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MRI Brain Image Analysis Using Deep Learning Techniques and Multi-Class Support Vector Machine

Shenbagarajan Anantharajan

Assistant Professor/Artificial Intelligence & Data Science, Mepco Schlenk Engineering College, Sivakasi - 626005, Virudhunagar, Tamilnadu, India

Shenbagalakshmi Gunasekaran

Assistant Professor/Computer Science and Engineering, Mepco Schlenk Engineering College, Sivakasi - 626005, Virudhunagar, Tamilnadu, India

Thavasi Subramanian

Assistant Professor/Computer Science and Engineering, Mepco Schlenk Engineering College, Sivakasi - 626005, Virudhunagar, Tamilnadu, India

Abstract---In recent times, an identification and classification of brain tumour become more essential to save human life. Brain tumour detection is considered most challenging problem and many researchers are finding optimized solution for early diagnosis. It occurs because of the irrepressible growth of cells in the brain and classified as malignant and benign tumour. In this research work, an automatic brain tumour detection system using CNN with Softmax and CNN with Multiclass SVM (M-SVM). It was clearly comprehend that the correct learning procedures and matching must yield perfect results. A database of the medical image was complex to divide. Classifying and identifying brain tumour a novel learning procedure, the combination of CNN and M-SVM were used to classify the input MRI Brain image is tumour or non-tumour. This Proposed method evaluated by the fig share dataset and proves the proposed method produced high accuracy. Evaluation and testing of the process used 5 fold validation process with Harvard, Radiopaedia and Figshare dataset. The proposed methods evaluated using Figshare dataset and classifier produced classification accuracy of 98.9% of CNN with Softmax and produced an accuracy of 99.2% of CNN with M-SVM.

Keywords---convolutional neural network, deep learning, magnetic resonance image, support vector machine.

Introduction

A diseases of Computer aided Diagnosis was a considerable progress in the current times [1]. A technique of imaging, advent of learning ideas, tool of better image processing and a theory fo AML are made CAD possible. A medical image retrieval depend reference, disease kinds and detecting disease are famous topics in research regarding medical image analysis and processing [2]. An approach to detect disease and kinds of disease using medical images adopted different extraction in feature and algorithm classification. The correct combination of classifier and feature was examined as a tough tash. This combination relies on heuristics. An architecture of deep learning has CNN for some extent. The design of convolutional neural network acts as joined unit and contains a classifier and extractor. At present there is an important interest in the execution of CAD systemby convolutional neural network. The present work applies convolutional neural network on histological features for breast cancer kinds into malignant and benign. This work was extended to various issues. One work evaluates and narrates tissue behaviour as a kind of lund diagnosis. This paper gives details on the hyperparameter and an analysis of results [3]. An issues faced during the model and execution of CAD process using convolutional neural network which are diverse in nature. At first, the model in convolutional neural network determined the characteristics extraction of the CNN process. And second, the information amount during training determines the capability of convolutional neural network on the information [5]. An unusual cells was developed by unlimited classification of cells inside and around the human brain. This type of cells surely damage the correct process of brain and strong cells of brain. This type of brain tumor may lead to person disability and sometimes dead condition. [6]. The brain tumor was divided into 2 types they are malignant and benign tumor. The tumor benign do not spread outside suddenly and the strong tissues of brain do not affect this benign tumor. The malignant tumor can directly affect the person and leads to death. One of the important scanning method was MRI. To save human from this severe disease, it is mandatory to detect at beginning stage of the Brain tumor. The Magnetic resonance imaging process was special method to identify the tumor. Necessary information about MRI Brain image features can be found through MRI process. This process provides procedures to identify the tissue errors. It is very strong machine for screening features of brain awareness like malignant and normal tumors.[7-10].

In this research, it examines an algorithm to segment tumor region by magnetic resonance imaging images. it defines objective as a three classification issue for dividing brain features. It has 3 kinds, they are pituitary, glioma and meningioma tumour [11], these three are the important kinds of brain tumors. A deep convolutional neural network was modelled for image extracting and various SVM which was employed. The uses of evaluation was considred from fig share. A perfect CAD for the 3 tumor should be supported the medical practioners in their treatment, second high perfection succeed in the current challenging task which used for strategy of deep learning and robust classifiers.

