Predicting the Existence of Brain Tumor in Mri Images by Applying FCNN

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Abstract

Brain tumors are major causes of death in today's world and methods of detecting them prematurely require vast improvement. The objective of this project is to detect the tumors early from MR image scans by utilizing deep convolutional networks to locate the tumor.The tumor is divided at first in the main stage and the generated bounding box is utilized for the center of the tumor in second step. This is trailed by division based on the bounding box of the tumor center division result. Examinations are performed with the BraTS 2017 validation set. This is a numerous division issue.

Keywords: *Image processing, Machine learning, Deep Learning, Neural Networks, Fully Connected Convolutional Neural Networks, Image Segmentation, Tumor Detection, HGG, LGG, Convolutional Layer.*

Introduction

Brain Tumors are one of the world's leading causes to high increase in mortality rate. Detecting tumors has always been a challenge to doctors. Predicting tumors in the brain has always been a hit or miss situation with most of the predictions being less accurate. To mitigate this problem and increase the accuracy we propose an automated solution by utilising image processing and segmentation techniques by which the rate of predicting tumors could be improved.

In this paper, we discuss about the various utilizations of CNN in the field of medical imagery and detection of brain tumors from Magnetic Resonance (MR) images. Convolutional neural network has demonstrated their fortitude in the field of Image Processing and Segmentation. The results provided by convolutional neural networks are reliable and accurate. The methods by which Deep Convolutional Neural Networks can be applied to the problem of predicting the existence of tumors in the brain is explained and discussed in detail. The images utilized for validation of our model is the BraTS 2017 MRI scan images.

In study conducted by Ronneberger et.al., they suggested a method of utilising a FCNN to segment the given images utilising the sliding window protocol to mark the region of interest in the image and later classify the provided images as scans of patients with cases of tumor and patients without tumor.[1] This method was promising as it was able to accurately predict the classifications.

In this paper, authors devised an innovative method in training the convolutional neural network by releasing Tensor Layer a high-level module that allows to extract the operations towards neuron layers, network models and dependent training jobs.[2] It offers a basic yet advanced interface enabling developers to implant low-level controls with a backend motor. It is profoundly versatile and gives an unrivalled performance.

In this paper, a method proposed for an automatic and reliable segmentation approach based on CNN by exploring small 3 x 3 kernels.[3] The utilization of small kernels permits developing more profound architecture other than evacuating the plausibility of over fitting

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given the smaller number of loads in the system. Through examination strategies including both CNN-based division techniques with information, enlargement demonstrated to be exceptionally powerful for MRI pictures.

The authors of this paper proposed a method to utilize K-means algorithm for color-based segmentation. In their proposed strategy, the procedure is utilized to follow tumor objects in MR brain pictures.[4] The procedure includes the transformation of given grey level MR pictures into a color space picture and separates the position of the tumor object from different things of MR picture utilizing K-means bunching and histogram clustering.

In this study, Pham et al. presented a critical appraisal and comment on the various automated and semi-automated methods for segmentation of anatomical medical images.[5] Current advances in segmentation approaches are viewed on basis of their respective advantages and disadvantages respectively.

In this paper, authors have described a methodology by which the brain scan is retrieved from the patient's database during which the noise and artifact of the image are removed.[6] This method utilizes HSom for image segmentation which is used to classify an image row by row. It improves on computational speed and ensures that noise is very less in the image before classification.

In this study, Kaus et al. proposed a mechanized brain tumor division approach which was trained and tested against manual division strategies with three-dimensional MR images with MGG and LGG.[7] The proposed strategy permitted quicker identification of brain and tumor tissue with great preciseness and reproducibility comparable to manual division.

In this paper, the authors have proposed a technique for detection of tumors in digital mammography.[8] This technique involves two strategies, division by which regions of intrigue are extracted from pictures by adaptive thresholding. By using an altered Markov Random Field-based strategy division is done precisely. The classification was done on the segmented images by a fuzzy binary decision tree to get accurate results.

In this work, Sharif et al. described the advantages and disadvantages of utilising Convolutional Neural Networks based on a series of classifications performed on ILSVRC13 dataset utilizing the over feat network model for object classification.[9] They conclude that convolutional neural networks are the best for image classification and object recognition tasks.

The authors of this work presented a flexible framework for object instance segmentation.[10] This strategy at the same time recognizes objects of interest and furthermore produces a great division cover for each example. This technique is named Mask R-CNN which expands Faster R-CNN by including an expectation branch alongside the current branch for bounding box acknowledgement. It is anything but difficult to prepare and doesn't include any computational overhead since it works in parallel with the current procedure.

