Convolutional Neural Network based Image Classification and Detection of Abnormalities in MRI Brain Images

P. Muthu Krishnammal and S.Selvakumar Raja

***Abstract*—Quantitative analysis of many neurological diseases depends on automated and accurate segmentation and classification of structures. Nowadays, the deep learning based image classification and segmentation methods have gained interest of research because of their self-learning capabilities over huge amounts of dataset. This paper focuses on the use of Convolutional Neural Network which takes the feature maps preprocessed in Curvelet domain to classify the MRI brain image datasets. Curvelets provide better sparse representation and the features extracted are more accurate than traditional wavelet transform due to its multi-directional capability. Next, the segmentation methods to study the anatomical structures and localization of brain tumors is dealt and finally the performance of the CNN is discussed. Comparing with the wavelet transform and classification using traditional classification methods like SVM, PNN, the feature extraction in Curvelet domain and CNN provides an increase in accuracy**

***Index Terms*—Deep Learning, Convolutional Neural Networks, Curvelet transform, GLCM, K-means Segmentation, MRI brain imaging.**

I. Introduction

MAGNETIC Resonance Imaging (MRI) is a non-invasive utilized for the finding and envisioning the inner structure of the human body, and it provides the detailed information about various body tissues with high contrast and spatial resolution and subsequently it is broadly utilized for the anatomical auxiliary examination of cerebrum tissues [1-2]. Brain tumor is an uncontrolled development of cancer cells in the brain. The different types of tumors are: benign and malignant [3]. The benign tumors are non-destructive tumors have uniform structure and do not spread or attack other parts of body and consequently less risky. Meningiomas and Neuromas are examples of benign tumors. On the other hand, malignant tumors are destructive tumors and invade the surrounding tissues and may spread to other parts through the blood or lymph framework. Carcinoma, Sarcoma, Lymphoma are some of the examples of malignant tumors [4]. Hence brain tumor localization, detection, segmentation and classification processes have become most challenging task in the clinical diagnosis [5].Texture is defined by a certain scale, directionality and regularity and describes the homogeneity of the images and the texture analysis is based on intensity variations. The different methods used for the textural analysis include: wavelet transform, statistical methods, fractal methods etc. Among the statistical methods, GLCM is most commonly used for textural description [6]. Wavelet transform, a multi-scale and multi-resolution method that provides good effect on texture classification. For some images which are characterized by distinct distribution of texture, the inherent information may be lost and thereby the directionality and spatial correlation between texture and pattern gets suppressed which limits the classification accuracy [7]. The missing directional selectivity of DWT [8-9] can be resolved by the utilization of curvelet transform which allows optimal sparse representation for the objects having discontinuities along smooth curves [10-11]. The different transforms that are used for representing directional information are: include ridgelets, curvelets, contourlets, etc [12-16]. Besides the significant efforts, automated segmentation and detection of abnormalities is still a great challenge due to the variations in the anatomy of brain morphology, imperfections in image acquisition, variations in scanner settings and pathological variations in appearance. The state-of-the-art technique known as deep learning can stay away from the confinements of conventional machine learning methods due to its self-learning ability over large amounts of datasets [17]. The expanded GPU processing power has also empowered the advancement of deep learning algorithms and finds applications such as object detection, segmentation of region of interest from images or videos, detection and classification of abnormalities, speech recognition etc.CNNs match the with structural data that is captures using a spatial structure and this special property of the CNN makes it best suited for classifying images, videos etc. [18] CNNs architectures are different from the classical machine learning algorithms in the aspects such as they do not require hand-crafted feature extraction as they learn the features to be extracted by backpropagation, do not require human experts for segmentation and are of more hunger of data as it requires to estimate millions of learnable parameters which in turn becomes more computationally expensive and requires GPU for model training [19]. Segmentation methods are needed for detection and localization of abnormalities which is crucial for further treatment planning such as diagnosis, chemo or

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978-1-5386-7595-3/19/$31.00 ©2019 IEEE

radiotherapy planning and postoperative analysis [20]. The rest of paper is organized as follows: Section II deals with the methods proposed. Section III deals the feature extraction using FDCT and GLCM and section IV and V deals about the classification of tumors using CNN and segmentation using k-means respectively.Results are discussed in Section VI and finally Concludes the paper in Section VII.

