A

Report on

Segmentation and Classification of Brain Tumor Using Convolution Neural Network

By

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Dedicated to

1. My parents, without whom, I would `not have been able to reach where I am right now.

2. My mentor, who looked over me and guided me at every step with a big heart and kind words.

3. My seniors and friends, who advised me whenever I got stuck at any point in time.

Declaration

1. The work contained in this report is original and has been done by myself and the general supervision of my supervisor.

2. The work has not been submitted for any project.

3. Whenever any material (data, theoretical analysis, results) is used from other sources, credits have been given to them by citing them in the text of the thesis and giving their details in the references.

4. Whenever I have quoted written materials from other sources, I have put them under quotation marks and give due credit to the sources by citing them and giving the required details in the references.

Place IIT(BHU) Varanasi
Date:12/07/2023

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Certificate

This is to certify that the work contained in this report entitled "Segmentation and Classification of Brain Tumor Using Convolution Neural Network" being submitted by Jaydip Kumar Singh, carried out in the Department of Computer Science and Engineering, Indian Institute of Technology (BHU) Varanasi, is a bona fide work of my supervision.

Place: IIT (BHU) Varanasi
Date:12 /07/2023

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Date:12 /07/2023

Abstract: Clinicians must have knowledge of the symptoms and locations of brain tumours in order to diagnose and treat patients. It is essential for the diagnosis, follow up, and therapy planning of the condition to automatically segment brain tumours using 3D MRI.Manual delineation techniques are expensive, time-consuming, labor intensive, and subject to human mistake. Here we describe method to classify brain tumor into one of the three classes .

Contents

Introduction

1.1 Overview

Deep learning-based brain tumor classification from brain magnetic resonance imaging (MRI) is a significant research problem. The research problem encounters a major challenge. The training datasets used to develop deep learning algorithms could be imbalanced with significantly more samples for one type of tumor than others. This imbalance in the training dataset affects the performance of tumor classification using deep learning models as the classifier performance gets biased towards the majority class.

The objective of this study is to develop a model for detecting and classifying objects in images. The accurate identification of objects in images has various applications in computer vision and object recognition tasks. This methodology outlines the steps taken to build and train a convolutional neural network (CNN) model for this purpose.

1.2 Motivation

Medical image classification constitutes a fundamental task in the expert systems for computer-aided disease diagnosis. A well- researched topic in this area is brain tumor classification from magnetic resonance imaging (MRI). Prompt and accurate classification determines the effectiveness of therapeutic planning.

There are various state of the art solutions, which address this problem. But, fur ther improvement in performance faces numerous challenges. To name a few, there is limited availability of medical images for training deep learning models. Many of the available datasets for a particular category of tumor are small-sized. Training deep learning models on small datasets encounters a serious drawback. Another challenge is the imbalance concerning the class-specific samples in a training dataset. This problem leads to a trained model that has a biased performance and results in mis classifications between the majority class and the minority classes.

Most of the existing works stress upon the improvement in loss functions and have not focussed much on the classifiers. So, in this article, the overall performance of the model is optimized by modifying the classifier.

1.3 Organization of the Report

In the first chapter, we give the background and motivation of our project. Also, we discuss the various open issues and challenges in Brain MRI Classification using CNN. Then in the second chapter, we provide, the literature review of the research in this area. In the third chapter, we explain the implemented model. In the fourth chapter, we analyse the results of our model . Finally, in the fifth chapter, we conclude our project

Literature Review

2.1. Related Work

2. In another approach [2], a content-based medical image retrieval (CBMIR) sys tem was proposed for the retrieval of magnetic resonance imaging (MRI) images of the brain. The proposed system used GoogLeNet encodings via transfer learn ing as image features. A Siamese Neural Network was designed, to represent the GoogLeNet encodings in a (2-D) feature space. The similarity, between a query image and the database images, was measured by the Euclidean metric in the lower dimensional feature space. The proposed approach adopted a com putationally, less intensive design for the SNN.Though this approach was able to reduce the dimension of deep CNN features effectively, but the use of two trainable neural networks in the algorithm for feature extraction and similarity learning made it less preferable.