Related work

A disease like glioma was basic tumor that will be low affective and also known as low rank in a body of patient. It is also known as high rank and its life time may be two years. Magnetic resonance imaging provides everyone in deep images and prescribed exams which is used to found brain tumors. A segment of brain tumour supports us to identify development rate and organize medical methods. (Havaei, 2017) Magnetic Resonance imaging was proved as powerful method which do not tend to spread diseases and three dimensional assessment of function, processing the tissue, analysis, imaging, metabolism and physiology. (Prasad, 2006). An output of Magnetic Resonance Image increases the normal knowledge and analysis the organism structure and its parts for research regarding medical. Some tumors such as meningioma was segmented easily and glioblastomas, gliomas tumor are not localized easily. A tumors like glioblastomas and gliomas are diffused frequently and very complex to segment images [13]. Cerebrum of the Brain Image was examined an appearance of tissue which was difficult when its generative process and image monitor a shape or signal of tumor which analyzed and differentiate it from non-tumor brain structure. (Clark et al., 1998) procedures based on the design of structural occurred after the three dimensional Magnetic resonance images on a measured pattern from non-tumor brain. [14] A traditional multiplicative design of Magnetic Resonance Image in the report. (Prastawa et al. (2004). Gathering various levels of data like high or low grade Magnetic resonance images which comes under the preparing level of clinical image process.

Proposed Method

Overall architecture of the proposed method is shown in Figure 1. It has two , preprocessing module, feature extraction module and classification model with training and testing phases.

Preprocessing

Magnetic Resonance Imaging was varied in size (256 X 256). It grey values was normalized to the numbers between zero and one. A practical followed the 5 folded method of cross validation. The group of 245 patients corresponds to the 3067 images in the data set. An information set was clustered into 5 sub sets of rough sizes. The No. of patients involved to a particular cluster of tumor which was equal [16]. The steps in pre- processing was shown in the Figure 2. One sub set was allotted as a test and other as a training in every validation stage. Every Magnetic resonance imaging gets examined and divided by the model after the 5 levels of validation. Table 2 shows the experiment parameters.

