

Transfer Learning for Classification of 2D Brain MRI Images and Tumor Segmentation

Onkar Rajesh Mulay, Hemprasad Yashwant Patil

Abstract: The focus of the paper is to classify the images into tumorous and non-tumorous and then locate the tumor. Amongst many medical imaging applications segmentation of Brain Tumors is an important and arduous task as the data acquired is disrupted due to artifacts being produced and acquisition time being very less, so classifying and finding the exact location of tumor is one of the most important jobs. In the paper, deep learning specifically the convolutional neural network is used to demonstrate its potential for image classification task. As the learning from available dataset will be low, so we use transfer learning [4] approach, as it is a developing AI strategy that overwhelms with the best outcomes on several image classification assignments because the pre-trained models have gained good knowledge about the features by training on a large number of images. Since, medical image datasets are hard to collect so transfer learning (Alexnet) [1] is used. Later on, after successful classification the aim is to find the exact location of the tumor and this is achieved using basics of image processing inspired by well-known technique of Mask R-CNN [9].

Keywords: Alexnet, Classification, Convolutional Neural Network, Transfer Learning.

I. INTRODUCTION

In medical imaging, Classification using Deep Learning is highly emerging as the best technique. In this paper dataset of Brain tumor Classification from a competition on Kaggle is used for research purpose. Pre-processing of images still play an important role before we feed them to any network. So, images have been brightened as to enhance their features and with this the tumor becomes prominently visible and helps in easily differentiating it from non-tumorous images and thus, this will help in easy classification and hence improve the accuracy of the model. Image Classification i.e. Tumor Classification is done with the help of transfer learning [4]. Medical Imaging data is not available in large amounts so, transfer learning [4] is now a days used for deep learning applications. It allows us to import a trained network and make the necessary changes and modify the network. An Alexnet [1] is a pretrained CNN that was trained on approximately one million of images and helps us in classification. Alexnet [1] can classify images into 1000

categories. The final updated weights of the Alexnet [1] that were computed for a million of images are of the most importance. Here, the change is made in the third last layer which is fully connected layer to classify the images into two categories instead of 1000 and also change the last layer which is the output of classification, such that it doesn't classify it into any object rather the classification is done on the basis of images of two classes i.e. yes and no. Instead of training a network from scratch with randomly initialized weights a tuned network with transfer learning [4] is used and this process is much faster and easier. Then, comes another important task after classification i.e. finding the exact location of the tumor here, the tumor location is identified through basic image processing. The technique to segment the tumor is inspired from Mask R-CNN [9] technique where Support Vector Machine is used for classifying the tumor from non-tumorous cells and regressor box to show the exact location and the boundary of the tumor.

II. METHODS

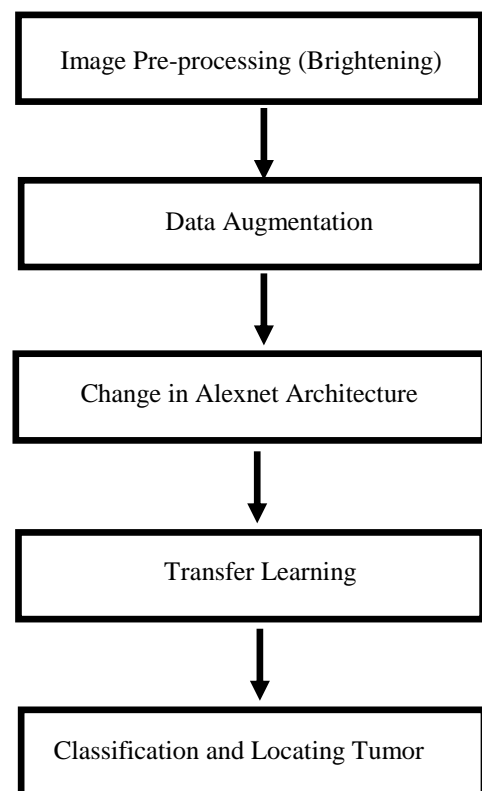


Figure 1. Implementation

Revised Manuscript Received on March 04, 2020.

* Correspondence Author

Onkar Rajesh Mulay, is currently a 4th year student pursuing Bachelors of Technology in Biomedical Engineering from Vellore Institute of Technology, Vellore, Tamil Nadu.