II. MATERIALS AND METHODS

The proposed strategy is based on the Convolutional Neural Network architecture for cerebrum tumor classification. The steps involved are as follows:

Step1: Acquisition of MRI brain image dataset
Step2: Feature extraction using FDCT and GLCM.
Step3: Classification using CNN
Step4: Image segmentation using K-Means

III. FEATURE EXTRACTION

A. Curvelet Transform

Curvelet transform is a unique member of the transforms used for Multiscale Geometric Analysis (MGA) which attempts to overcome the limitation of traditional DWTs. The curvelet transform is a multiscale pyramid with numerous directions and positions at each length scale, and needle-shaped elements at fine scales [21].

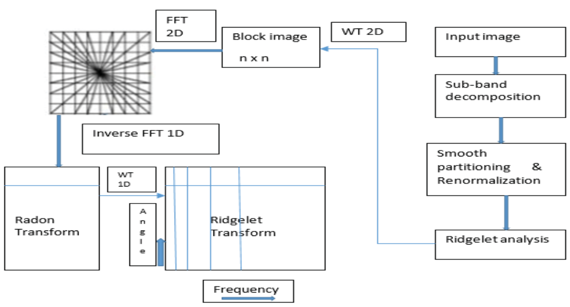


Fig. 1.The Process of curvelet transform

The two strategies used to obtain the curvelet coefficients are: USFFT (Unequal Space Fast Fourier Transform) and wrapping based methods. Irregular sampling the Fourier samples of the image is done in USFFT, whereas wrapping based method uses a sequence of translation and wrap around method to obtain the curvelet coefficients. The output produced by both of the methods are same, but wrapping based method is efficient in computation [22]. In the proposed work, wrapping based method is used. The coefficients of curvelet are generated using FFT operations [12]. The process of curvelet is delineated in Fig. 1. The curvelet decomposition takes place in the following four phases [23]

- Subband Decomposition
- Smooth partitioning
- Renormalization
- Ridgelet Analysis.

The number of scales represent resolution and number of scales represent the orientations. It is essential to select the significant subbands to avoid the redundant information in the feature extraction stage.

B. Feature extraction by GLCM

By the selection and determination of distinct features such as texture, shape, contrast and color, the accuracy of the medical investigation system can be enhanced effectively [24-27]. Gray Level Co-occurrence (GLCM) is a second order statistical method [28-30] for feature extraction which computes the GLCM and calculation of textual features [3]. In general, mean and variance of the intensity of the voxels are the first order features. The second order features are characterized by taking the relationship between the voxels into account [8]. GLCM details about the frequency of occurrence of gray levels in different directions. The different directions are generally ϕ=0 °, ϕ = 45 °, ϕ = 90 °, and ϕ = 135°. Haralick [9] proposed 14 features out of which the salient features such as energy (Angular Second Moment), contrast, correlation, homogeneity (inverse difference moment) and entropy are calculated to extract the features [6-7].

- The homogeneity (Inverse difference moment) of images is best described by its texture using the texture element that has a certain scale, directionality and regularity

$$IDE = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j) \qquad (1)$$

- Angular second moment describes the uniformity and regularity of the image distribution.

$$Energy = \sum_{i=1}^{N} \sum_{j=1}^{N} \{\mathrm{p(i,j)}\}^2 \qquad (2)$$

- Contrast defines the smoothness and depth of the image texture structure.

$$contrast = \sum_{i=1}^{N} n^2 \{\sum_{i=1}^{N} \sum_{j=1}^{N} \{\mathrm{p(i,j)}\}\} \qquad (3)$$

- Correlation defines the similarity of the image texture in a horizontal direction or vertical direction.

$$correlation = \frac{\sum_i \sum_j (ij) P(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \qquad (4)$$

Where

$$\bar{x} = \sum_i^N i \sum_j^N P(i,j);\ \bar{y} = \sum_j^N j \sum_i^N P(i,j); \qquad (5)$$

$$\sigma_x^2 = \sum_i^N (i-\bar{x})^2 \sum_j^N P(i,j); \quad \sigma_y^2 = \sum_j^N (i-\bar{y})^2 \sum_i^N P(i,j)$$