In this work, Ren et al. proposed a methodology called Region Proposal Network which offers full-image convolutional features with the discovery network enabling nearly cost-free region.[11] An RPN is an FCN that all the while predicts object limits and objectless scores at each position. RPNs are prepared end to end to create top-notch locale recommendations, which are utilized by Fast R-CNN for identification. The preciseness of this model is significantly higher contrasted with different models and the ideal opportunity for preparing is likewise less contrasted with the nonexclusive convolutional neural net models

The authors discussed a methodology of extending the pre-existing CNN architectures in this paper for the purposes of medical imaging.[12] The method of annotating images and training the images on a convolutional neural network is discussed in great detail in this paper.

In this paper, Krizhevsky et al. discussed a method by which overfitting can be prevented in convolutional neural networks by employing a regularization method while training the network on high resolution images in the LSVRC-2010 ImageNet training set on 1000 different classes.[13]

In this study, creators have talked about an enhanced adaptation of image object identification and acknowledgement with a neural algorithm of artistic style that can isolate and recombine the picture substance and style of the normal image.[14] The algorithm enables new bits of knowledge to profound picture portrayals learned by Convolutional Neural Networks and exhibit their potential for high-level image synthesis and manipulation.

The creators of this work explained the utilization of the 100-layer Tiramisu design for the division of cerebrum tumor from multi-modular MRI, which is developed by coordinating a densely connected FCNN, followed by post-handling utilizing a Dense Conditional Random Field (DCRF).[15] The system comprises of squares of thickly associated layers, progress down layers in down-examining way and change up layers in up-inspecting way. The proposed system accomplishes a mean entire tumor, tumor center and dynamic tumor dice score of 0.87, 0.68 and 0.65. Separately on the BraTS '17 approval set and 0.83, 0.65 and 0.65 on the Brats '17 test set.

Material and Method

The comparative analysis utilizes a FCNN for the purposes of segmentation of the input image and several classifiers to get predictions on the possibility of a patient having a tumor. The additional classifiers were added to check for the possibility of increased accuracy in the prediction scores. The input image is fed into the FCNN and allowed to train on the network for 150000 epochs. At the end of the training process the image is segmented. The Convolutional Neural Network is able to extract features from the images. Each layer's output serves as an input for the other layer and so on. The implementation is done by using Keras framework with TensorFlow backend. To save time in training the network, both the LGG and HGG images are trained simultaneously on the network. The proposed method gets the confidence score from the FCNN and the confidence values are then fed into the above-mentioned classifiers to get an accurate prediction. The segmentation of the images results in accurate region localization of the tumors present in the scans. The results obtained are then fed into the rudimentary classifiers for post-processing and getting an accurate result. Figure 1 is the process flow of the proposed network for one epoch. The result of segmentation for one image is tabulated as follows in Table 1.

Table 1: Values for Tumor Score Measures

Volume ID: HGG/Brats17TCIA3741	
Measure	**Value**
Dice Complete Tumor Score	0.8921
Dice Core Tumor Score	0.8914
Dice Enhancing Tumor Score	0.8379
Sensitivity Complete Tumor Score	0.9906
Sensitivity Core Tumor Score	0.9331
Sensitivity Enhanced Tumor Score	0.7697
Specificity Complete Tumor Score	0.9966
Hausdorff Complete Tumor Score	10.2956
Hausdorff Core Tumor Score	7.8102
Hausdorff Enhancing Tumor Score	9.0554

