affect the accuracy of the models that use the, so data augmentation of cropping those black areas is implemented to all the images in the dataset. The augmented data are depicted in Figure 3:

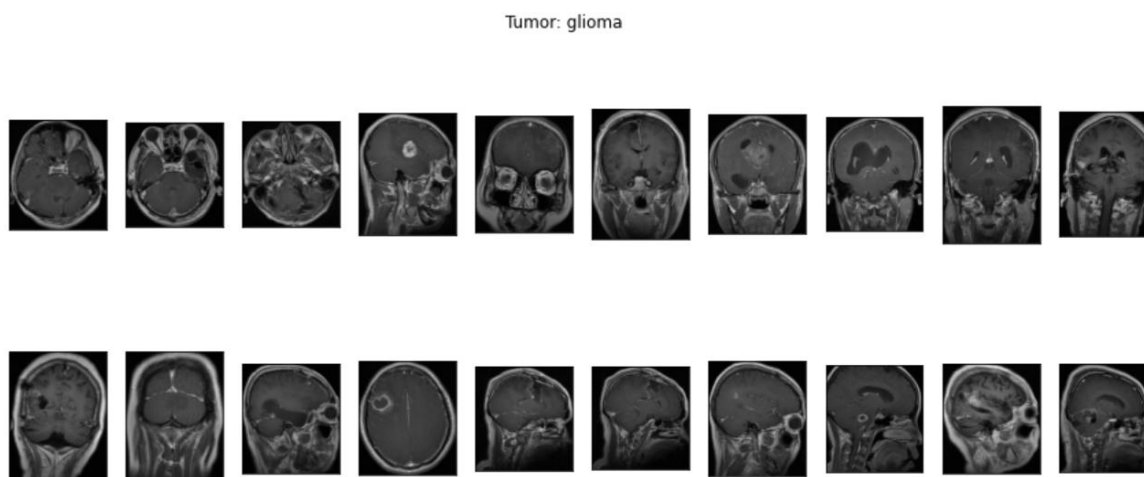


Figure 3. Visualization of cropped glioma images

The augmented data will increase the image quality and will be helpful in building better deep learning models.

3.3. CNN

CNN is utilized in this study. CNN is an algorithm in deep learning which extracts information from input images by convolving them using filters or kernels [11]. It has many layers, which includes convolutional, non-linearity, max pooling and fully connected layers. CNN excels at machine learning tasks, particularly those involving image classification, computer vision, and natural language processing (NLP) [12]. A CNN network passes an image to multiple layers. Each layer receives as input the preceding layer's convolved output along with some learned features, then passes into batch normalization that normalizes the results across all feature maps [13] and passes to a max pooling layer that calculates the max value for patches of a feature map. The outputs then go to a flatten layer that flattens the inputs into one-dimensional result. This is used in the transaction of convolved layer into fully connected layer. It then uses the flattened layer's output and assigns weights to determine the proper label. The output then goes to the final layer, which is a softmax classifier that can give the probability of each label [13].

3.4. Proposed CNN Model

This study's proposed CNN model is developed in Python by using the TensorFlow library and Keras library. Figure 4 illustrates the CNN model's structure:

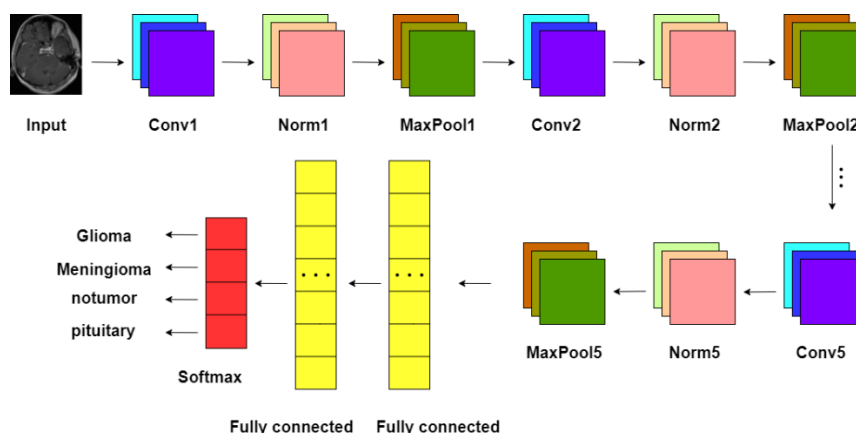


Figure 4. Proposed CNN model structure

As depicted in Figure 4, the model is made up of five convolution layers, with one batch normalization and one max pooling layer after each convolution layer, 2 fully-connected layers and 1 softmax classifier.

3.5. VGG16

Other than the proposed model, the pre-trained VGG16 model is also used in this study, as a comparison of the proposed model. Karen Simonyan and Andrew Zisserman proposed in 2014 the VGG16 model, a CNN model with 16 convolution layers [14]. There are in total 21 layers in the model, including 13 convolutional layers and together with 5 max pooling layers among them. At the end of the model are 3 dense layers. Figure 5 demonstrates the structure of the VGG16 model.