- Entropy defines the measure of image information. $H = -\sum_i \sum_j p(i,j)\ log\{(i,j)\}$ (6)

IV. CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORKS

The CNN architecture is a mathematic construct that comprises of collection of feed forward layers such as convolution layer and pooling layer, trailed by one or more fully connected layers [19, 21]. The first two layers, convolution and pooling perform feature extraction, and the extracted features are mapped to final output by converting 2D feature maps into 1D vector to classify the images by the fully connected layer. For image classification, the CNN can be trained from the scratch, or a pre-trained CNN features can be used off-the-shelf, or unsupervised pre-training of CNN can be performed and fine-tuned with supervised methods [22]. The architecture schematic used for MRI image segmentation is shown in Fig. 2. Among the three CNN models, namely, AlexNet, Visual Geometry Group (VGG)-16, and VGG-19 [22], AlexNet is preferred in the proposed work due to its flexibility for modification, its ability to train faster and the capability to lessen over fitting using drop outs etc.

A. Convolution layer

Convolution layer plays a significant role in CNN that performs a stack of mathematical functions such as convolution. A feature map is produced via convolving the kernel (an optimizable feature extractor) with the input image whose pixels are stored in 2D array [17, 19]. It is done by an element-wise multiplication between the input tensor and each element of the kernel at every location of the tensor and gets summed up to obtain the output tensor, which is called a feature map. The depth of output feature map depends on the size of the kernel (usually 3x3 or 5x5). The example of convolution operation is shown in Fig. 3.

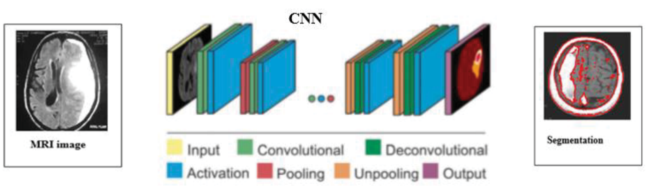


Fig. 2. CNN architecture for brain tumor segmentation task

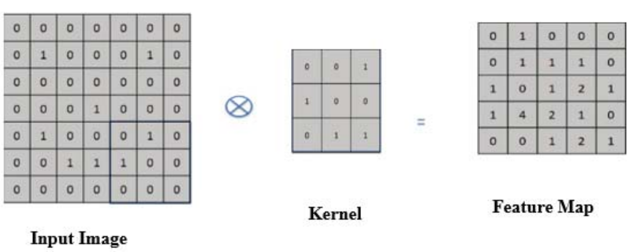


Fig. 3. An example of convolution operation with a kernel size of 3× 3, without zero padding, and a stride of 1

This convolution operation usually reduces the dimensions of the feature map at the output and hence zero padding is employed in order to retain the in-plane dimensions. The distance between the two positions of the successive kernel is termed as stride (usually 1). Higher values of stride is used for down sampling the characteristic maps [19].

B. Receptive Field

In most of the neural networks, every neuron is connected to each neuron in the next layer thus forming a fully connected network. But in CNN, a region of input volume is connected to one neuron in the next and this region is called the receptive field and this is usually a square. For example, if the input dimensions are 28x28x3 and receptive field is 5x5, then each neuron in the convolution layer is connected to 5x5x3 and hence each neuron will have 75 weighted inputs and generates the activations for the next layer [18].

C. Activation functions

The nonlinear activation functions such as ReLu (Rectified Linear Unit), sigmoid, tanh function pass the output of the convolution operation. ReLu is the most frequently used activation function which calculates the function as, $f(y) = \max(0, y)$ [19]. Fig. 4 shows the common activation functions used in neural networks. ReLu transforms any negative value into zero and positive values are passed to output [17].

