Detecting Tumors in MRI Scans using a Convolutional Neural Network

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Abstract

A brain tumor is a dangerous cancer that develops when cells divide uncontrollably and abnormally. Recent advancements in deep learning have aided the medical imaging industry in diagnosing various disorders medically. Convolutional neural networks are the most often used machine learning algorithm for visual recognition and learning. Additionally, we demonstrate by using CNN to classify brain MRI images into two categories: cancer and non-cancer. Using the transfer learning method, we evaluated our convolutional model's performance to previously trained ResNet-v2-152, Inception-v3, and Inception-Resnet-v2 models. As a result of the experiment, a moderate dataset was used. However, the test result indicates that the suggested model's accuracy was adequate, reaching 99 percent, compared to 98 percent for ResNet-v2-152, 98 percent for Inception-v3, and 97 percent for Inception-Resnet-v2. The suggested model requires far less computational resources and is more efficient.

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By Amid Seyedhashemi and Dr. Mehdi Esmaeili keywords: Tumors, MRI scans, Convolutional Neural Network (CNN), Medical imaging, Computer-aided diagnosis (CAD)

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Introduction

Brain tumors are caused by an unusual growth of cells in the brain and can either be primary (non-cancerous) or secondary (cancerous). Primary tumors are benign and don't spread, but secondary tumors can spread to other areas of the brain and body. As a tumor grows, it increases pressure on the brain, which can be dangerous. Early detection of brain tumors is important for successful treatment. Brain tumors are considered to be one of the most serious and deadly forms of cancer that both adults and children can get. However, if treated early and properly, it can prevent the disease from spread, stop the growth of tumors, and reduce the cost of medicine and treatment. Today, specialists can diagnose brain tumors using computer systems with modern technology, making it easier for professionals to identify tumors while avoiding errors in traditional methods. In the past, biopsy was used for diagnosis but it was uncomfortable for patients and required prior MRI or CT scans. MRI is a safer option as it doesn't use radiation and provides precise imaging of malignancies. However, manual examination of many MRI images is time-consuming and not always accurate. Automated detection using convolutional neural networks has shown to provide more accurate results than traditional methods, as radiologists can miss between 10-30% of cancers during both diagnostic and screening stages.

Related work

Abdul Hannan Khan and et al., [1] presents a hierarchical deep learning (HDL2BT) model, leveraging convolutional neural networks (CNNs), for tumor classification into four categories: glioma, meningioma, pituitary, and no tumor. The model demonstrated an accuracy of 92.13% and an error rate of 7.87%. Sidra Sajid and et al., [2] propose a method that involves a pre-processing stage for normalizing the images and correcting bias field, followed by a feed-forward pass through a CNN, and a post-processing stage to eliminate false positives around the skull region. The proposed method is evaluated on the BRATS 2013 dataset, attaining DICE score, sensitivity, and specificity scores of 0.86, 0.86, and 0.91 for the whole tumor region, respectively.

Masoumeh Siar and Mohammad Teshnehlab., [3] proposed a model that utilizes a Radial Basis Function (RBF) classifier and a Decision Tree (DT) to obtain an accuracy of 97.34% and 94.24% respectively in a Convolutional Neural Network (CNN). The results indicate that the Softmax classifier achieved the highest accuracy within the CNN. The proposed method demonstrated an accuracy of 99.12% on the test data. Tanzila Saba and et al., [4] proposed a method that uses the Grab Cut technique to precisely segment real lesion marks, utilizing a transfer learning model (VGG-19). The method was tested using the Dice similarity coefficient (DSC) on the BRATS 2015, 2016, and 2017 datasets, resulting in scores of 0.99, 1.00, and 0.99, respectively.

Hari Mohan Rai and Kalyan Chatterjee,. [5] proposed a method for abnormality detection from brain MR images using the U-Net model architecture with less and less complex layers (LeU-Net) is proposed. The LeU-Net model results overall record of 98% accuracy on cropped images and 94% accuracy on uncropped images. Zheshu Jia and et al., [6] presented a Fully Automatic Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM) method for brain tumor segmentation utilizing deep learning techniques. The numerical results demonstrate an accuracy of approximately 98.51% in separating abnormal and normal tissue in brain magnetic resonance images.

