



Article Title: Brain Tumor Detection Using Deep Convolutional Neural Network

Brain Tumor Detection Using Deep Convolutional Neural Network

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ABSTRACT

Brain tumor is the third-most common cause of cancer related deaths in the world. Fortunately, it can be detected using MRI. Computer-aided diagnosis (CADx) systems can help clinicians identify cancer from brain diseases more accurately. In this project, propose a CAD system that distinguishes and classifies brain tumor from pre-cancerous conditions. The system uses a deep learning model. Deep CNN which involves depth wise separable convolutions, to classify cancer and non-cancers.

The proposed method consist of two steps:

Google's Auto Augment for augmentation and the CV2 based feature selection for image segmentation during pre- processing. These approaches produce a feasible methods of distinguishing and classifying cancers from other brain diseases. Our methods are fully automated without the manual specification of region-of-interests for the test and with a random selection of images for model training. This methodology may play a crucial role in selecting effective treatment options without the need for a surgical biopsy.

1 Introduction

According to the worldwide brain incidence statistics released in 2019 by the International Agency for Research on Cancer, the world's leading cancer research institute, brain tumor is the fifth most frequently diagnosed cancer and the third leading cause of cancer death. Computer vision is a rapidly expanding area that is dependent on the capability to automatically segment. Classify and interpret images. Segmentation is central to the successful extraction of image features and their subsequent classification. Region-based segmentation techniques are primarily used to identify various regions with similar features in once image. Region based approaches are generally less sensitive to noise than the boundary based methods. Hierarchical segmentation algorithm can process all regions (in a region growing manner) in a parallel and recursive fashion. Clustering refers to a class of algorithms used extensively for image segmentation. Clustering assembles unabled data by sets. Or clusters of data points with strong internal similarity. Data point values represent characteristic features of interest such as grayscale. A CNN is a type of deep neural network. Neural networks consist of many artificial neurons, which are the core of the algorithm intelligence.

Convolutional Layer

Convolutional layers are essential layers in CNNs, producing feature maps from input images or lower level feature maps. Convolutional layers includes a kernel (or filter).



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Pooling Layer

Pooling layers are also known as down sampling layers. A commonly used pooling method is maxpooling.

Over fitting

Over fitting is a problem that arises in neural network training. When a model is over fitted to the training data, it loses its capability of generalization.

Back propagation

The CNN requires to adjust and update its kernel parameters, or weights, for the given training data. Back propagation is an efficient method for computing gradients required to perform gradient-based optimization of the weights.

Hyper parameter

Tuning Training a network is done by a process called back propagation. Within the process of training, there are many choices regarding learning rate, optimizer, drop out and batch size.

Patch-wise training

Image size for training is limited by computer memory and Graphics Processing Unit (GPU).

2 Deep Learning

In this work, CNN is used as the deep learning architecture which consists of stack of the convolution layer (CL), rectified linear unit (ReLU unit) layer, maximum-pooling layer (MP), fully connected layer (FC) and classifier layer. In the convolution layer the input Brain image is convolve with the filter bank having six filter kernels. In the ReLU layer, negative values are rounded to the zero to increase the non-linear nature of the data. The max-pooling layer removes the unimportant features and decreases the size of the feature vector. This progression of computations through the network is called forward propagation.

The input and output layers of a deep neural network are called visible layers.

- Supervised Learning-Based Diagnosis Of Brain Cancer
- Image Recognition Based On Semi-Supervised And Unsupervised Learning In Brain Tumor

The major objectives of this work are highlighted as follows:

- A new method for Brain lesion recognition based on a deep learning network that can successfully classify the cancer from pre-cancerous MRI images is presented.
- Here also propose a method that combines image segmentation and augmentation algorithms.
- Our method is fully automated without manual specification of the region of interest for testing and random selection of images for model training.
- Experimental results demonstrate that the efficiency and effectiveness of the proposed



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task are superior to the basic deep learning model.

3 Recent Works

A. Harshavardhan, Dr. Suresh Babu, Dr. T. Venugopal (2017) The segmentation of tumor region in the MRI brain images was proposed in the paper. Even though table 3 showed the acceptable results for the proposed method regarding segmentation accuracy and execution time, the proposed method has to be validated with the implementation of feature extraction and classification phases for detailed diagnosis results. Segmentation of brain MRI images for clinical analysis is a challenging task. Cheng, Chen and Lin proposed FCM based Automatic Thresholding Algorithm for segmenting the MRI brain images. The multi-resolution images are segmented using Support Vector Machine Classifier. The proposed method was analyzed based on Sensitivity (99.4%), Specificity (99.6%), Positive Predictivity (97.03%) and Accuracy (99.5%) respectively. The segmented brain tumor images were compared with the ground truth images to prove its superiority or accuracy. Even though the authors claimed for higher tumor segmentation accuracy, they failed to specify the datasets used and the number of images used for evaluation. Authors would like to integrate those phases as the future work and validate the performance of the proposed method.