Dr. Hemprasad Yashwant Patil, Assistant Professor Vellore Institute of Technology, Vellore, India

1) Image Pre-processing

Brightening of the image involves making every pixel of an image look lighter. This is a technique that enhances images that are dark. Here, brightening of image plays an important role in classification of Brain Tumor images as the tumor in images seems to appear little lighter than rest of the image so, to enhance it we tend to make the images lighter.

Equation:

$$f(x, y) = \alpha \cdot g(x, y) + \beta \quad (1)$$

Here, α is the factor which controls the brightness and β is taken to be 0.

2) Data Augmentation

Everyday a new method is being introduced in field of deep learning to improve the accuracy of the models in pre-processing stage. Data Augmentation is a technique of image pre-processing. This technique is given importance when the data available for the training process is less, so it helps in increasing the diversity of the data without any requirement of new data. Data Augmentation involves rotating, flipping, padding, and cropping of an image. As we know that the medical data available for specific purpose is low so, data augmentation technique helps in increasing the heterogeneity of the data available.

3) 2D Convolution Layer

Convolution operation involves extracting the features from an input image. It is a mathematical operation that is used to sustain relation between smallest unit of an image. Convolution is performed between input image and a filter or a kernel of 11*11 dimension which tends to change as the dimensions of image change after every convolution operation. The filter is slide over the image and pixel-wise multiplication is done and the results are added to obtain a feature map. Similarly, many feature maps are collected and stacked together. A stride of 4 means the filter or kernel is moved 4 places after one operation.

Equation:

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) \cdot g(t - \tau) d\tau \quad (2)$$

4) Average Pooling

After Convolution pooling is performed on the large sized images to reduce the dimensions of the image, this is done so as to reduce the parameters and bring down the training time which also helps to overcome problem of overfitting. It is also called down-sampling. In average pooling the average of all values inside pooling window is considered. The importance of this is down sampling while keeping the important information. Average Pooling is done as brightening of image has already scaled up the level of pixels.

5) Relu

A single image has a lot of information and images also have many objects that is the reason an image is considered to be highly non-linear. An activation function that performs the operation to introduce non-linearity which is required by the Convolutional Net to be powerful is Rectified Linear Unit. For application of medical image classification there is a need that Convolutional Net learns from non-negative linear values.

Equation:

$$z = \max(0, x) \quad (3)$$

6) Fully Connected Layer

We add a fully connected layer to the network after pooling and convolution operations to combine the CNN. The output of convolution and pooling has to be flattened as FC layer expects 1D vector. In order to feed vector to our fully connected layer we convert the matrix of the feature maps into vectors for eg. (a1, a2, a3...). This layer helps in combining the features to create a complete model.

7) SoftMax Layer

As the end result has to be a classification as 'Yes' or 'No', so an activation function called SoftMax is used. It converts the scores into probability and helps in classifying the output. It increases the differences and brings the result close to 0 or 1.

Equation:

$$\sigma(s)_i = \frac{e^{s_i}}{\sum_{j=1}^K e^{s_j}} \text{ for } i=1\dots, K \text{ and } s = (s_1\dots, s_k) \in R^K$$

(4)

8) Alexnet Architecture

One of the Deep Convolutional Neural Networks which is used for classification of images is Alexnet [1]. [1] is composed of 25 layers. A few layers are for 2d convolution, some are fully connected layers and between the convolution layers there are layers for pooling and increasing non-linearity of the image. For 1 to 5 layers we have an input image size of 227*227*3, the first layer of [1] is convolutional layer with the filter size being 11*11 and strides being 4 and number of filters is 96. Then is a relu layer followed by cross channel normalization and max pooling layer. Similarly, we have 6-9 layers of convolution, pooling, relu and normalization. Then 10-15 we have layers of convolution and relu layer followed by 16th layer of Max pooling. 17-22 layers are composed of fully connected layer, relu and dropout layer. Finally, there is a fully connected layer followed by a layer of activation function (SoftMax) and Classification Output layer.

9) Transfer Learning

Alexnet [1] a pretrained model is used and suitable changes are made to its architecture to classify the Brain Tumor images. Now a days using transfer learning [4] is taken as a common approach when it is applied for medical imaging purpose. Using a pre-trained deep learning model for challenging classification tasks is found to provide results with best accuracy. Alexnet [1] is trained on millions of images of about 1000 classes, so it has the knowledge about the edges, features etc. of the images.

