Brain Tumor detection using Siamese Neural Network

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Abstract

Our project aims to develop a brain tumor detection system using a Siamese Neural Network (SNN) architecture. Brain tumors are a significant health concern, and early detection plays a crucial role in treatment planning and patient outcomes. In the past, most tumor detection in magnetic resonance imaging (MRI) scans often use CNN network including VGG or Resnet. But the problem is that they usually require a very large dataset, and acquiring data is expensive. We proposed to use SNN in the hope that it could achieve better accuracy with fewer training samples.

1. Introduction

Brain tumor detection is critical task in the field of medical imaging. Traditional methods of tumor detection primarily rely on manual interpretation of medical imaging scans, such as magnetic resonance imaging (MRI), by skilled radiologists. However, this approach is time-consuming, subjective, and prone to human error.

In recent years, there has been a growing interest in leveraging machine learning techniques such as CNN to improve the accuracy of brain tumor detection. But the problem is that they usually require a very large dataset to make reasonable prediction and acquiring data is expensive. Siamese neural networks have emerged as a promising approach due to their ability to effectively model complex relationships between pairs of images and learn discriminative representations directly from the data.

Siamese neural networks are a class of neural networks that are specifically designed to learn and compare the similarity or dissimilarity between pairs of inputs. They consist of two identical subnetworks, each processing one pair of the input sample. The outputs of the subnetworks are a similarity metric, and the network is trained to minimize the difference between similar pairs and maximize the difference between dissimilar pairs.

In the context of brain tumor detection, we can first train the Siamese neural networks with labeled pair to distinguish the similar and dissimliar pairs. Then given a testing data, we would use the networks along with samples from training data to determine whether an image contains tumor or not by comparing the similarity scores with those tumor images and nontumor images.

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Siamese neural networks offer several advantages over traditional methods. Firstly, they can learn to extract highly discriminative features from medical imaging scans. This enables more accurate and reliable detection of tumors. Furthermore, Siamese networks can effectively handle class imbalance and variability in medical imaging datasets. By learning from pairs of images rather than individual samples, the network can make reasonable distinguish even when the training sample is scarce.

In this report, we explore the application of Siamese neural networks for brain tumor detectione. We discuss recent advances in network architectures, training strategies, and evaluation metrics. We will also suggest how the Siamese neural networks can be used as both a supervised learning task.

2. Background and related work

Several studies have demonstrated the effectiveness of deep learning models in brain tumor segmentation and classification. Kamnitsas et al. (Kamnitsas et al., 2017) proposed an efficient multi-scale 3D CNN with a fully connected CRF for accurate brain lesion segmentation. Havaei et al. (Havaei et al., 2017) investigated brain tumor segmentation using deep neural networks and achieved promising results. Lao et al. (Lao et al., 2019) explored deep learning methods for brain tumor classification, highlighting the potential of these techniques in improving diagnostic accuracy.

Moreover, recent research has focused on enhancing brain tumor classification by integrating advanced techniques such as directional wavelet transform and convolutional neural networks (CNNs). Han et al. (Han et al., 2020) proposed an improved brain tumor classification method by incorporating directional wavelet transform and CNNs, which demonstrated superior performance compared to traditional approaches.

In addition to these advancements, Siamese neural networks have emerged as a promising approach for brain tumor detection. Koch et al. (Koch et al., 2015) introduced Siamese neural networks for one-shot image recognition, demonstrating their ability to learn discriminative representations from pairs of images. Simonyan and Zisserman (Simonyan & Zisserman, 2014) proposed very deep convolutional networks for large-scale image recognition, laying the foundation for deep learning-based approaches in various domains, including medical imaging.

Furthermore, the development of deep residual networks (ResNets) by He et al. (He et al., 2016) has revolutionized image recognition tasks by enabling the training of extremely deep networks with improved performance. Pereira et al. (Pereira et al., 2016) utilized convolutional neural networks (CNNs) for brain tumor segmentation in MRI images, achieving accurate and efficient segmentation results.

