Brain Tumor Segmentation Using DL Method CNN and SVM Classification

K.Sowbhagya Lakshmi[1]
Dr. B.Naga Jyothi[2]
[1]*Mtech Student Dept of ECE, DMSSVH College of Engineering, Machilipatanam.*
[2]*Professor & HOD, Dept of ECE, DMSSVH College of Engineering, Machilipatanam.*
[1]sow2010k@gmail.com

Abstract*—Brain tumor segmentation is an important task in medical image processing. Early diagnosis of brain tumors plays an important role in improving treatment possibilities and increases the survival rate of the patients. Manual segmentation of the brain tumors for cancer diagnosis, from large amount of MRI images generated in clinical routine, is a difficult and time consuming task. There is a need for automatic brain tumor image segmentation. Magnetic resonance imaging (MRI) technology has high resolution of soft tissue, can accurately describe the anatomy of the brain, and has important significance in the diagnosis, treatment and surgical guidance of brain tumors [1]. In this paper an automatic segmentation method based on Convolutional Neural Networks (CNN) is proposed, exploring small 3×3 kernels. The use of small kernels allows designing a deeper architecture, besides having a positive effect against over fitting, given the fewer number of weights in the network. We also investigated the use of intensity normalization as a pre-processing step, which though not common in CNN-based segmentation methods, proved together with data augmentation to be very effective for brain tumor segmentation in MRI images. Proposed study is validated on the Brain Tumor Segmentation Challenge 2013 database (BRATS 2013) using CNN and Support vector machine (SVM). The experimental results are simulated using matlab software tool.

Keywords— *MRI Images, CNN, SVM and BRATS dataset.*

1. Introduction

Image processing is processing of images using mathematical operations by using any form of signal processing for which the input is an image, a series of images, or a video, such as a photographer video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a dimensional signal and applying standard signal-processing techniques to it. Images are also processed as three-dimensional signals where the third-dimension being time or the z-axis. Image processing usually refers to digital image processing, but optical and analog image processing also are possible. This work is about general techniques that apply to all of them. The acquisition of images (producing the input image in the first place) is referred to as imaging. Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. It is among rapidly growing technologies today, with its applications in various aspects of a business. Image Processing forms core research area within engineering and computer science disciplines too.

- Analyzing and manipulating the image which includes data compression and image enhancement and spotting patterns that are not to human eyes like satellite photographs.
- Output is the last stage in which result can be altered image or report that is based on image analysis.

Image Processing Toolbox supports a diverse set of image types, including high dynamic range, giga pixel resolution, embedded ICC profile, and tomographic. Visualization functions and apps let's to explore images and videos, examine a region of pixels, adjust color and contrast, create contours or histograms, and manipulate regions of interest (ROIs). The toolbox supports workflows for processing, displaying, and navigating large images. Conversely, Neural Networks (NN) usually used method for their good enactment over the most recent few years. However freshly, Deep Learning (DL) models fixed a stirring trend in machine learning as the subterranean architecture can efficiently represent complex relationships without needing a large number of nodes like in the superficial architectures e.g. K-Nearest Neighbor (KNN).Consequently, they grew quickly to become the state of the art in unlike health informatics areas for example medical image analysis, medical informatics and bioinformatics.

2. Related works

The Fuzzy C-Means (FCM) segmentation is applied to separate the tumor and non-tumor region of brain [1]. Also wavelet features are extracted by using multilevel Discrete Wavelet Transform (DWT). Finally, Deep Neural Network (DNN) is incorporated for brain tumor classification with high accuracy. This technique is compared with KNN, Linear Discriminant Analysis (LDA) and Sequential Minimal Optimization (SMO) classification methods. An accuracy rate of 96.97% in the analysis of DNN based brain tumor classification is possible but the complexity is very high and performance is very poor.

A novel bio-physiomechanical tumor growth modeling is presented to analyze the step by steps tumor growth of patients. It will be applied for glioma and solid tumor with individual margins to seizure the significant tumor mass effect. The discrete and continuous methods are combined to make a tumor growth modeling. The proposed scheme provides the likelihood to tacitly segment tumor-bearing brain images based on atlas-based registration. This technique is mainly used for brain tissue segmentation. But the computation time is high [2] .The new multi-fractal (MultiFD) feature extraction and improved AdaBoost classification schemes are used to detect and segment the brain tumor. The texture of brain tumor tissue is extracted by using Multi FD feature extraction scheme. The improved AdaBoost classification methods are used to find the given brain tissue is tumor or non-tumor tissue [3] . Complexity is high. Local independent projection-based classification (LIPC) method is used to classify the voxel of the brain [4] . Also path feature is extracted in this method. Hence no need to perform explicit regularization in LIPC. The accuracy is low. A seeded tumor segmentation method with new Cellular Automata (CA) technique is presented, which is compared with graph cut based segmentation method. The seed selection and Volume Of Interest (VOI) is calculated for efficient brain tumor segmentation [5]. Also tumor cut segmentation is incorporated into this work. The complexity is low. But the accuracy is low.

