Effects of Filter on the Classification of Brain MRI Image using Convolutional Neural Network

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***Abstract*—Brain MRI image produces a clear anatomical view of brain and any small abnormality of brain is perceptible by MRI image. Brain tumor classification, detection, and segmentation are huge concern of researchers. Among various machine-learning algorithms such as - K-Nearest Neighbour, Support Vector Machine, Artificial Neural Network, and Convolutional Neural Network (CNN); CNN acquired better position in image classification. CNN classification accuracy depends on some network parameter as convolutional filters, rectification functions, polling functions, and iteration numbers etc. It is a problem to determine effective values of convolution filter size, number and convolution stride for better accuracy in classification. CNN has capabilities to produce and learn effective features on large datasets. We have provided some directions to determine effective values for CNN filter size and number in Brain MRI image classification. Our research work's findings are - square filters are better than rectangular filter; accuracy of filter size 3*3 to 10*10 higher than larger filter size; larger number of filters produce more complexities with higher classification accuracy; increasing of convolutional stride results decrease in network accuracy. This work will be helpful and may be a direction for researchers who are interested to work with Convolutional Neural Network in image classification fields.**

Keywords*—CNN Filter Size and Stride, CNN Effectiveness, Brain MRI, Classification Accuracy.

I. INTRODUCTION

Brain is an important and complex organ of human body. Brain controls all functionalities of human body and organs. Human brain is combination of three kinds of tissue: (1) Cerebrospinal Fluid (CSF), (2) White Matter (WM), and (3) Gray Matter (GM). For any abnormalities of brain, a person cannot perform his duties normally. These abnormalities occurred for different reasons; one of these is brain tumor. Brain tumors are uncontrolled and abnormal proliferation of brain cells. If any tumor originates in brain then it will fail to control own functions accurately which may lead a dangerous harm for patient even patient may die. Survey states that 23,800 adults (13,450 men and 10,350 women) and more than 4,830 children and teens in the United States will be diagnosed with primary cancerous tumors of the brain and spinal cord this year. It is assumed that 16,700 adults (9,620 men and 7,080 women) will die for primary cancerous brain and CNS tumors this year [1].

Now-a-days tumor detection is very time consuming for doctors because of anatomical complexities of brain and huge brain cancerous patient. Among different imaging modalities, MRI represents brain anatomical view and abnormalities very clearly. There are 4 types of MRI data acquisitions as: T1 (spin-lattice relaxation), T1C (T1-contrasted), T2 (spin-spin relaxation), and FLAIR (fluid attenuation inversion recovery) are widely used for brain tumor research. Brain tumor size, position, shape and danger level varies from person to person depends on age, sex, and duration of illness etc. Software based clinical diagnosis would be more accurate & faster.

Researchers use different techniques as: ANN [3], CNN [3]-[4], K-NN [7], SVM [7]-[8] for human brain image classification. Each technique's has some merits and demerits. Lung pattern classification has been done for interstitial lung diseases using CNN [16]. They used 512 × 512 pixels CT images collecting from Hospital. CNN consists of 5 convolutional layers with 2 × 2 kernels, LeakyReLU activations, average pooling, three dense layer etc. Authors declared classification performance about 85.5%. It may bring better classification results for 3 × 3, 5 × 5 kernels. The authors of [18] designed a sophisticated CNN model for Brain Tumor classification. They have used 5 × 5, 3 × 3, 2 × 2 filters for convolution layers. The average efficiency shown in this paper is more than 99%. Present research is undergoing for effective classification. Effective classification depends on different parameters of classification technique. Among different parameters of CNN, convolutional filter has very important role for better classification accuracy. In CNN architecture, it is a major problem to determine effective CNN filter size and number for effective classification. In our research, we have investigated different parameters of CNN as- filter size, filter number, convolution stride. These CNN parameters will help to demonstrate effective architecture to classify brain MRI datasets. For our reliable datasets and after huge trail different CNN parameters value and their relations are appreciable. Researchers are working with CNN for image classification and segmentation will get an excellent direction for choosing filter size and number from our collected results.

Left part of paper organized as - section II for related works, Section III describes methodology, section IV is description of implementation theory, result and discussion are in section V, and finally section VI for conclusion.