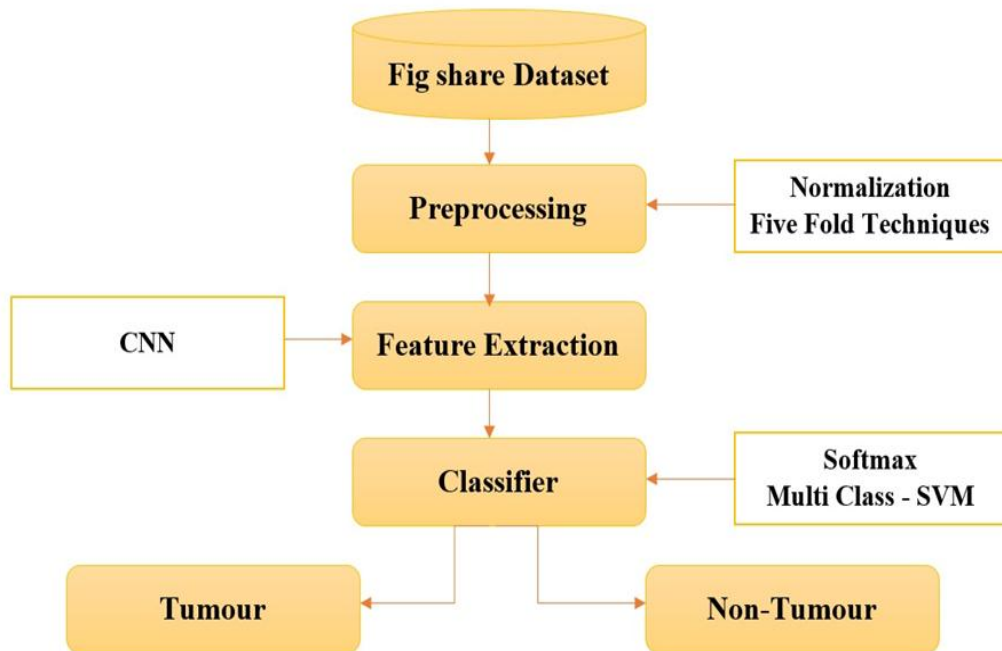


Figure 1. Overall architect of the propoed method

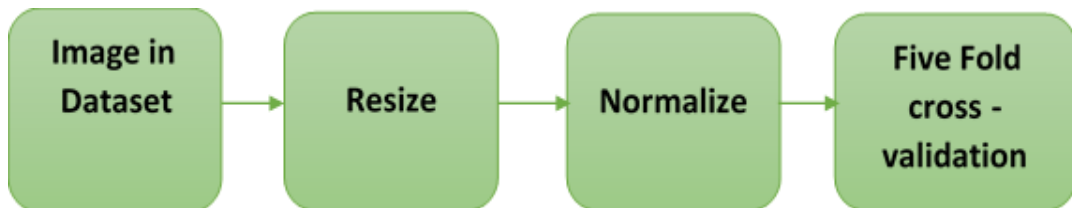


Figure 2. Preprocessing of the proposed method

CNN architecture

In this proposed system, Convolution Neural Network designed to obtained features from input MRI to classify the brain image size of 256 X 256 with 5 layer of convolution and 2 complete jointed segments shown in the Figure 3. The convolution weight was linked with the complete joint form the parameters in a convolution neural network design. Various filters were applied in the proposed method with various functions for the similar image. A thickness of one pixel was associated to protect the image borders. Various size in kernel are selected at various segments to take the representation at different resolution.

Table 1
Hyper-parameter settings of the experiment

Hyper parameter	CNN-Softmax	CNN-SVM
Initial learning rate	0.001	0.001
Optimizer	Adam	Adam
L2 regularization factor	0.0001	0.0001
Mini-batch size	128	128
Epochs	20	20
Classifier model	Softmax	SVM-ECOC
Loss	Cross-entropy	Hinge
Coding	-	One-vs-all
Kernel	-	Linear

A layer dimensions follows the terms which are given under. An input dimension thickness was (X_1, Y_1, Z_1) , linked with the filter K along with the size of (F, F) , output size was (X_2, Y_2, K) , X_2 and Y_2 are measured as,

$$X_2 = \frac{X_1 - F + 2P}{S_x} + 1 \quad (1)$$

$$Y_2 = \frac{Y_1 - F + 2P}{S_x} + 1 \quad (2)$$

where S_x is striding value and P is padding value. These two are united in this model. There was a normal segment which correspond to the convolution segment. Convolution segment normalizes the the training samples in the size of 129. An activation of ReLu was given after the normal layer. Pooling Max was given after the process of ReLu. The main aim was to decrease the output dimension in successive levels. The critical pooling appealed in this model which uses a max filter with the size of $(3,3)$, stride as $(3,3)$ and no padding. FC first segment has 10 neurons and FC second segment have 3 neurons [18].

The values in the model of the examined convolution neural network add the memory needs and difficulties in computational. The model consideration limited the convolution neural network to have 2 segments and blocked to have small filters in convolution. The level of convolution and dense joints of fc segments accounts for the computations in an analysis of convolution neural network design. A operation of convolution was multiplication in layers and also addition in layers. The number of multiplication and addition process in a layer of convolution based on the dimension filters like K_x , F_2 , F_1 and the characteristics of output dimension was X_a , Y_b , Z_c

$$Ops_{conv} = F_1 * F_2 * K_x * X_a * Y_b * Z_c \quad (3)$$

Overall multiplication and addition process in the layer of FC was equal to the parameters. The entire mac process of the whole network was addition of the number of mac process.