Ali Mohammad Alqudah and et al., [7] applied a Convolutional Neural Network (CNN) to classify brain tumors into three classes (glioma, meningioma, and pituitary tumor) using a dataset of 3064 T1 contrast-enhanced brain MR images. The model showed an overall accuracy of 98.93% and sensitivity of 98.18% for cut lesions and 99% accuracy and 98.52% sensitivity for uncut lesions. For segmented lesion images, the model achieved an accuracy of 97.62% and sensitivity of 97.40%. Nadim Mahmud Dipu and et al., [8] used the Yolo and FastAi libraries to apply it to the BRATS 2018 dataset. The results showed that the YOLOv5 model achieved an accuracy of 85.95%, while the FastAi classification model achieved an accuracy of 95.78%.

Neelum Noreen and et al., [9] investigated the use of two pre-trained deep learning models, Inception-v3 and DensNet201, for tumor detection. The results showed that the models achieved a test accuracy of 99.34% and 99.51%, respectively. P Gokila Brindha and et al., [10] proposed the use of a self-defined artificial neural network (ANN) and a convolutional neural network (CNN) for brain tumor detection and analyzed their performance. The ANN model generated in this work achieved a test accuracy of 65.21%. Ahmad Saleh and et al., [11] trained a brain tumor dataset using five pre-trained models: Xception, ResNet50, InceptionV3, VGG16, and MobileNet. The F1 score measurement of unseen images achieved 98.75%, 98.50%, 98.00%, 97.50%, and 97.25% respectively.

Suggested techniques

The research evaluated 3,000 brain MRI scans (Figure. 3-1) by using image processing techniques. A six-layer convolution model was employed for training purposes and its performance was compared to pre-existing models such as ResNet-v2-152, Inception-v3, and Inception-Resnetv2. The dataset used consisted of 1,500 images of malignant cancers and another 1,500 images of benign non-cancerous tumors.

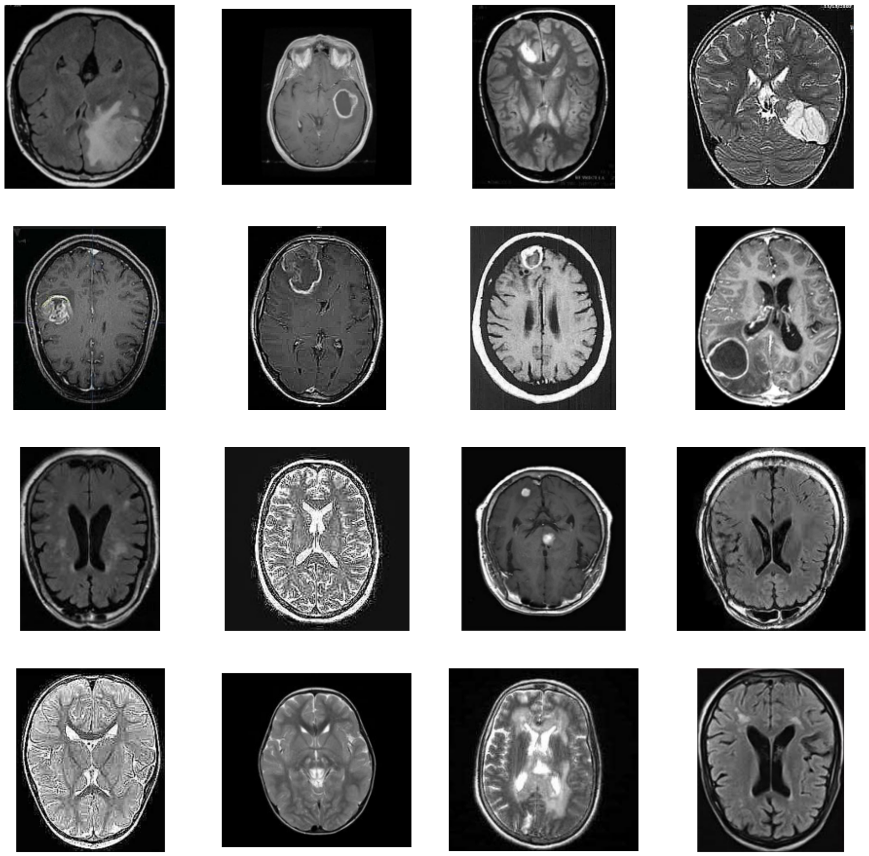

Figure. 3-1

The data was divided into three subsets: training, validation, and testing. The training data trains the models, the validation data is used to assess and adjust the model's parameters, and the test data finalizes the proposed model. The method proposed involves several steps and is illustrated in a high-level overview in Figure (3-2).