3. In the next paper [3], the authors focussed on developing accurate models that could be trained effectively using a smaller number of data samples. A siamese neural network (SNN) with a 3-layer, fully connected neural network was de signed to extract features from brain magnetic resonance imaging (MRI) images with a nearest neighbourhood analysis, using Euclidean and Mahalanobis dis tances. The designed SNN had lesser complexity and fewer parameters than deep transfer-learned convolutional neural networks (CNN), but it was found that for larger datasets, the proposed SNN (with the current design) did not outperform a transfer-learned deep CNN.

4. In the proceeding paper [4], a fully automatic classification algorithm for brain tumors using MRI images was proposed. A deep CNN was designed for ex tracting image features and a multiclass SVM was employed for the classifi cation

process. The SVM classifier was observed to perform better than the softmax classifier for the CNN features. Also, compared to transfer learning basedclassification, the adopted strategy of CNN-SVM had lesser computations

and memory requirements, but still the issue of mis-classification of minor class prevailed.

5. The following research [5] addressed the challenge of training data imbalance by proposing a novel class-weighted focal loss. Additionally, they proposed a novel scheme for deep feature fusion where the features were extracted from identical CNN models, each trained using different loss functions. The features extracted were fused and provided to a proven classifier model. The misclassifications concerning the minority class (meningioma) was considerably reduced with the use of a class-weighted focal loss.

3.1 Dataset

In this work, we have used dataset from Figshare (Dataset 1 2018) [6]. It is an open data set extensively used for the research problems in medical image classifcation and medical image retrieval. The dataset is a collection of 3064 T1-weighted contrast enhanced (CE) MRI slices belonging to 233 patients.

The 2D slices are labelled and correspond to one among the three tumor classes of glioma, meningioma and pituitary tumor. The dataset is unbalanced, consisting of 1426 MRI images with glioma, 708 and 930 images cor- responding to meningioma and pituitary tumor, respectively.The dataset contains multi-view slices of axial, sagittal and coronal sections. Each slice (image) is of size 512 × 512 and is available as a .mat fle. Table 1 provides details of the dataset. Our work made use of tumor masks available in the dataset to extract the ROI. Morphological dilations augmented the ROI.

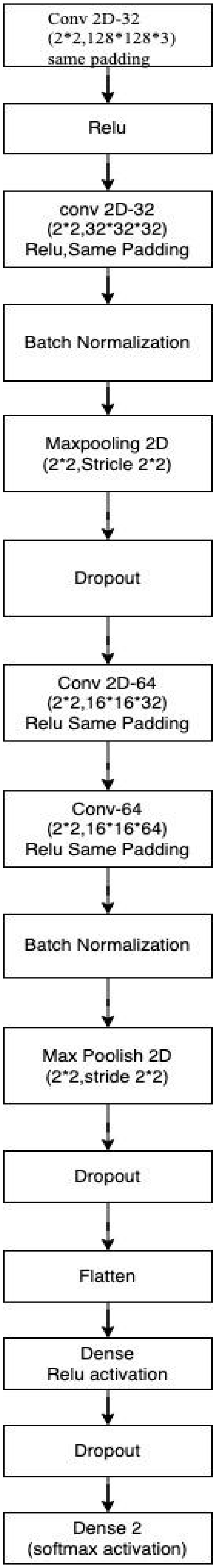
4.1.Model Architecture

The model architecture used in this study is a sequential CNN. The model consists of multiple layers, each serving a specific purpose. The architecture includes two sets of convolutional layers followed by batch normalization and max pooling layers. These convolutional layers extract relevant features from the input images. ReLU activation is applied to introduce non-linearity and enhance the model's representational power.

Dropout layers are included to prevent overfitting by randomly deactivating a fraction of the neurons during training.

Following the convolutional layers, a flatten layer is introduced to convert the multi -dimensional feature maps into a one-dimensional feature vector. This vector is then passed through two fully connected layers, each with a ReLU activation function.

The first fully connected layer consists of 512 units and helps to learn complex patterns and representations. Dropout is applied again to reduce overfitting. The final layer consists of two units with softmax activation, enabling the model to output class probabilities for the objects being detected.