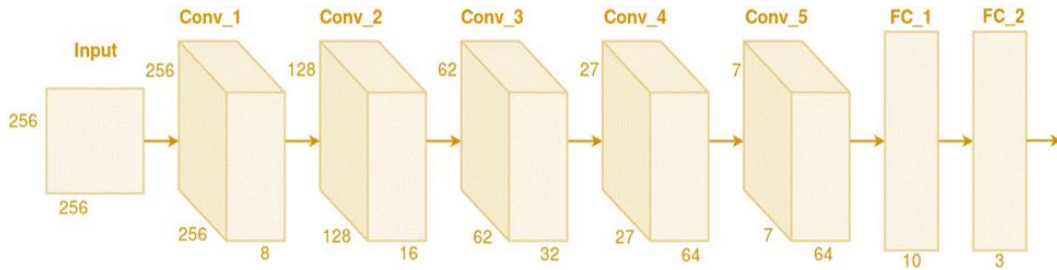


Figure 3. Proposed CNN layers

Space complexity of CNN

The amount of memory space for the execution of convolution neural network design based on the parameters. A correct weight was examined by the layer of convolution and the layer of FC. The no. of parameters for a layer of convolution ($Param_{conv}$) and fully connected layer ($Param_{FC}$) is calculated using equation 4 and 5, where z denotes the no. of input layer, $X_{preceed}$, $Y_{preceed}$ and $Z_{preceed}$ represents the size of the layer preceeded to FCpreceed layer. FCoutput represents the number of output layer.

$$Param_{conv} = FC_1 * FC_2 * Ker * Z_{input} + KL \quad (4)$$

$$Param_{FC} = X_{preceed} * Y_{preceed} * Z_{preceed} * FC_{preceed} + FC_{output} \quad (5)$$

Classification using M-SVM

Extracted features are provided to the M-SVM to identify the input MRI as abnormal or normal. In General, SVM is a two class classifier and it was consumed to deploy the process of various bi-class SVM classifier which is known Multiple class SVM. 3 set of mariginal planes was utilized to classify 6 classes of information in magnetic resonance image. Vectors may be act as a input information components to describe the boundary from training information for image [23]. An important multiple class separation does not resolve the various complexes. The vector features was analyzed from the joint which contains the characteristic of input images. The classifier may examine the class during the experiment time and it was measured as

$$b = \operatorname{argmax}_b \bar{w}^T \phi(\bar{a}, b) \quad (6)$$

Therefore, the quadratic program formulation is given in equation 7. The margin was formed by the adjacent and accurate class.

$$\Theta_i \Theta_b \neq b_i \bar{w}^T \Phi(\bar{a}_i, b_i) - \bar{w}^T \Phi(\bar{a}_i, b_i) \geq 1 - \xi_i \quad (7)$$

MRI input image can be tumor or non-tumor is classified by M-SVM based on the extracted features using convolution neural network.

Classifier

Convolution neural network design has a layer of softmax. convolution neural network with a layer of softmax develops a stand with classifier. The convolution neural network gets affected because of the overfitting phenomenon.

Softmax

Convolution neural network used an activation of softmax and its cross entropy is given in equation 8 and 9 respectively,

$$\sum_{j=1}^N x_j \quad (8)$$

$$L_c = -\sum q_i \log(q_i) \quad (9)$$

where q and q' were predicted measures and fact for result class. A loss gives a low value where the true and predicted values are close. A loss in entropy calculates the closeness in the judgements and valuation which was examined for gradient and better calculations. MSE loss punishments for incorrect answers. MSE was not suited for a possibility interpretation which is suited for numerical results.

Experimental set-up and dataset

The proposed method have been tested on the Figshare dataset which consists 233 patients MRI images. Totally 3064 T1-weighted contrast-enhanced (CE) MRI slices consisting of 1426 MRI images with glioma, 930 and 708 images with size of 512 X 512. The experiment is carried out on a high end computing machine with Matlab 2020 software. The proposed method examined using other Radiopaedia and Harvard datasets and performance were compared with Figshare dataset. Table 2 and 3 shows the performance of proposed methods with start of art methods over Radiopaedia dataset and Harvard dataset. For both Radiopaedia and Harvard dataset, proposed method with CNN and Softmax, CNN and M-SVM produced higher accuracy as 97.4% and 98.1% for Radiopaedia and 98.2 % and 98.8% for Harvard dataset respectively.

The proposed method takes time for training is about two hours six minutes for one full trial of 5 fold method. Therefore the analysis concludes the testing time which is fast and below one second. Training and validation losses of the proposed system is shown in Figure 3.

Table 2
Classification accuracy of proposed method using radiopaedia dataset

Proposed Method	Technique for Features Extraction	Proposed Classifier	Classification Accuracy (%)
CNN	CNN	CNN	96.5
CNN-Softmax	CNN	Softmax	97.4
CNN-M-SVM	CNN	M-SVM	98.1

Table 3
Classification accuracy of proposed method using harvard dataset.