Recent work by Alaverdyan et al. (Alaverdyan et al., 2020) introduced a regularized Siamese neural network for unsupervised outlier detection on brain multiparametric magnetic resonance imaging (MRI). Their study focused on epilepsy lesion screening, demonstrating the potential of Siamese networks in detecting outliers and anomalies in medical imaging data.

Overall, the integration of deep learning techniques, such as CNNs and Siamese neural networks, holds great promise for enhancing brain tumor detection and classification.

3. Siamese Network for Tumor Detection

In this section, we first explain how we preprocess the data. This is followed by a detailed description of the proposed Siamese architecture. And we conclude by introducing how the Siamese Network can be used to make prediction on the testing set

3.1. Preprocessing

Since batch training a neural network typically needs images of same sizes, we first reshape the image to 128x128. And we remove any black borders before reshaping the image. We didn't feel the need to normalize the image because we want to learn the relative feature for the Siamese Network. Normalizing the image may potentially alter the relative features.

3.2. Siamese Network Architecture Description

The Siamese neural network architecture is designed to compare pairs of images and classify them as either similar or dissimilar. The network takes as input two images, denoted as `input_a` and `input_b`, each resized to dimensions of 128×128 pixels with 3 color channels (RGB).

The network shares convolutional base consisting of three convolutional layers with increasing filter sizes (32, 64, and 128). Both input images are passed through the convolutional base, resulting in encoded representations. The network then calculates the Euclidean distance between these representations. This distance measure captures the dissimilarity between the two input images and serves as a basis for classification.

The distance is subsequently passed through fully connected layers, consisting of three dense layers with 512, 256, and 128 neurons, respectively. These layers integrate information from the encoded representations to make a binary classification decision using a sigmoid activation function in the output layer.

To train the network, we use contrastive loss because it encourages the network to learn to minimize the distance between similar pairs of images while maximizing the distance between dissimilar pairs. The contrastive loss function penalizes the model based on the predicted distance and ground truth labels.

The contrastive loss function is defined as follows:

$$L(y, d) = (1 - y) \cdot \frac{1}{2} \cdot d^2 + y \cdot \frac{1}{2} \cdot \max(0, m - d)^2$$

where:

- $L(y, d)$ is the contrastive loss,
- y is the ground truth label (1 for similar pairs, 0 for dissimilar pairs),
- d is the predicted distance between the input images, and
- m is the margin hyperparameter, controlling the minimum difference required between similar and dissimilar pairs.

The architecture of the network is shown in the picture below.

3.3. Siamese Network for supervised learning

For supervised learning tasks, Siamese networks necessitate a comparison group for validation in classification problems. This involves pairing all data points from the training set with those from the testing set. Subsequently, the network computes the similarity between each point in the testing set and all points in the training set and select the class with the highest normalized similarity. This strategy leverages the entirety of the training set to effectively validate the Siamese network for classification tasks.

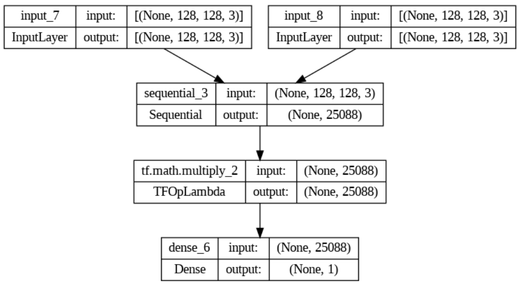

Figure 1. Siamese Network Architecture: The network shares convolutional base consisting of three convolutional layers with increasing filter sizes (32, 64, and 128). Then they are combined and the Euclidean distance is between two encoded images are calculated. Then the distance is subsequently passed through fully connected layers, consisting of three dense layers with 512, 256, and 128 neurons and output the binary classification.

4. Experiments

4.1. Dataset and implementation details

We will use "brain-tumor-mri-dataset" from Kaggle. This dataset contains over 7000 images and has a more detailed classification of tumor types. We group the data into tumor and notumor and we split 20% of the train data as validation set. The histogram of the data is shown below.