T. A. Jemimma, Y. Jacob Vetharaj (2019) the proposed brain tumor segmentation and classification is implemented through the Water Shed Algorithm (WSA), Dynamic Angle Projection Pattern features and these features are classified by using CNN. The importance of the watershed segmentation algorithm is which extracts the tumor regions in an effective manner for proficient DAPP feature extraction. The DAPP extracts the texture features from the segmented tumor regions and histogram features are obtained. These feature vectors are promoted to the input for CNN classifier which performs the classification. The segmentation and classification of MRI brain image are necessary for the proficient diagnosis of brain tumor. Everyone pooling layer in the CNN is parallel to the antecedent to the convolution layer. The pretty ss region of the convolution layer is combined with neurons in the pooling layer. The feature vectors are depicted for the input image away from the convolution and pooling layers. The spatial knowledge of the input pixel incorporated in nearby regions is restricted in these features. After that, for classification, the learned features are promoted to the logistic reversion. The experimental results are implemented through the BRATS database which achieves better dice score efficiency 93.5% and sensitivity 94.2%. In the future work, for classification and segmentation of brain tumor, some other different features can be compared to get more accuracy. It can also be extended to identify the other types of tumors such as a pancreatic tumor, adenomas, Fibromas.

Jagadeesh Kakarla, Bala Venkateswarlu Isunuri (2019) Threshold-based segmentation is a fast technique for brain Tumor extraction. We implemented an adaptive threshold selection network to predict tumor region with two phases. The proposed method starts with a training phase to achieve image specific adaptive threshold from each image of train dataset. Then, the



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mean of the image specific adaptive threshold is considered as the required adaptive Threshold. Simple image thresholding with adaptive threshold will be performed to extract the tumor region in the training phase. We considered brain tumor dataset of 2295 images for comparison of results. We used 765 images of train dataset for training and the remaining 1530 images are considered for performance evaluation. Our method retained maximum tumor region with accurate location. In order to exhibit the performance of ATSN, we adopted five vital measures including dice similarity, jaccard coefficient, accuracy, sensitivity, and specificity. The results section exhibits improved results when compared with conventional methods. However, our method unable to improve specificity and accuracy due to single threshold for all types of tumors. This work can be extended by considering a range of threshold values instead of a single threshold to improve the specificity.

Parnian Afshar, Konstantinos N. Plataniotis, and Arash Mohammadi (2020) Deep learning networks, including capsule networks, can have a variety of architectures, influencing their performance. Exploring all these architectures need powerful computation resources. In this work, we presented a capsule network based boosting framework that eliminates the need for exploring different architectures. The capsule network embedded in this framework is capable of extracting features from the whole brain tissue, and at the same time, focusing on the main target, by taking both the brain image and the tumor rough boundary box as inputs. Our results show that the proposed method, referred to as the Boost Caps, can outperform its counterpart. We used a brain cancer dataset [21], consisting of 3064 brain MRI images from 233 patients, where 20% of the data is set aside for testing purposes. We have trained our proposed Boost Caps framework, using 10 capsule networks as the weak learners. Although the number of the weak learners is usually much larger than 10, a deep learning model can bring training error to zero after a few steps. Further investigation on larger datasets is, however, required to verify the clinical applicability of the proposed framework. Our future direction also includes investigating other capsule networks-based ensembles for the brain tumor classification.

Yu Zhu, Pengfei Zhe, Hong Zhou (2020) Imperfect channel knowledge can lead to significant performance degradation to the existing FDE design which is based on the perfect channel estimation assumption. More training overhead or more transmit power has to be paid to overcome such degradation in the implementation of FDE for practical systems if there is no specific consideration in the FDE design. This paper addressed this challenge by studying the robust FDE scheme not only in the coefficients optimization, but also in the joint design with channel estimation and channel decoding. We evaluated the performance of the robust FDE scheme not only by doing simulations but also providing theoretical performance analysis. Numerical results have shown that the proposed robust FDE scheme can achieve 2-6dB performance improvement in E_b/N_0 over the existing non-robust counterpart for different fading channels.

It is worth noting that although the methods in both robust equalization design and performance analysis in this paper were proposed for the single input and single output channel, they can be



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extended to the multiple input and multiple output (MIMO) channel, which deserves further investigation in future work.

4 Proposed Work

CADx systems that use deep learning have developed significantly. However, they typically rely on large labeled datasets and significant expert knowledge and incur a high computational cost. Data collection is time consuming and costly because patients require privacy and researchers require institutional review board (IRB) approval.