Proposed Method	Technique for Features Extraction	Proposed Classifier	Classification Accuracy (%)
CNN	DWT	CNN	97.5
CNN-Softmax	CNN	Softmax	98.2
CNN-M-SVM	CNN	M-SVM	98.8

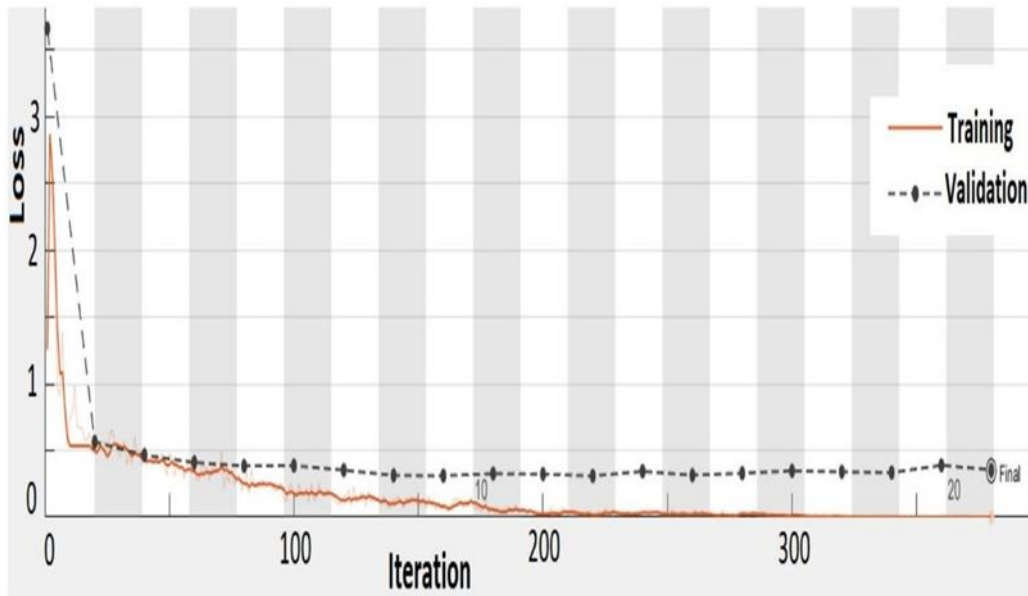


Figure 4. Training and validation losses

CNN with Softmax function classifies information depend on the possibility calculates the result. The CNN disadvantages was overfitting. The loss in training leads to zero but the loss in validation do not leads to zero. This was clearly shown in the figure 4. The characteristics denotes that overfitting acquired with the design of CNN. M-SVM classifies information by converting it to high dimensional value. This was maximum optimization depend on loss of hinge. The maximum margin design of M-SVM was less. The M-SVM characteristics was an important consideration for image related problems. The experimental result is given in table 4.

Table 4
Summary of the experiments

Type of Problem	Dataset used	Classification Accuracy CNN-Softmax (%)	Classification Accuracy CNN-M-SVM (%)
3-class	Figshare	98.9	99.2
2-class	Radiopaedia	97.4	98.1
4- class	Harvard	98.2	98.8

Conclusion

This Proposed method of CNN with Softmax and CNN with M-SVM evaluated by the fig share dataset and proves the proposed method produced high accuracy. Evaluation and testing of the process used 5-fold validation process with Harvard, Radiopaedia and Figshare dataset. The dataset consists 233 patients MRI images. Totally 3064 T1-weighted contrast-enhanced (CE) MRI slices consisting of 1426 MRI images with glioma, 930 and 708 images with size of 512 X 512. The proposed methods evaluated and compared with existing methods using Figshare dataset, Radiopaedia and Harvard dataset. The proposed classifier produced classification accuracy of 98.9% of CNN with Softmax and produced an accuracy of 99.2% of CNN with M-SVM on Figshare dataset, proposed method with CNN and Softmax, CNN and M-SVM produced higher accuracy as 97.4% and 98.1% for Radiopaedia and 98.2 % and 98.8% for Harvard dataset respectively.

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