3-1. Convolutional model

In our research, we proposed a simple convolutional neural network model that processed 229x229 MRI image data. The model incorporated RGB color channels with a batch size of 64 for the input size. To recognize curves, arcs, and borders, we added a 16-filter CNN layer with a filter size of 3x3, followed by a max-pooling layer with a filter size of 2x2. To capture a comprehensive view of the image, we included convolution layers and filters with increasing numbers (16, 32, 64, 128, 256, and 512) and 3x3 filter sizes, based on the Resnet and VGG networks. The model was able to identify larger patterns by increasing the number of filters and merging the layers, and the max-pooling layers applied to the CNN layers provided the most benefits. Finally, we combined the Softmax output layer with a fully connected dense layer of 1024 neurons, which calculated the probability for each class and determined whether the input MRI image contained cancer or not. To improve the efficiency of the proposed model, we also applied the Drop Out technique for network regularization and pruning. The proposed convolution architectural plan is shown in Figure 3-3.

Figure 3-3. Proposed convolution model architecture

3-1-1. Activation function:

ReLU (Rectified Linear Unit) [12] is a commonly used activation function in neural networks. It replaces all negative values in the input with 0 and returns the positive values unchanged. Mathematically, ReLU can be represented as y = max(0, x), where x is the input and y is the output. ReLU activation is preferred over sigmoid and hyperbolic tangent activation functions for hidden layers as it introduces non-linearity and does not face the vanishing gradient problem.

3-1-2. Loss function:

A loss function [13] is a mathematical function used to measure the difference between the predicted output and the true output in machine learning. The goal of training a model is to minimize the loss function, indicating that the model's predictions are close to the true output. Loss functions can be different for different types of problems, such as classification and regression, and must be carefully chosen to match the requirements of the problem. The choice of loss function can greatly impact the model's performance, as different loss functions may prioritize different aspects of the prediction, such as accuracy or robustness.

3-1-3. Optimization:

The optimization process involves identifying the optimal solution out of all possible solutions for a problem in mathematics and computer science. In the context of machine learning, it entails modifying the model's parameters in order to reduce the loss function and enhance the accuracy of the model's predictions. Also Optimization plays a vital role in the training phase of machine learning models and has a significant impact on their effectiveness. The optimization procedure is usually a repeated process of modifying the model parameters until the loss function reaches its minimum value. In our research, we apply the Adaptive Moment Estimation(Adam) optimizer [14].

3-1-4. Regularization:

Regularization [13] is a method in machine learning aimed at reducing overfitting by adding a penalty term to the model's loss function. Overfitting occurs when a model fits the training data too well, leading to poor performance on new data. The added penalty discourages the model from assigning too much weight to certain features and helps prevent overfitting. Different types of regularization exist, including L1, L2, early stopping, and dropout, and the choice of which to use depends on the problem and model. Regularization plays a crucial role in improving the performance of machine learning models.

3-1-5. Dropout:

Dropout [15] is a method employed in deep learning to keep the model from overfitting to the training data by dropping out neurons randomly during the training process. The aim is to make the model learn more generalized features and avoid memorizing the training data. The ratio of dropped out neurons is a hyperparameter that can be fine-tuned to achieve the ideal balance between overfitting and underfitting. Dropout is often combined with other regularization techniques to enhance the performance of models in computer vision and natural language processing applications.

3-2. Transfer Learning:

Transfer learning is a machine learning strategy that uses a pre-trained model as a starting point to solve a new, but related, problem. Instead of training a model from scratch, transfer learning allows to fine-tune the pre-trained model to the new task or to use it as a feature extractor to train a new classifier. This approach saves time and resources, and can result in improved performance on the new task. Transfer learning is commonly applied to computer vision and natural language processing problems, using pre-trained models on large datasets as the starting point for new tasks.

3-2-1. ResNet-v2-152:

ResNet-v2-152 [16] is a deep neural network architecture with 152 layers, based on the ResNet (Residual Network) design. It is an updated version of the original ResNet, which aims to overcome some of the challenges faced during deep network training. With a large number of parameters, ResNet-v2-152 is considered a very deep network, making it suitable for computer vision tasks such as image classification, object detection, and segmentation. Its depth and the residual connections in its design allow the network to effectively learn hierarchical features and handle high-level abstractions.