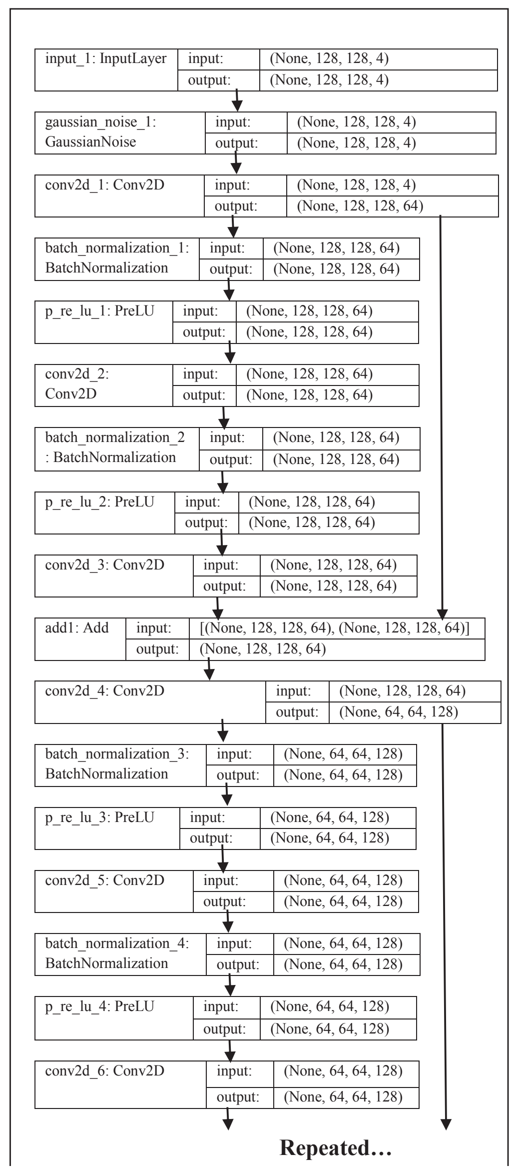

Figure 1: Process Flow of FCNN

The process of classification begins after each image is iterated through and the individual scores are saved as a csv file for further classification process as shown in Algorithm 1. The results from the CSV are then fed as input into five different classifiers.

Result: Preprocessed Images with csv for training network

Step 1: Extract Images

Step 2: Prepare for downsizing

Step 3: Split into training and test images

Step 4: Input images into FCNN

while images present **do**

Step 5: Calculate Dice Score

Step 6: Calculate Specificity Score

Step 7: Calculate Sensitivity Score

if Scores **then**

Step 7: Write to CSV

Step 8: Feed into SVM, KNN, and other algorithms for classification

else

continue

end if

end loop

Algorithm 1: Algorithmic representation of methodology

By using the CSV that was generated by the previous stage of processing we first make a threshold level for the results (refer Algorithm 2). By considering the specificity and sensitivity values we label the classes as tumor and benign. The results of the classification are expressed in terms of accuracy, precision, F1-score and recall.

Result: Precision, Recall, F1 score and accuracy

Step 1: Read CSV

Step 2: Split into train and test images

Step 3: Input data into KNN

while *Algorithm* **do**

Step 4: Print Precision score

Step 5: Print Recall score

Step 6: Print F1-score

if *Scores* **then**

Step 7: Plot respective graphs

else

continue

end if

end loop

Algorithm 2: Process of getting predictions from various algorithms

Findings and Discussion

The following results are inferences which were got from the various classifiers utilized. Performance of the classifiers are measured by using standard measures like accuracy, F1-score, precision and recall.

Figure 2 describes the accuracy score of the various classifiers plotted on a bar-graph to show the best of the five chosen classifiers. Preciseness is one metric for assessing arrangement models. In our analysis Decision tree classifier was able to get a better accurate prediction while comparing the other classifiers. Multilayer perceptron performed the second best in accurately classifying the provided data samples.

Figure 2 also describes the precision score of the various classifiers plotted on a bar-graph to show the precision of the chosen five classification algorithms. Precision score is highest in Decision Tree Classifier and Multilayer Perceptron Classifier proving for the second time that these classifiers perform well for our testing dataset.

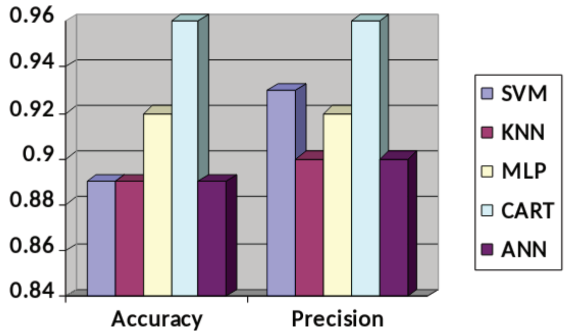

Figure 2: Accuracy and Precision Charts for the Used Classifiers

Figure 3 portrays the F1-score of the different classifiers plotted on a bar graph to show the F1-score of the picked five grouping calculations. F1-score is most noteworthy in Decision tree classifier and Multilayer Perceptron classifier. These classifiers are appropriate for our testing dataset.

Figure 3 also describes the recall-score of the various classifiers plotted on a bar-graph to show the recall score of the five classifiers used in this experiment. Recall-score is highest in Decision tree classifier and Multilayer Perceptron classifier. These classifiers are well suited for our testing dataset. From these results we can conclude that we can utilize a decision tree classifier or a multilayer perceptron classifier to augment the results obtained from the Fully Connected Convolutional Neural Network Architecture.