10) Tumor Location

Regionprops provides the properties of a labelled image, here, the requirement is of area, solidity and bounding box around the tumor identified, bwlable to label the image for each object (tumor) as to form connected component, ismember function used along with regionprops to select some regions from an image, it returns logical true if components of one set are in another. These three commands are generally used to Identify, Classify and Count the number of objects in an image. Tumor is considered as an object which will be classified, identified and bounding box will be created around the tumor(s).

III. EXPERIMENTAL RESULTS

Dataset

Kaggle Competition [10].

Table- I. Sample Dataset

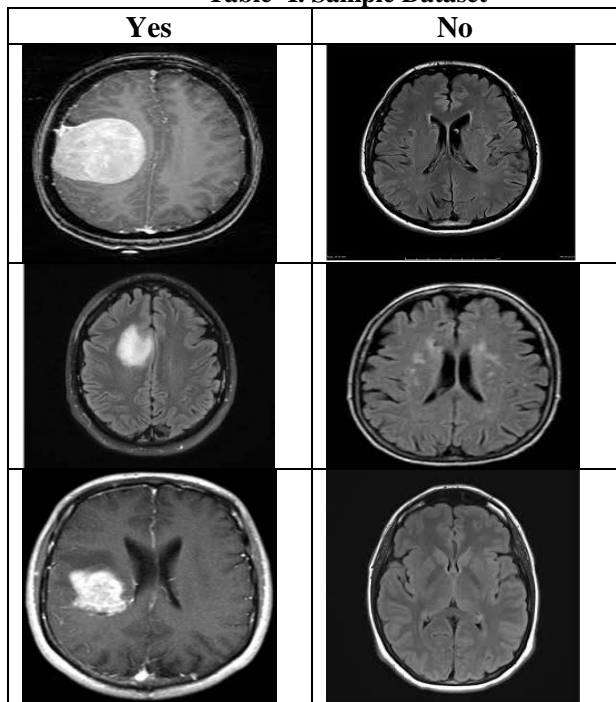
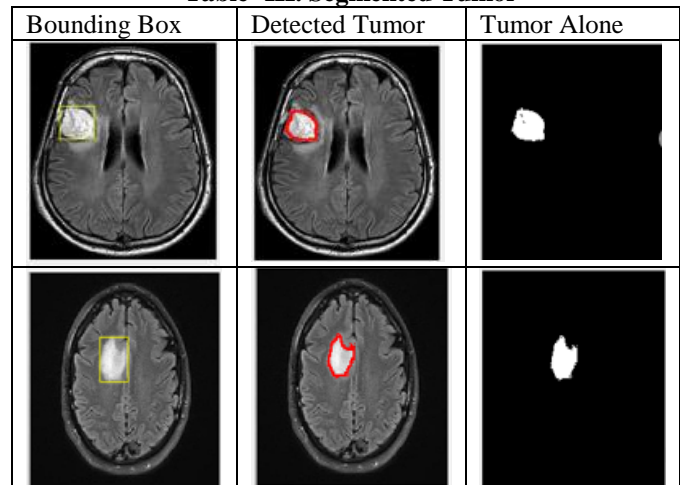


Table- III. Segmented Tumor



Accuracy of 97.7% has been achieved for classifying brain tumor images after brightening operation and tumors have been segmented.

IV. CONCLUSION

From the methods followed it is observed that Alexnet [1] turns out to be the best model for this Classification task using transfer learning [4] compared to VGG16, Squeezenet and ResNet50, this shows that the final weights and the combination of layers of Alexnet [1] is perfect for this task. Applying transfer learning using Alexnet [1] and changing layers of max-pooling with average pooling brings up the accuracy to 97.7%. Amongst the image pre-processing techniques image brightening helps the model to increase the accuracy for classification task. Thus, before applying any model it is better to pre-process the images in case of Convolutional Neural Networks. Tumor is segmented through basic image processing techniques as it requires less computational time.