- Training images are feed to Augmentation to enlarge the dataset for better finding solution
- Augmented images are then filtered through cv2 based feature selection.
- The extracted features are then feed to the CNN based model to train the data
- After the training is completed model is saved for feature identification
- To identify whether the image consist of cancer or not the image is first feed to extract features through cv2 model then its sended to trained model.
- Trained model will analyse the features and verify based on the training of that model and will predict whether it's a cancerous or non-cancerous image.

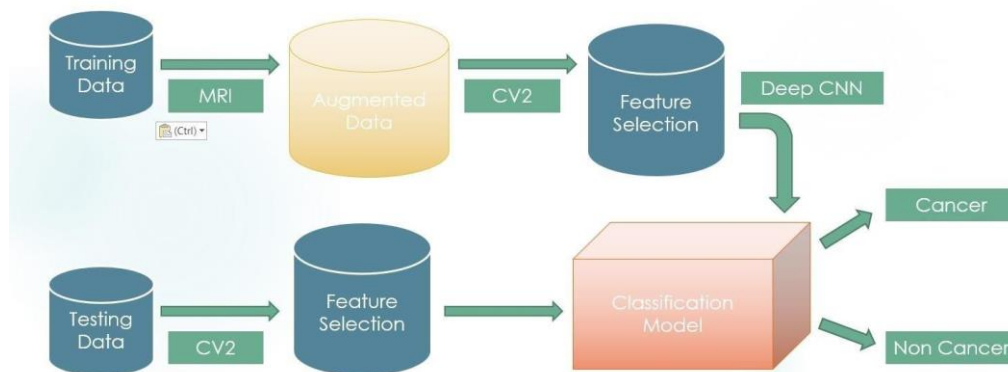


Figure 1: Proposed Block Diagram

Proposed system having 5 modules:

- Data Collection.
- Data Augmentation.
- Feature Selection.
- Classification Model.

4.1 Data Collection

All MRI image data were selected by internists and verified via medical examination and



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biopsy. The total of 253 MRI image data were collected from 69 patients. There are 619 images used for training and 85 for testing. The training set included 155 cancer and 98 non-cancer images, and the test set included 52 cancer and 33 non-cancer images.

Types of lesions include Meningioma, Asrtrocytoma, Gliomas, and Glioblastoma.

4.2 Data Augmentation

A controller recurrent neural network (RNN) samples a policy S , to which the images are to be appended. Using a child network, various augment policies are applied to the dataset. It is an algorithm that obtains performance accuracy R and updates it in the controller RNN to find the best augment policy by applying the optimized data augmentation policies, high accuracy uses of public data.

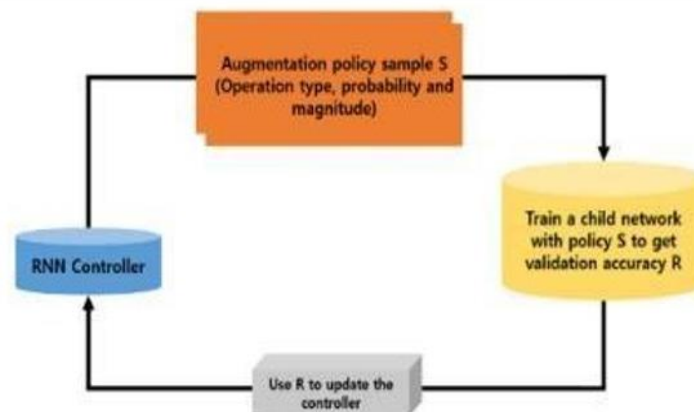


Figure 2: Process of Auto Augment

4.3 Feature Selection

CV2 based feature selection is done by initially applying gaussian blur along with thresholding in image. CV2 based dilate and erode are used to remove the grains present in the image to get the features.

It is detected the edges by canny edge detection algorithm and then normalized and then converted to tensor shape and size of deep CNN model.

4.4 Classification Model

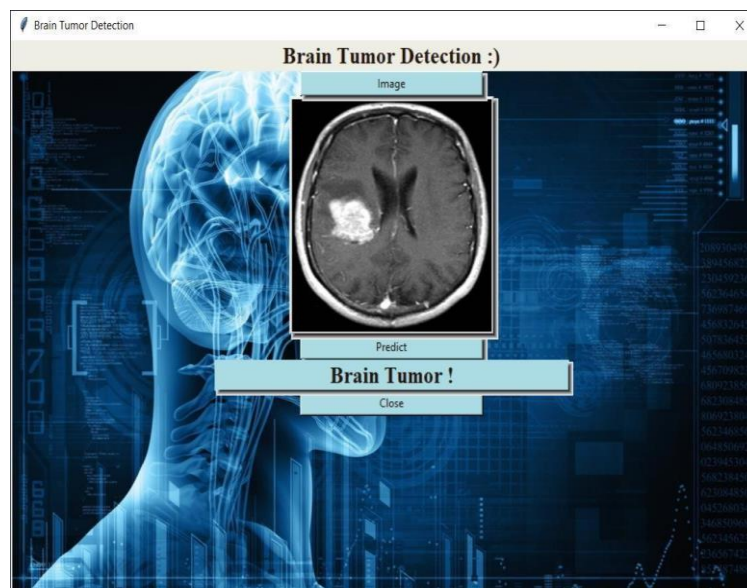
The Deep CNN architecture has 32 convolutional layers forming the feature extraction base of the network. Inception module that separately operates 1×1 and 3×3 convolution operations of all channels of the resultant feature map. Zero-padding is given to the stride of 2×2 . Batch-normalization layer is added along with axis 3. The 2 layers of max – pooling is applied with stride of 4×4 in each. An inner activation layer is applied with ReLU activation and the model is flatten. A fully connected layer of sigmoid activation function is used for classify the end result