D. Pooling Layer (subsampling)

The pooling is positioned after the convolutional layer that samples down and the main utility is that in-space dimension reduction of feature maps. Less computational overhead for the upcoming layers and capability to work against over fitting are the two benefits of size reduction using pooling layer [17, 18]. The most frequently used pooling operations are max pooling and average pooling and expressed mathematically as:

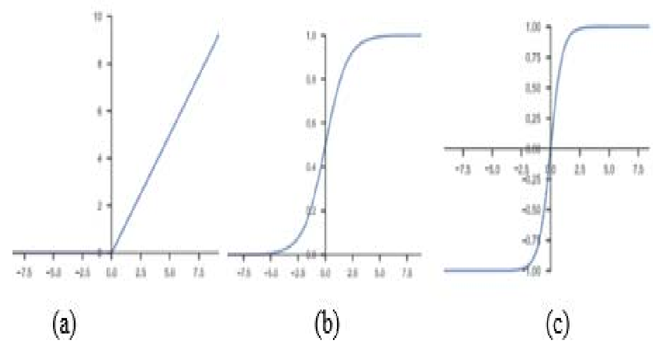


Fig. 4. activation functions used in neural networks :(a) ReLU (b) sigmoid (c) tanh

$$a_j = \max_{(p,q)\in R_{ij}} a_{kpq} \qquad \text{(Max pooling)}$$

$$a_{kij} = \frac{1}{|R_{ij}|} \sum_{(p,q)\in R_{ij}} a_{kpq} \qquad \text{(Average Pooling)}$$

E. Dense layer (Fully connected layer)

The feature maps from the final convolution or pooling layers is transformed into one dimensional vector and are connected to one or more dense layers to map the network's final output [19]. Usually Softmax is the last layer of the network to classify the image and activation function for softmax function is given by[19]

$$y_r = \frac{\exp(a_r)}{\sum_{j=1}^{k} \exp(a_j)} \qquad (6)$$

The network is trained to minimize the difference between the labels of ground truth labels and the output predicted (using constraints on regularization). The loss function (usually, cross entropy for multi-class problems) is deployed as the layer of CNN, to measure the compatibility between the predictions and the ground truth labels and is formulated as,

$$E(\theta) = -\sum_{i=1}^{n} \sum_{j=1}^{k} t_{ij} \ln y_j(x_i, \theta) \qquad (7)$$

Where θ is the parameter vector, t_{ij} indicates that the sample i belongs to the j class and $y_j(x_i, \theta)$ is the output for ith sample. The list of hyper parameters used in the various layers of CNN is given in Table I.

V. K-Means Algorithm Segmentation Algorithm

The K-means algorithm is a classical method that is simple and effective in solving clustering based problems. Using this

algorithm, a sample set X (x_1, x_2, ⋯, x_n) is classified into 'k' clusters which aims to minimize an objective function, by calculating the minimum square distance between cluster center and all clustering domain points. Let n be the number of samples and Ci be the cluster center defined as, $C_i = \frac{1}{N_i}\sum_{x \in x_i} x, i = 1,2, \dots, k$, and N_i is the sample number of the ith cluster (x_i). The objective function J can be given as:

$$J_{K-means} = \sum_{i=1}^{k}\sum_{j=1}^{k}\left\|x_j^{(i)} - C_i\right\|^2 \quad (8)$$

where $\left\|x_j^{(i)} - C_i\right\|^2$ represents the measure of Euclidean distance between a data point x_j and the cluster center C_i. The algorithmic steps involved are:

(i) Initialization of the cluster centroids C_i with k random samples;

(ii) Assignment of each sample point x_j to the nearest cluster center

TABLE I
THE LIST OF PARAMETERS USED IN A CONVOLUTIONAL NEURAL NETWORK

Layer	Parameters	Hyper parameters
Convolutional layer	Kernels	Number of kernels, kernel size, padding, stride and activation functions.
Pooling Layer	None	Method of pooling, filter size, padding and stride
Fully connected layer	Weights	Number of weights and activation functions
Other		Architecture model, , learning rate, weight initialization, database splitting , mini-batch size, epochs, optimizer, regularization, loss function etc

(iii)Recalculate each clustering center using $C_i = \frac{1}{N_i}\sum_{x \in x_i} x, i = 1,2, \dots, k$

(iv)Repeat steps (ii) and (iii) until the cluster centroid Ci changes any more.

