

Context aware convolutional neural network using self-attention mechanism for brain tumor classification

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1 Executive Summary

Brain Tumor is an abnormal growth of the brain cells[4]. Brain tumor leads to brain cancer and death[4]. Computer aided diagnosis (CAD) tools assists clinician to make a brain Tumor diagnosis. Deep learning [8] models, namely Convolutional Neural Network (CNN) [9], have shown a great performance in computer vision problems including object detection[5][6][12][11], object recognition[13][7] and many others. This study proposes a Deep learning Network that exploit self-attention mechanism [15] to capture context relationship between extracted feature. Features are extracted using a stack of convolutional layers that exploit a high transformation cardinality[16] on top of learned residual mapping[7].

2 Survey of Background Literature

2.1 Overview

Brain Tumor is an abnormal growth of the brain cells[4]. Brain tumor leads to brain cancer and death[4]. Brain tumor is a source of many disabilities. For example, larger tumors in the frontal lobe can cause changes in the ability to think. However, a smaller tumor in an area such as Wernicke's area (small area responsible for language comprehension) can result in a greater loss of function. CAD can help to automate brain tumor detection and help medical stuff utilizing their efforts for series causes.

2.2 Background

Deep learning[8], namely convolutional neural networks(CNN)[9], solved many computer vision problem. Convolutional neural networks is composed of two parts which is convbase and denseBase. ConvBase part consists of stack of convolutional layers. These convolutional layers are responsible for learning representative features for current problem. Lower order layers are responsible

for learning simple and primitive feature such as edges. While higher order layers are responsible for learning more complicated features such as objects. CNN can be pictured as universal function approximator but not all functions are easy to approximate. Residual learning[7] emerges. Residual learning can reduce the required training time and reduce vanishing gradient problem. Residual learning allows feature reusability.

2.3 Related Works

[1] proposes an architecture that is simpler than current a state-of-the-art classification networks. Authors have used 3064 T-1 weighted CE-MRI of brain tumor images dataset[3]. They achieve a training and validation accuracies of architecture 2 at best is 98.51% and 84.19%, respectively. Their architecture suffer from severe overfitting.

[2] developed network is simpler than already-existing pre-trained networks, and it was tested on T1-weighted contrast-enhanced magnetic resonance images[3]. 10-fold cross-validation method was obtained for the record-wise cross-validation for the augmented data set, and, in that case, the accuracy was 96.56%. Residual learning[7] can enhance the performance and reduce the train time However, it is not applied.

[10] fine-tuned googLeNet[14] network by replacing the last 5 layer with a new 15 convolutional layers. Their method ware tested on T1-weighted contrast-enhanced magnetic resonance images[3]. Their method achieved 99.67% accuracy, 99.6% precision, 100% recall, and a 99.66% F1-score.

3 Proposed Methodology

This study proposes a Deep learning Network that exploit self-attention mechanism [15] to capture context relationship between extracted feature. Features are extracted using a stack of convolutional layers that exploit a high transformation cardinality[16] on top of learned residual mapping[7]. Proposed Network will be trained using an augmented T1-weighted contrast-enhanced magnetic resonance images[3] and tested using 5-fold cross validation.

4 Resources

Training and validation of the proposal require Google Colab Pro subscription for GPU access. Subscription cost a \$10/month.

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