3-2-2. Inception-v3 : Inception-v3 [17] is a deep neural network architecture for image classification. It is a variation of the Inception architecture, which was created to tackle challenges associated with training deep networks, such as computational and memory demands. Inception-v3 has been optimized to be computationally efficient while still delivering high accuracy in image classification tasks. The architecture features a modular design, utilizing multiple Inception modules that perform convolution and pooling with various kernel sizes, allowing the network to learn both detailed and broad features. This architecture has been trained on the massive ImageNet dataset and has been shown to achieve top results in different computer vision tasks.

3-2-3. Inception-ResNet-v2:

Inception-ResNet-v2 [18] is a deep convolutional neural network architecture . It combines the Inception architecture with residual connections from ResNet to form a hybrid architecture that has both the ability to learn hierarchical features and the ability to alleviate the vanishing gradient problem in deep networks. The architecture has been used for various computer vision tasks, including image classification and object detection.

Simulation and results:

Data is gathered from the brain tumor MRI image database by Ahmad Hamada [19]. This data set, which contains 3,000 actual brain scans produced by radiologists using data from patients with malignancies, is open to the public. There are lots of good data sources for machine learning tournaments, such as Kaggle, which has a lot of datasets available. Our data is split into two sections: training and validation. The model includes 2550 images for training, 224 images for validation, and 226 images for testing With a batch size of 64, we trained the models for 16 epochs. On the Google Colab Pro platform, this experiment was conducted using Python's TensorFlow and Keras libraries. Our suggested model was 100 percent accurate in our training data, and in our validation dataset, it was 99 percent accurate.

We employed the transfer learning approach to compare our convolution model to the pre-trained ResNet-v2-152, Inception-v3, and Inception-Resnet-v2 models on a dataset. ResNet-v2-152 has a 100 percent accuracy in training data and a 99 percent accuracy in validation data, Inception-v3 has a 99 percent accuracy in training data and a 96 percent accuracy in validation data, and Inception-Resnet-v2 has a 97 percent accuracy in training data and a 99 percent accuracy in validation data. In validation data, it achieved a 98 percent success rate. On Figure 3-8, we can see how accurate our suggested models were during the test and validation phases during the iterative process.

Figure 4-1. Accuracy diagrams of different models

The terms True Positive (TP) and True Negative (TN) denote incorrect classification. True Positive corresponds to unusual brain images, and True Negative corresponds to the presence of normal brain images. On the other hand, False Positive (FP) and False Negative (FN) results indicate faulty classification, with FP showing that standard brain images were incorrectly categorized as tumors and FN indicating that unusual brain images were incorrectly categorized as negative tumors.

Table 1

Models name	(TP)	(TN)	(FP)	(FN)

Models name	(TP)	(TN)	(FP)	(FN)
Suggested Model	111	113	2	0
ResNet-v2-152	111	111	2	2
Inception-v3	110	113	3	0
Inception-Resnet-v2	107	113	6	0

In Table 2, some measurement values for CNN models are listed, as well as the training time for each model.

Table 2

Models name	Accuracy	Precision	Recall	F1-Score	ROC-AUC	Training time (Second)
	0.99	0.99	0.99	0.99	0.9999	153
ResNet-v2-152	0.98	0.98	0.98	0.98	0.9992	300
Inception-v3	0.98	0.99	0.99	0.99	0.9958	164
Inception-Resnet-v2	0.97	0.97	0.97	0.97	0.9989	246

The Rock Curve (ROC Curve), known as the Receiver Operating Characteristics, is a graphical diagram that demonstrates the ability to detect a binary classification measurement system

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Figure 4-2

Conclusion:

Using a CNN network for brain tumor categorization, we evaluate the efficacy of the network in this study. We have found that although though a large amount of data is required to train the neural network, we can get almost 100 percent accuracy with a medium-sized dataset, according to our experiments.Our accuracy is better than ResNet-v2-152, Inception-v3, and Inception-Resnet-v2. Suggested model takes 153 seconds, compared to 300 seconds for the ResNet-v2-152, 164 seconds for the Inception-v3, and 246 seconds for the Inception-Resnet-v2. As a result, suggested model requires fewer computing parameters due to its shorter run time. Suggested model is significantly more accurate than ResNet-v2-152, Inception-v3, and Inception-Resnet-v2. Our proposed method may be predictive in diagnosing cancers in patients with brain tumors. A detailed hyperparameter configuration and a more efficient preprocessing strategy can be considered to improve the model's efficiency further. However, in future work, the proposed method could be extended to other classification problems such as identifying brain tumors, and it could be used to detect dangerous diseases early in other medical cases areas and related to medical imaging, such as lung and breast cancer, which have extremely high global mortality rates.

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