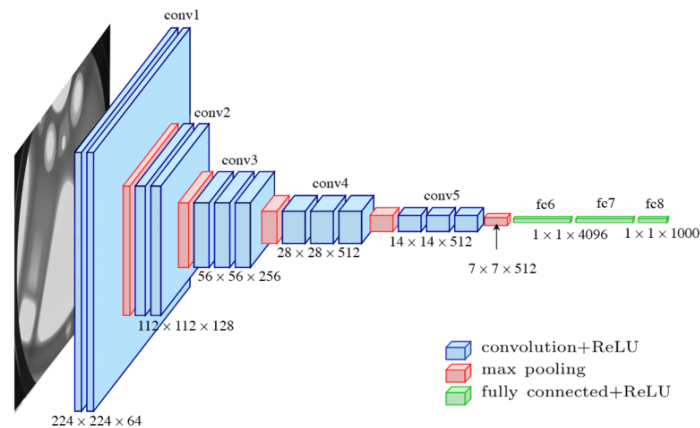


Figure 5. VGG16 structure

4. Results

The original and augmented images are trained by using both the proposed and VGG16 model. Each model is trained for 100 epochs using TensorFlow GPU with Nvidia RTX 3070. The batch size for training is 32 and the learning rate is 0.001. The time took to train each epoch is 18s. Table 1 below shows the model evaluation comparison.

Table 1. Results comparison

Model	Dataset	Accuracy	Loss
Proposed CNN	Original	0.7625	0.6639
	Augmented	0.9486	0.2185
VGG16	Original	0.9410	3.6927
	Augmented	0.9168	7.2522

The proposed CNN model has the highest accuracy, 0.95, and the lowest loss, 0.21, as shown in Table 1. Although the VGG16 model with the original dataset has similar accuracy, compared to the proposed CNN model with the augmented dataset, the loss is much higher.

Table 2 below shows the classification report of the two models with different dataset. The numbers in the proposed CNN model with augmented dataset outperform the others.

Table 2. Classification reports

Model	Dataset	Metric	Glioma	Meningioma	Notumor	Pituitary	Overall accuracy
Proposed CNN	Original	Precision	0.85	0.58	0.86	0.93	0.76
		Recall	0.52	0.9	1	0.54	
		F1-score	0.64	0.7	0.92	0.68	
	Augmented	Precision	0.96	0.89	0.99	0.94	0.95
		Recall	0.87	0.92	1	0.99	
		F1-score	0.92	0.9	1	0.96	
VGG16	Original	Precision	0.89	0.93	1	0.93	0.94
		Recall	0.93	0.83	1	0.99	
		F1-score	0.91	0.88	1	0.96	
	Augmented	Precision	0.8	0.99	1	0.89	0.92
		Recall	0.97	0.69	1	0.99	
		F1-score	0.88	0.81	1	0.94	

Model testing is done using the testing dataset. Figure 6 to Figure 9 below show the confusion matrix of the prediction result of the testing set.

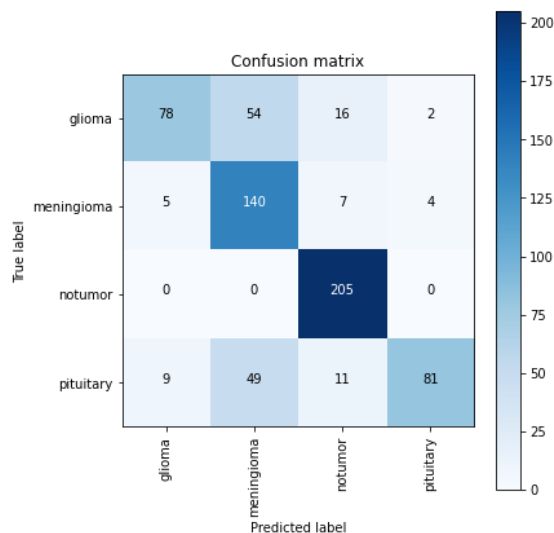


Figure 6. Prediction confusion matrix on proposed CNN model with original dataset

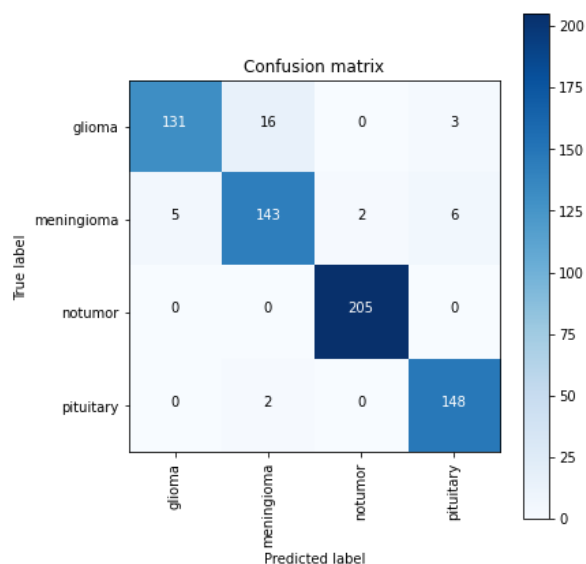


Figure 7. Prediction confusion matrix on proposed CNN model with augmented dataset