Conv 2D-32
(2*2,128*128*3)
same padding
Relu
conv 2D-32
(2*2,32*32*32)
Relu,Same Padding
Batch Normalization
Maxpooling 2D
(2*2,Stricle 2*2)
Dropout
Conv 2D-64
(2*2,16*16*32)
Relu Same Padding
Conv-64
(2*2,16*16*64)
Relu Same Padding
Batch Normalization
Max Poolish 2D
(2*2,stride 2*2)
Dropout
Flatten
Dense
Relu activation
Dropout
Dense 2
(softmax activation)

Training

The model is trained using the categorical cross-entropy loss function, suitable for multi-class classification problems. The Adamax optimizer is utilized to optimize the model's weights and biases. The training process involves iteratively updating the parameters based on mini-batches of the data. A batch size of 30 is used, and the model is trained for 40. A learning rate schedule may be employed to adjust the learning rate during training to achieve better convergence.

During training, the model's performance is evaluated on a separate validation set. Additional evaluation metrics, such as accuracy, precision, recall, and the F1 score, are calculated to assess the model's performance on various aspects. Early stopping may be implemented to halt training if the model's performance on the validation set does not improve after a certain number of epochs.

Batch normalization

Batch normalization is a technique used for training deep neural networks that has gained significant popularity since its introduction. In this response, I will provide a comprehensive explanation of batch normalization, discussing its motivation, principles, benefits, and implementation details.
By the end, you should have a thorough understanding of batch normalization and its role in training deep network.

Batch normalization offers several advantages for training deep neural networks. Improved training speed: By reducing the internal covariate shift, where the distribution of inputs to each layer changes during training, batch normalization allows networks to converge faster. This leads to a significant reduction in the number of training epochs required.

Regularization effect: Batch normalization acts as a regularizer by adding a small amount of noise to the network during training. This noise improves generalization and reduces the need for other regularization techniques, such as dropout.

Handling different mini-batch sizes: Batch normalization is effective even when the mini-batch sizes vary. This flexibility makes it suitable for various training scenarios and allows for efficient training on hardware with limited memory.Reducing sensitivity to weight initialization: Batch normalization makes networks less sensitive to the choice of initial weights. This property simplifies the process of weight initialization and facilitates easier training.Batch normalization can be applied to various types of layers, such as fully connected layers and convolutional layers. The implementation typically involves adding a batch normalization layer after the affine transformation of a layer and before the activation function. During training, the mean and standard deviation are estimated for each mini-batch. During inference, the population statistics (estimated from the entire training set) are used for normalization.

While batch normalization has proven to be a highly effective technique, it is not without limitations. It introduces some computational overhead due to the additional operations required for normalization and the need to estimate mean and standard deviation for each mini-batch. However, the benefits it provides in terms of improved training stability and convergence speed often outweigh these costs.In conclusion, batch normalization is a powerful technique that has revolutionized the training of deep neural networks.

By normalizing the inputs to each layer, it addresses issues like internal covariate shift, accelerates training, and improves generalization. Batch normalization has become a standard practice in deep learning and has significantly contributed to advancements in various domains, ranging from computer vision to natural language processing.