Results

Output Class →

Table- II. Confusion Matrix

No	1	92.9%
13 29.5%	2.3%	7.1%
Yes	30	100%
0 0.0%	68.2%	0.0%
100%	96.8%	97.7%
0.0%	3.2%	2.3%

No Yes Output
Target Class

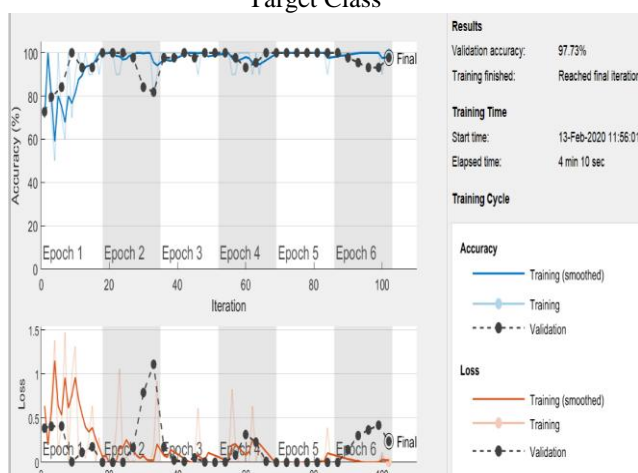


Figure 2. Training Process

REFERENCES

- Nawaz, Wajahat, et al. "Classification of breast cancer histology images using alexnet." International conference image analysis and recognition. Springer, Cham, 2018. Huynh, B. Q., Li, H., & Giger, M. L. (2016). Digital mammographic tumor classification using transfer learning from deep convolutional neural networks. Journal of Medical Imaging, 3(3), 034501.
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems (pp. 1097-1105).
- A. A. Novikov, D. Lenis, D. Major, J. Hladůvka, M. Wimmer and K. Bühler, "Fully Convolutional Architectures for Multiclass Segmentation in Chest Radiographs," in IEEE Transactions on Medical Imaging, vol. 37, no. 8, pp. 1865-1876, Aug. 2018.
- Huynh BQ, Li H, Giger ML. Digital mammographic tumor classification using transfer learning from deep convolutional neural networks. J Med Imaging (Bellingham). 2016 Jul;3(3) 034501. doi:10.1117/1.JMI.3.3.034501. PMID: 27610399; PMCID: PMC4992049.
- BVLC AlexNet Model. https://github.com/BVLC/caffe/tree/master/models/bvlc_alexnet
- Moradi, Mehdi & Mousavi, Parvin & Boag, Alexander & Sauerbrei, Eric & Siemens, D. & Abolmaesumi, Purang. (2009). Augmenting Detection of Prostate Cancer in Transrectal Ultrasound Images Using SVM and RF Time Series. Biomedical Engineering, IEEE Transactions on. 56. 2214 - 2224.

Transfer Learning for Classification of 2D Brain MRI Images and Tumor Segmentation

10.1109/TBME.2008.2009766.

7. D. Kwon, H. Akbari, X. Da, B. Gaonkar, C. Davatzikos, "Multimodal brain tumor image segmentation using GLISTR", MICCAI Brain Tumor Segmentation (BraTS) Challenge Manuscripts, pp. 18-19, 2014.
8. M.D. Zeiler, R. Fergus, "Visualizing and understanding convolutional neural networks", pp. 1311-2901, 2013.
9. He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask r-cnn. In Proceedings of the IEEE international conference on computer vision (pp. 2961-2969).
10. Navoneel Chakrabarty (2019, April). Brain MRI Images for Brain Tumor Detection, Version 1. Retrieved January 20, 2020 from <https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection>.

AUTHORS PROFILE



Onkar Rajesh Mulay, is currently a 4th year student pursuing Bachelors of Technology in Biomedical Engineering from Vellore Institute of Technology, Vellore, Tamil Nadu. His major fields of research include Machine Learning, Deep Learning (Convolutional Neural Networks) and AI in field of Healthcare and Image Processing. He was the member of IEEE EMBS, VIT for academic year 2017-2018. He was also a core committee member of Youth Red Cross, VIT for year 2018-2019. Biomedical Program Representative for academic year 2018-2019. Academic Achiever in VIT for academic years 2017-2018 and 2018-2019.



Dr. Hemprasad Yashwant Patil, is presently working at Vellore Institute of Technology, Vellore, India as Assistant Professor. He has completed Ph.D. from VNIT Nagpur in 2015. He has published more than 20 research articles in reputed journals and conferences in the domain of Image processing, Deep learning (Convolutional Neural Networks), Machine learning and computer vision. He also serves as a reviewer to journals like IEEE Transactions on Information Forensics and Security, Neurocomputing etc.