3. Convolutional Neural Networks:

Recent performances of deep learning methods, specifically CNN, in several object recognition and biological image segmentation challenges increased their popularity among researches. In contrast to traditional classification methods, where hand crafted features are fed into, CNN automatically learn representative complex features directly from the data itself. Due to this property, research on CNN based brain tumor segmentation mainly focuses on network architecture design rather than image processing to extract features. CNN take patches extracted from the images as inputs and use trainable convolutional filters and local subsampling to extract a hierarchy of increasingly complex features. Although currently very few in number compared to other traditional brain tumor segmentation methods, due to state-of-the-art results obtained by CNN based brain tumor segmentation methods

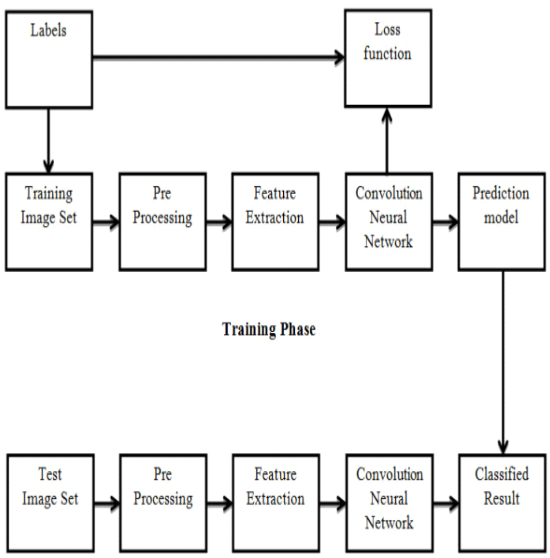

Fig. 1. System model using CNN

They have wide applications in image and video recognition, recommender systems and processing. The convolutional neural network is also known as shift invariant or space invariant artificial neural network (SIANN), which is named based on its shared weights architecture and translation invariance characteristics.

Algorithm for CNN based Classification

- Apply convolution filter in first layer
- The sensitivity of filter is reduced by smoothing the convolution filter (i.e) sub sampling
- The signal transfers from one layer to another layer is controlled by activation layer
- Fasten the training period by using rectified linear unit (RELU)
- The neurons in proceeding layer is connected to every neuron in subsequent layer
- During training Loss layer is added at the end to give a feedback to neural network

4. SVM Classification:

Among classification techniques like Navies bayesian, Linear regression and SVM, SVM classification is one of the most promising technique which is used in recent times. SVM is a linear classifier and also known as maximum margin classifier. In our work, we have calculated different parameters for the brain image. Parameters like Mean, Standard Deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness, IDM, Contrast , Correlation, Energy, Homogenity. Based on these parameter value the type of tumor is been identified.

The process of detecting tumor:

A. Selecting data Set:

Initial stage of the project is selection of data for which classification need to be performed. In this project MRI images data set is been selection to perform the operation.

B. Training and testing the data set:

Take the data set, train the data set to identify the similarity functions. Monitoring of the data and finding different values. The experiments where performed on the data. After this, for the trained data different other functions have been added for testing.

C. Feature extraction

After testing the data, the features were achieved and formed into a data matrix. This data is used to identify the regions and locations. So that it will be useful in utilizing the spatial locations due to the spread of the ECG channels over the scalp.

D. Feature selection:

The feature selection is based on the receiver operating characteristics. The values are computed based on the Area under the curve for individual features. Empirical process has been adopted to find minimum number of features by ranking them in descending order.

F. Classifying the data:

The data set will be classified based on the specified features mentioned. While classifying the data the reduced set of features are considered as independent variables and the corresponding treatment outcomes were considered as dependent variables. Hence the type of tumor i.e Malignant Tumor or beneign tumor is been identified.

5. Results:

The results obtained by using CNN show below. The input brain image is been given for training and testing.