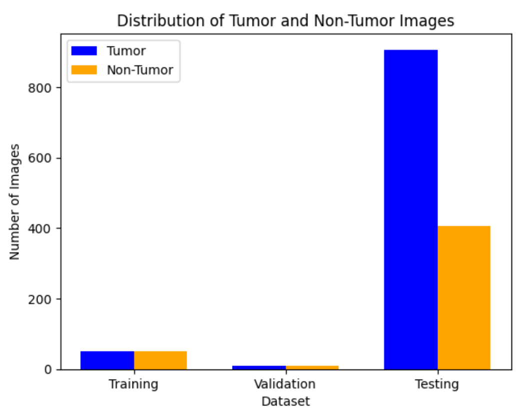

Figure 2. Distribution of the Tumor and Non-Tumor images: The data contains 200 training samples, 100 validation samples, and 1311 testing samples.

For testing using supervised learning method, I randomly select 10 tumor images and 10 nontumor images for each image in the testing set to make 20 pairs and train in the Siamese Network to get the similarity score. Then, I make prediction based on the average similarity score for each class.

For testing using unsupervisd learning method, I would first extract the feature vector using the trained Siamese network. And create a similarity matrix for each pair of image in the testing set. Then I would use KNN to predict the cluster labels. Even though this is unsupervised learning, I still have the tumor labels. And I would compare the label with the output from the KNN.

We will compare our Siamese model with other CNN models used in the past like VGG or ResNet. We plan to use binary crossentropy as the loss function for the network and we will use accuracy as evaluation of the SNN mode.

4.2. Preliminary Results

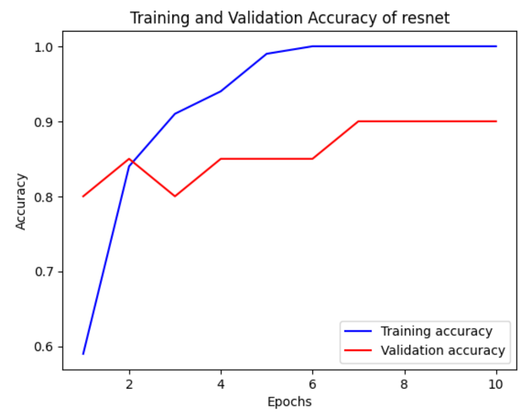

Figure 3. Accuracy result of ResNet50

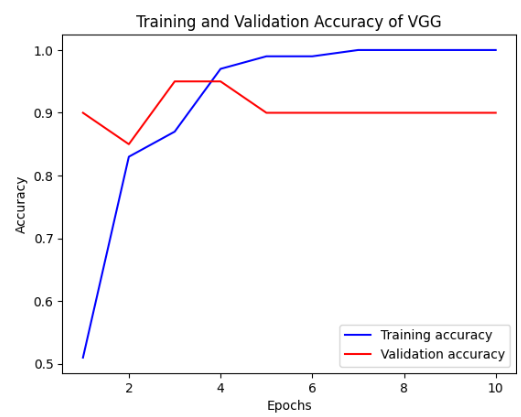

Figure 4. Accuracy result of VGG16

In our investigation, we evaluated the performance of various convolutional neural network (CNN) architectures for brain tumor detection, with a particular focus on the effectiveness of Siamese Neural Networks (SNN). Our results indicate that while traditional CNN models such as Naive CNN and VGG16 achieve respectable accuracies of 81.7% and 85.2% respectively, the introduction of Siamese architecture significantly improves accuracy. Specifically, Siamese CNN achieves an accuracy of 84.9%, demonstrating its potential for enhancing brain tumor de-