The K-means algorithm is therefore an unsupervised clustering algorithm that minimizes the sum squared error. The advantages of the algorithm are simplicity and very high execution speed but it does not converge with the noisy images [23-28].

VI. Results And Discussion

The MRI brain images used in this study have been taken from public databases and images are in DICOM format. The images preprocessed are taken as the input for curvelet based feature extraction. In different scales and orientations, the images are decomposed into subbands. For instance, an image of 256x256 is decomposed at the scales 3 (coarse and fine) and angles 8. Fig. 7(c), Fig. 8(c) and Fig. 9(c) show the decomposition of an image that produces the one approximate and eight detailed subbands. Low frequency components are captured by the approximate subband and high frequency components are captured by rest of the subbands at different orientations. The coefficients thus obtained in curvelet domain serves as the set of input features and the important features such as energy, contrast, correlation, homogeneity and entropy are extracted (Table II) using the above described GLCM approach which serves as the feature set for CNN classification.

The pre-trained Alexnet model from MatConvNet toolbox [29-30] is used in the study which consists of 25 layers with weights. The input image of dimensions 227×227×3 is defined in the first layer. Then ReLu activation function and max pooling layers are intervened between a series of convolution layers. The classification layer with1000 classes is used as the final layer. The network uses five convolution layers, five pooling layers, and three fully-connected layers. The CNN model is trained for 100 epochs with the mini-batch size of 100 image instances out of which 70% for training and 30% images were used for testing. Training convergence is observed within 100 epochs with base learning rate 0.0001. Benign and malignant tumor images digitized at 256 × 256 were used. After classification, segmentation and localization of tumor is done with k-means clustering based segmentation method.

TABLE II
CURVELET FEATURES

Feature	Normal case		Benign case		Malignant case	
	LH3 (1.0e+03)	HL3 (1.0e+03)	LH3 (1.0e+03)	HL3 (1.0e+03)	LH3	HL3
Energy	0.0001	0.0005	0.0004	0.0002	0.3109	0.3450
Con	1.3569	0.0029	1.3345	0.0276	391.20 48	4.1582
Corr	0.0009	0.0008	0.0009	0.0008	0.9502	0.8614
IDE	0.0006	0.0009	0.0007	0.0007	0.7078	0.7766
Entropy	0.0071	0.0023	0.0044	0.0049	4.6586	3.6213

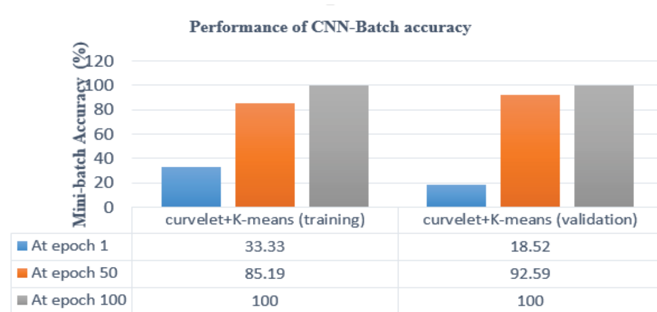


Fig. 5. Performance of CNN – Batch accuracy (Training and Validation)

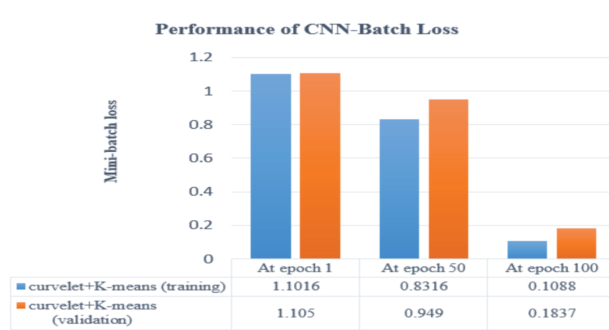
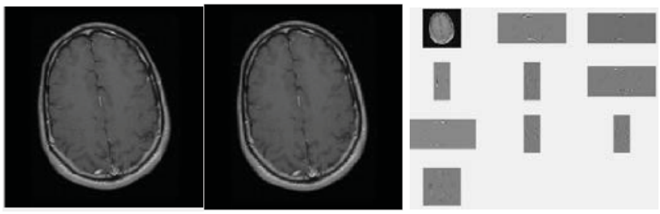


Fig. 6. Performance of CNN – Batch accuracy (Training and Validation)

Table III shows the features extracted using GLCM. Fig. 5 and Fig. 6 depict the performance of CNN in terms of batch accuracy and batch loss functions for training and validation stages. Fig. 7, Fig. 8 and Fig. 9 shows the tumor segmentation using k-means algorithm for normal, benign and malignant classes of tumors.