Convolutional Neural Network

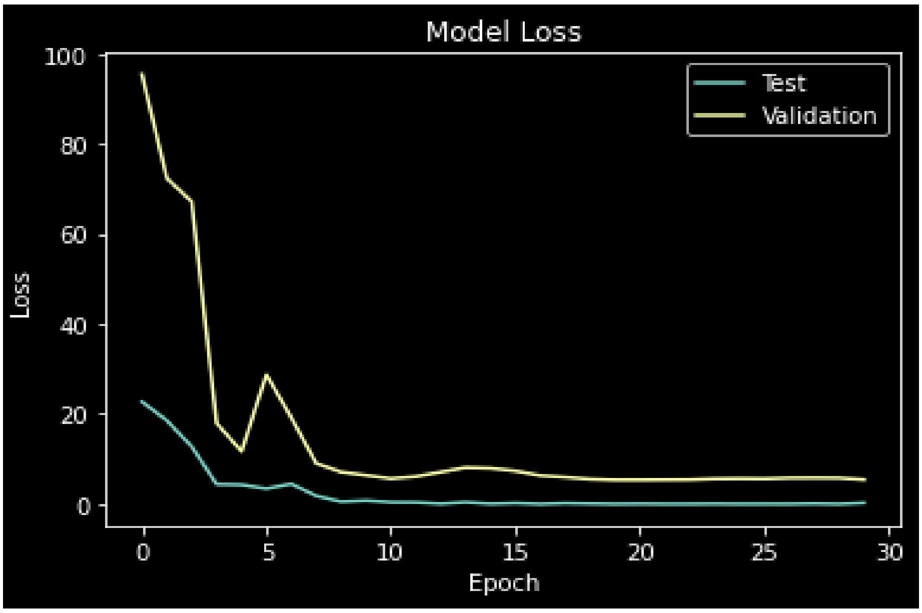
Brain tumor segmentation and classification using CNNs is a widely researched area in medical image analysis. CNNs are a type of deep learning model that can automatically learn and extract relevant features from images. This makes them well-suited for tasks such as tumor segmentation and classification in medical imaging.Data collection and preprocessing: Medical imaging data, such as MRI or CT scans, are collected and prepared for analysis. Preprocessing steps may include resizing, normalization, and filtering to enhance the quality of the images.Data labeling: Experts manually label the images to create ground truth data, indicating the presence or absence of tumors and their boundaries. This labeled data is used to train the CNN model.Training the CNN model: The labeled images are used to train the CNN model. The CNN learns to recognize patterns and features that are indicative of tumors. The network's architecture typically consists of multiple convolutional layers, followed by pooling layers to extract features and reduce spatial dimensions. The output layers are responsible for classifying and segmenting the tumors.

Validation and evaluation: After training, the CNN model is evaluated using validation data that the model has not seen before. This step helps assess the model's performance, such as accuracy, sensitivity, and specificity, in segmenting and classifying brain tumors.

Testing and application: The trained CNN model can then be used to segment and classify brain tumors in new, unseen images. This can aid in clinical decision-making, treatment planning, and monitoring the progression of tumor

4.2.**Results**

The performance of the model was assessed by plotting the loss values duringtraining and validation. The model loss, represented by the training loss and validation loss, provides insights into the convergence and generalization capability of the model.The plot (Figure 1) displays the model loss over epochs.



The training loss (green line) shows the decrease in loss as the model iteratively learns from the training data. It indicates how well the model fits the training data. On the other hand, the validation loss (yellow line) demonstrates the loss computed on the validation set, representing the model's ability to generalize to unseen data.The plot shows that both the training and validation losses decrease over epochs. This indicates that the model is learning from the data and making progress in minimizing the prediction errors. The convergence of the loss values suggests that the model is improving its performance as training progresses.However, it is important to note that the training and validation losses may exhibit different trends. If the training loss continues to decrease while the validation loss starts to increase or remains stagnant, it could be an indication of overfitting. In such cases, the model may be too specialized to the training data and may not generalize well to new, unseen data.

Overall, the decreasing trends in both the training and validation losses suggest that the model is effectively learning from the data and making progress in minimizing the prediction errors. Further

analysis and evaluation metrics, such as accuracy or other performance measures, would

provide a more comprehensive assessment of the model's performance and generalization ability.

It is important to note that the performance of the model should be evaluated using additional metrics and possibly compared against other models or benchmarks to obtain a comprehensive understanding of its capabilities and limitations.

Conclusion:

In this study, we proposed a model architecture based on a deep convolutional neural network (CNN) for brain tumor type classification. The model demonstrated promising performance, achieving good accuracy in differentiating between various brain tumor types. The architecture consisted of multiple convolutional layers, batch normalization, max pooling, dropout, and dense layers, culminating in a softmax output layer for classification.

The model was trained using the Adamax optimizer and the categorical cross-entropy loss function.In the future, instead of deep CNN base methods, a transformerbased architecture can be proposed for brain tumor type classification

that can extract more information-rich feature maps and simplify thenetwork complexity to some extent

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