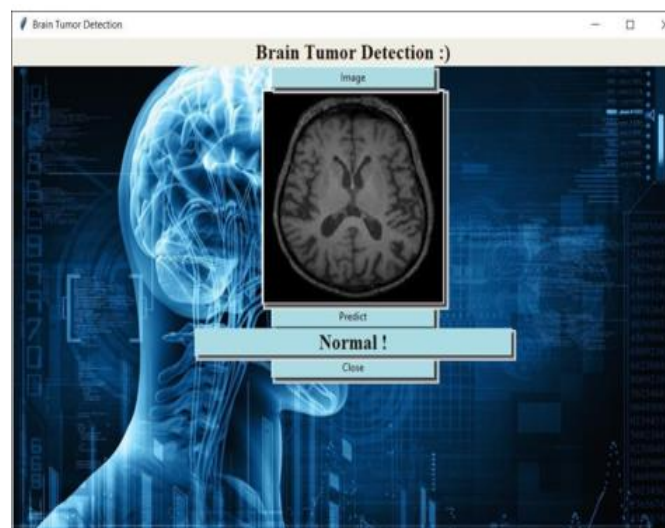
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5 Result

The results show that the models trained using augmentation and/or segmentation performed better than the one trained without them. This provides a solution for one of the biggest problems of deep learning in medical image analysis, which relies heavily on large amounts of data.



This Figure shows that it Predicts Cancer



This Figure shows the Prediction of Non - Cancer

6 Conclusion

Deep CNNs are powerful and useful algorithms that commonly work well when trained using a large amount of data. The shortage of labeled training data in brain tumor research is a major



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problem that limits the application of CNNs in the field of medical image analysis. In this paper, we proposed the CADx system, which can distinguish and classify brain tumor from other brain diseases. The system used the Deep CNN network, which involves depth-wise separable convolutions. The proposed method used two algorithms: Google's Auto Augment for augmentation and the CV2 feature selection model for image segmentation. As a result of analyzing the classification performance of the system, we found that augmentation and segmentation enabled the classification model to perform better because the applied data augmentation policy prevented overfitting. Additionally, the segmented images expertly identified as cancer or non-cancer by the internist facilitated our focus on the features of the lesion during training. In this study, we achieved a ROC curve of 0.96, which is 0.06 higher than that achieved when the two methods were not applied, indicating that it is meaningful to train by dividing the area of an augmented image. This methodology may play a vital role in selecting effective treatment options and survival predictions without the need for a surgical biopsy.

References

1. Justin S. Paul; Andrew J. Plassard; Bennett A. Landman; Daniel Fabbri, Year: 2017, "Deep Learning for Brain Tumor Classification," PROCEEDINGS OF SPIE, 2017.
2. Heba Mohsen; El-Sayed A. El-Dahshan; El-Sayed M. El-Horbaty; Abdel-Badeeh M. Salem, Year: 2018, "Classification using deep learning neural networks for brain tumors," Future Computing and Informatics Journal, Vol: 3, no: 1, pp. 68 – 71, 2018.
3. N. K. EI Abbadi; N. E. Kadhim, Year: 2017, "Brain Cancer classification Based on Features and Artificial Neural Network," International Journal of Advanced Research in Computer and Communication Engineering, Vol: 8, no: 1.
4. A. Krizhevsky; I. Sutskever, Year: 2012, "ImageNet Classification with Deep Convolutional Neural Networks," Neural Information Processing Systems (NIPS) 2012.
5. S. Sabour; N. Frosst; G. E. Hinton, Year: 2017, "Dynamic Routing Between Capsules," 31st Conference on Neural Information Processing Systems (NIPS 2017), 2017.
6. G. Hinton; S. Sabour; N. Frosst, Year: 2018, "Matrix Capsules With EM Routing," ICLR, 2018.
7. P. Afshar; A. Mohammadi; K.N. Plataniotis, Year: 2018, "Brain Tumor Type Classification via Capsule Networks," IEEE International Conference on Image Processing (ICIP), 2018.