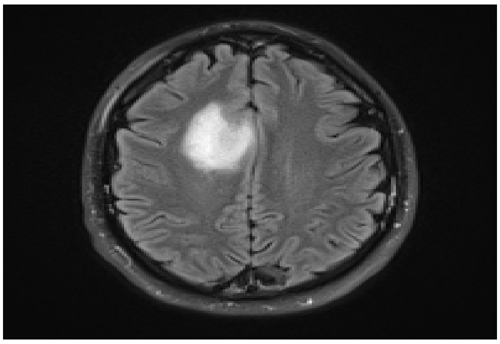

Fig. 2. Testing and Training Image

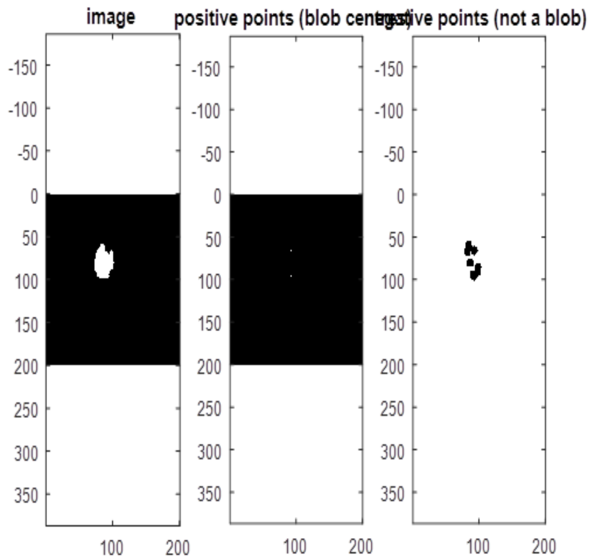

Fig. 3. Positive and Negatives of Image

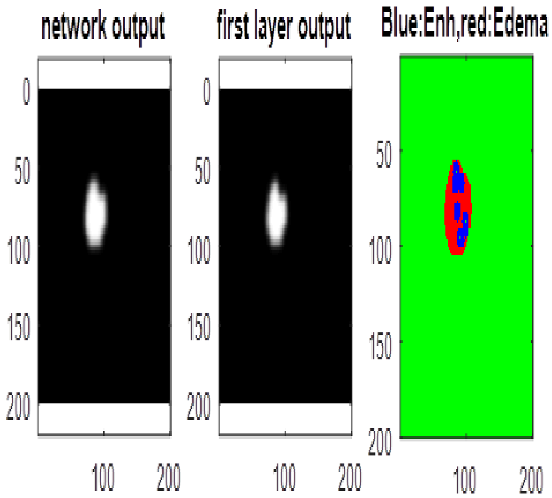

Fig. 4. CNN output

In figure 4 the CNN process is been done and output is obtained. The blue area shows the Enhanced tumor part which is HGG and red area shows the Edema tumor part which is LGG.

- Dice Similarity Coefficient: 98.998665
- Positive Predictive Value: 99.414520
- Sensitivity: 96.543779

The DSC, PPV and sensitivity are the image segmentation metrics which is useful to know the accuracy of the result obtained. The SVM results are shown below. For doing SVM classification the following parameters need to be calculated, based on these parameter values the tumor is identified as benign or malignant.

Mean = 2.438821e-01

Standard Deviation = 1.072265e-01

Entropy = 7.310287e-01

RMS = 9.246246e-01

Variance = 4.582930e-03

Smoothness = 8.969769e-02

Kurtosis = 3.548393e+00

Skewness = 8.980265e-02

IDM = 8.069418e-03

Contrast = 9.445937e-01

Correlation = 6.523500e+00

Energy = 6.203886e-01

Homogenity = 5.030334e-01

Fig. 5. Final output showing the disease

6. Conclusion:

The main goal of this research work is to design efficient automatic brain tumor classification with high accuracy, performance and low complexity. In the conventional brain tumor classification is performed by using FCM based segmentation, texture and shape feature extraction and DNN based classification are carried out. The complexity is low. But the computation time is high meanwhile accuracy is low. Further to improve the accuracy and to reduce the computation time, a convolution neural network based classification is introduced in the proposed scheme. Also the classification results are given as tumor or normal brain images. CNN is one of the deep learning methods, which contains sequence of feed forward layers. The training accuracy, validation accuracy and validation loss are calculated. The training accuracy is 97.5%. Similarly, the validation accuracy is high and validation loss is very low.

Similarly, the validation accuracy is high and validation loss is very low. SVM is proved to be one of the best techniques for efficient classification of the data

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