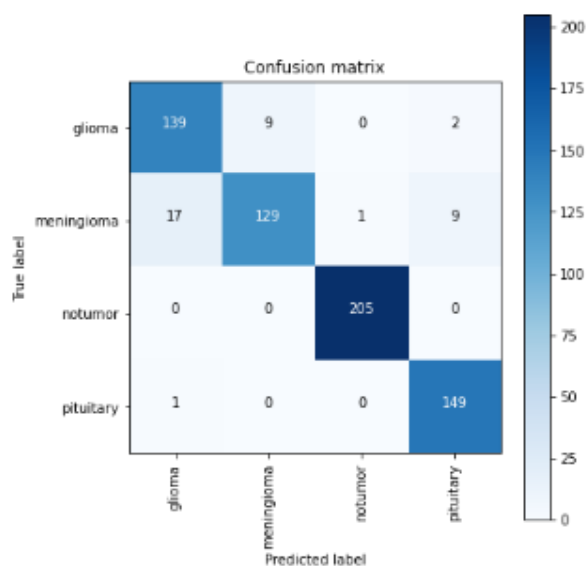


Figure 8. Prediction confusion matrix on VGG16 model with original dataset

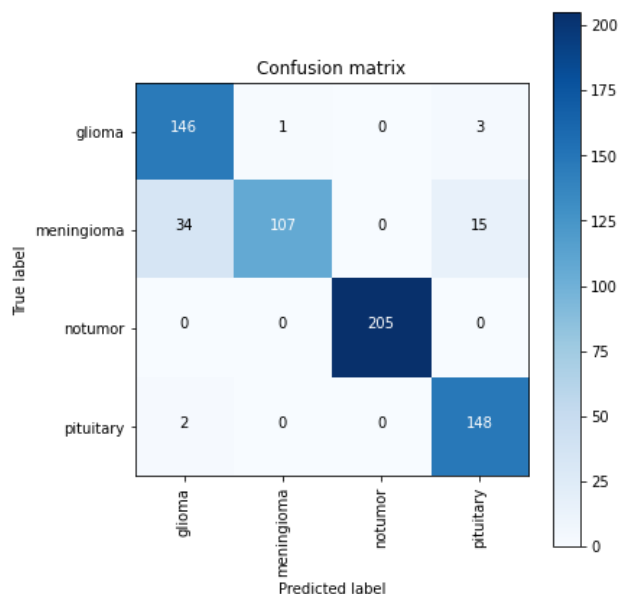


Figure 9. Prediction confusion matrix on VGG16 model with augmented dataset

5. Discussion

Given the high levels of accuracy that are achieved in the study's detection of brain tumors, the findings suggest that AI is now capable of being utilized in the field of medical. The application of AI in the medical area, for example tumor detection, can improve the efficiency and accuracy of patient diagnosis and is, as a result, an important contribution to the world. In relation to the model that has been suggested, it is absolutely necessary to carry out data preprocessing prior to the construction of models. According to the findings, making use of the preprocessed dataset rather than the original dataset results in a significant improvement of accuracy (nearly 19 percent). This result demonstrates that cropping parts of the data that are not useful for training deep learning models is an essential step that must be taken. There are many pretrained models, such as VGG16, that can be used directly in performing deep learning tasks. Nevertheless, the results may vary depending on the dataset that is being utilized. In this study, the VGG16 model, when applied to the primary dataset, is capable of achieving an accuracy of 0.94. Despite this, the model has a high loss of 3.6, which indicates that the model is not all that reliable. When applied to data that has been preprocessed, the model that has been proposed can achieve an accuracy of 0.95 with only 0.22 of loss. This demonstrates that the model that was proposed is more appropriate for the dataset at hand, and as a result, it can be considered valid. Due to hardware limitations, certain enhanced models, such as PCA+CNN and SVM+CNN, are unable to be utilized in this study. Because there are other models that might produce better results, it is recommended that additional research be done for this study.

6. Conclusion

Cancerous tumors pose a threat to human life. It is crucial to detect them at an early stage in order to give individuals a longer lifespan. Because of advancements in technology, determining the type of a tumor no longer relies solely on the method of manually identifying its presence by a medical professional. The results will be communicated in a more precise and timely manner by using deep learning models. In this study, a CNN model that was self-designed is offered as a method for diagnosing brain tumors. The suggested model is trained using magnetic resonance (MR) pictures of brain tumors. For the purposes of model training and evaluation, the input data is first preprocessed by cropping the black edges that surround the image. In addition to that, a pre-trained VGG16 model is employed for model comparison purposes. The results are as follows: accuracy of 0.76 when using the proposed model with the original (not preprocessed) dataset; accuracy of 0.95 when using the

proposed model with the preprocessed dataset; accuracy of 0.94 when using the VGG16 model with the original (not preprocessed) dataset; and accuracy of 0.92 when using the VGG16 model with the preprocessed dataset. According to the findings, the proposed model using the preprocessed dataset had the highest accuracy and the lowest loss of all the models tested.

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