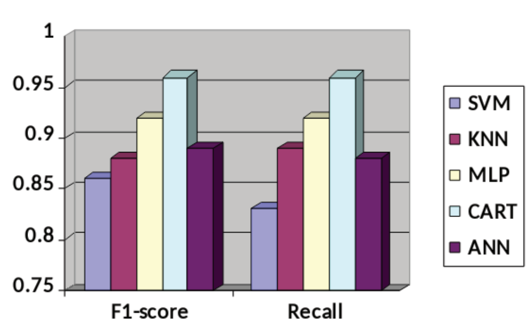

Figure 3: F1-Score and Recall Charts for the Used Classifiers

Conclusion

We have discussed a method of improving the accuracy and precision of predicting a tumor present in the BRATS2017 Brain Scan images by utilising a FCNN to segment the image and further classify and predict using the rudimentary classifiers like SVM, KNN, CART and ANN. This combined methodology reduces the time taken to train and predict the tumor and provides a considerably accurate prediction. The results that we obtained show that utilising a decision tree classifier (CART) to augment the FCNN architecture results provides the best performance metrics.

Conflict of Interest: The authors declare that they have no conflict of interest.

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References

[1] Ronneberger O, Fischer P, Brox T. U-net: Convolutional networks for biomedical image segmentation. InInternational Conference on Medical image computing and computer-assisted intervention 2015 Oct 5 (pp. 234-241). Springer, Cham.

[2] Dong H, Supratak A, Mai L, Liu F, Oehmichen A, Yu S, Guo Y. Tensorlayer: a versatile library for efficient deep learning development. InProceedings of the 25th ACM international conference on Multimedia 2017 Oct 19 (pp. 1201-1204).

[3] Pereira S, Pinto A, Alves V, Silva CA. Brain tumor segmentation using convolutional neural networks in MRI images. IEEE transactions on medical imaging. 2016 Mar 4;35(5):1240-51.

[4] Wu MN, Lin CC, Chang CC. Brain tumor detection using color-based k-means clustering segmentation. InThird International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP 2007) 2007 Nov 26 (Vol. 2, pp. 245-250). IEEE.

[5] Pham DL, Xu C, Prince JL. Current methods in medical image segmentation. Annual review of biomedical engineering. 2000 Aug;2(1):315-37.

[6] Logeswari T, Karnan M. An improved implementation of brain tumor detection using segmentation based on soft computing. Journal of Cancer Research and Experimental Oncology. 2010 Mar;2(1):006-14.

[7] Kaus MR, Warfield SK, Nabavi A, Black PM, Jolesz FA, Kikinis R. Automated segmentation of MR images of brain tumors. Radiology. 2001 Feb;218(2):586-91.

[8] Li HD, Kallergi M, Clarke LP, Jain VK, Clark RA. Markov random field for tumor detection in digital mammography. IEEE transactions on medical imaging. 1995 Sep;14(3):565-76.

[9] Sharif Razavian A, Azizpour H, Sullivan J, Carlsson S. CNN features off-the-shelf: an astounding baseline for recognition. InProceedings of the IEEE conference on computer vision and pattern recognition workshops 2014 (pp. 806-813).

[10] He K, Gkioxari G, Dollár P, Girshick R. Mask r-cnn. InProceedings of the IEEE international conference on computer vision 2017 (pp. 2961-2969).

[11] Ren S, He K, Girshick R, Sun J. Faster r-cnn: Towards real-time object detection with region proposal networks. InAdvances in neural information processing systems 2015 (pp. 91-99).

[12] Shin HC, Roth HR, Gao M, Lu L, Xu Z, Nogues I, Yao J, Mollura D, Summers RM. Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. IEEE transactions on medical imaging. 2016 Feb 11;35(5):1285-98.

[13] Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. InAdvances in neural information processing systems 2012 (pp. 1097-1105).

[14] Gatys LA, Ecker AS, Bethge M. Image style transfer using convolutional neural networks. InProceedings of the IEEE conference on computer vision and pattern recognition 2016 (pp. 2414-2423).

[15] Shaikh M, Anand G, Acharya G, Amrutkar A, Alex V, Krishnamurthi G. Brain tumor segmentation using dense fully convolutional neural network. InInternational MICCAI Brainlesion Workshop 2017 Sep 14 (pp. 309-319). Springer, Cham.