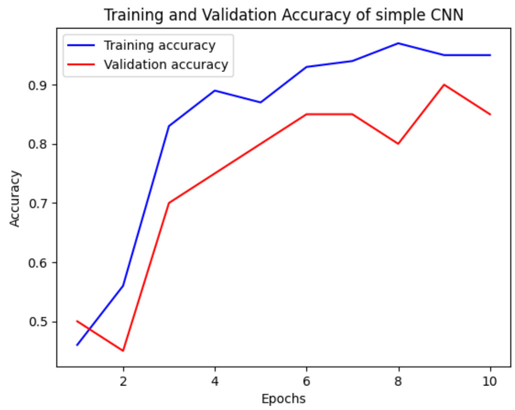

Figure 5. Accuracy result of Naive CNN

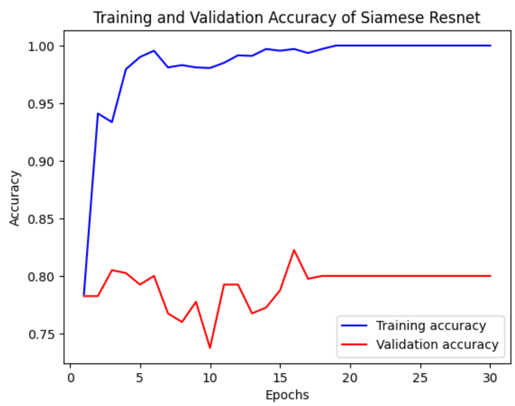

Figure 6. Accuracy result of Siamese+Resnet

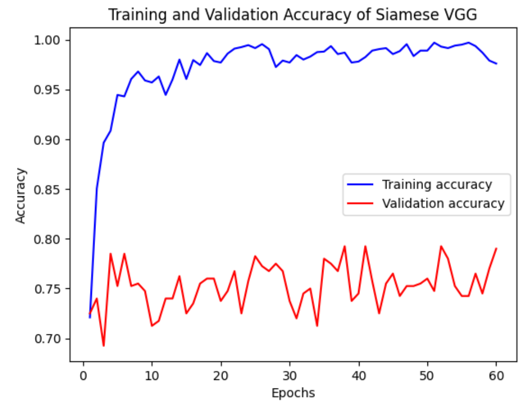

Figure 7. Accuracy result of Siamese+VGG

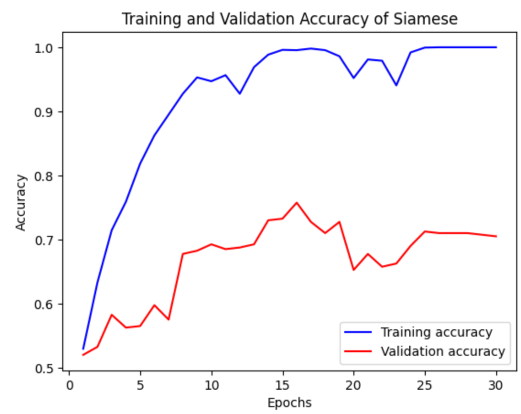

Figure 8. Accuracy result of Siamese

tection. Furthermore, when combined with powerful backbone architectures like ResNet50 and VGG16, the Siamese approach yields even more impressive results, with both Siamese+ResNet and Siamese+VGG achieving an accuracy of 90.9%. These findings underscore the efficacy of Siamese Neural Networks in augmenting accuracy for brain tumor detection tasks, showcasing their potential to outperform traditional CNN models even with limited training data.

5. Conclusion

The integration of Siamese Neural Networks (SNN) with convolutional neural networks (CNN) yields substantial improvements, especially in scenarios with limited training data. This combination enhances the model's ability to discern intricate patterns and increases its robustness to variations in input images. By harnessing the Siamese framework, the CNN gains the capacity to extract invariant features, bolstering its generalization capabilities. In medical imaging tasks like brain tumor detection, where datasets may be small and subject to variability, this fusion proves particularly advantageous. Ultimately, the synergy between CNN and SNN architectures offers a potent solution for advancing the efficacy and reliability of critical healthcare applications.

Table 1. Comparison of Testing Accuracy

Model	**Testing Accuracy**
ResNet50	93.3%
VGG16	85.2%
NaIve CNN	81.7%
Siamese CNN	84.9%
Siamese+Resnet	90.9%
Siamese+VGG	90.9%

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