Segmentation



(a) (b) (c)

Fig. 7. Results of normal image: (a) Input image (b) Test image (c) curvelet decomposition

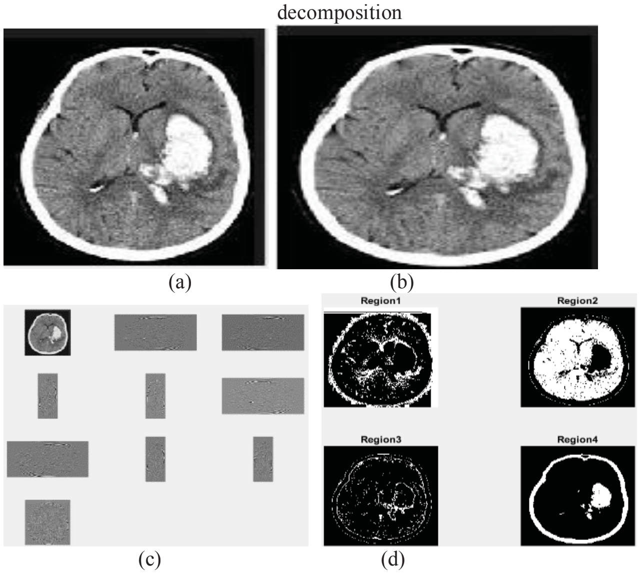
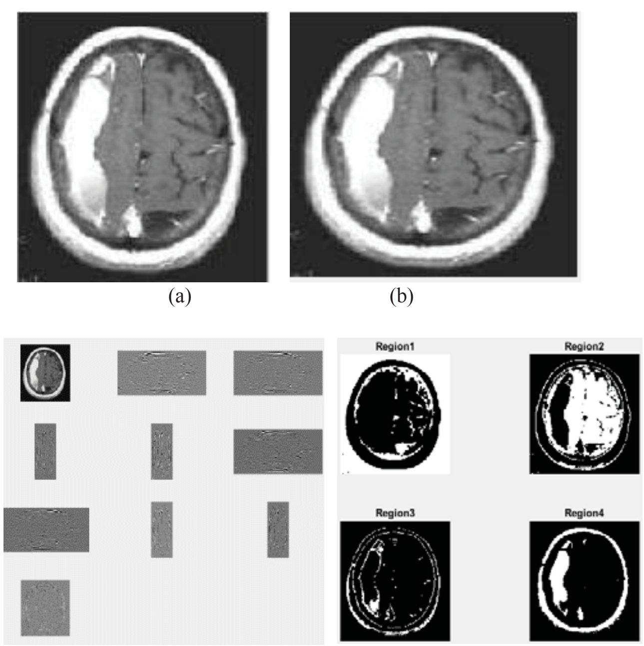


Fig. 8. Experimental results for benign case (a) Input image (b) Test image (c) Curvelet decomposition (d) K-means segmentation



(c) (d)

Fig. 9. Experimental results for benign case (a) Input image (b) Test image (c) Curvelet decomposition (d) K-means segmentation

VII. CONCLUSION

The main objectives of this paper are to classify the brain tumors and to localize the tumor accurately. The curvelet transform presented smooth feature extraction with good directionality and resolution. The CNN achieves 100% accuracy during training and validation phases. The tumor detection is evaluated by k-means algorithm. The various segmentation algorithms proposed in the literature can also be tested using this approach. Though CNN doesn't require feature extraction stage, training the CNN consumes more time as large labeled dataset is required for model training. This can be evaluated with GPU which can handle large amounts of dataset with increased accuracy.

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