II. Related Works

A lot of works had already done on image classification by CNN for its outperformed accuracy. CNN is applied to solve various problems such as- facial expression recognition [6], road sign detection, numerical digit classification, human activity recognition [10], x-ray image classification [11], mammogram image classification [15], and brain MRI image classification [9].

The authors of [3] compared classification accuracy of brain tumor based on 2 layer and 3 layer Neural Networks structure and Convolutional Neural Networks with 3 convolution layer structure. They showed maximum 18% improvement for CNN classification in BRATS 2014 brain tumor datasets of LGG and HGG. In [4], the authors described potential of using deep architectures with small convolutional kernels, intensity normalization, leaky rectifier linear unit (LReLU) instead of ReLU with huge descriptions. They also evaluated their proposed method in BRATS 2013 and 2015 databases and performed segmentation in post-processing. In [6], the authors described comparative studied of CNN and K-NN on Japanese Female Facial Expression Database (JAFFE) with some pre-processing. The authors of [12] studied transfer learning on CNN from natural image to medical image classification.

In [17], the authors written about polyp detection from colonoscopy image using fine-tuned CNN and fully trained CNN. Fine-tuned CNN are useful for medical image analysis, performing as well as fully trained. They used 11 × 11, 5 × 5, 3 × 3 sized filters for their networks. Reference [19] described about three-dimensional Convolutional Neural Network (CNN) with 22-layers. BRATS 2015 database is used for implementing this work. For this work, authors used 3 × 3 × 2 size filters in convolution layers.
The authors of [20] worked with breast cancer histology images classification using CNN. They worked in different directions with 2 and 4 class breast tissue images. They used 512 × 512 size images with 3 × 3 kernels for convolution layers. In [21], the authors studied a new imaging modality named **Hyperspectral Imagery which provides** spectral and spatial information. Data has been collected by composing the VariSpec Liquid Crystal Tunable Filters (LCTFs) with microscope and silicon charge-coupled devices. They performed human blood cell classification, distinguishing white cells and red cells.

III. Methodology

A well decorated procedure end with an excellent performance. A reliable brain MRI image dataset and effective CNN architecture is enough for our work. Pre-processing of image commonly involves removing of film artifacts, removal of Skull using Modified Tracking algorithm. Low-frequency background noise, normalizing the intensity of the individual image, edges sharpening removing reflections, masking, and filtering of images are part of image pre-processing. Median filtering is a technique used to remove noise that is used in our research [2]. Conversion of raw image to easily usable image format is another step of image pre-processing. We neglected unnecessary background portion for all images and produced desired image size to get better accuracy. Same size for all images is also a major concern for image classification field.

In convolutional neural network architecture, image taken in input layer then convolved image with some filters, performed rectification, polling, fully connected layer, and classification layer is used to classify MRI images. Our interest is on CNN filter size, filter number, and convolution stride. We have performed our work in two steps.

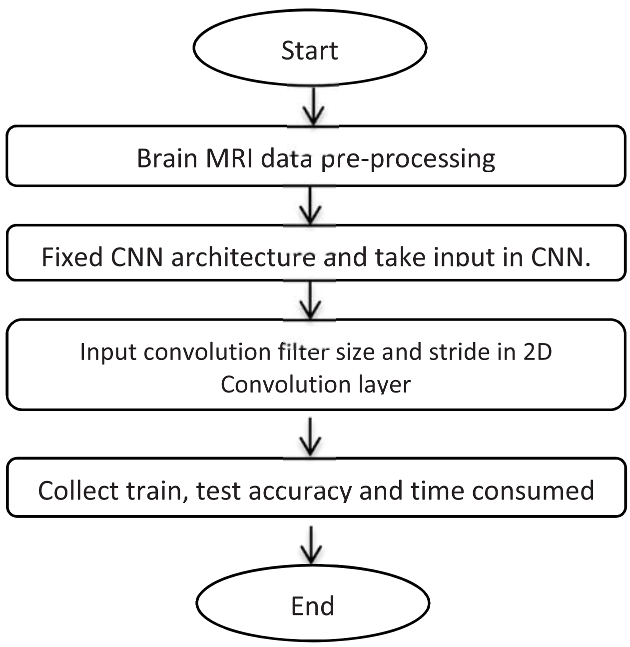

Fig. 1. Block diagram to collect result for different values of convolutional filter size and stride.

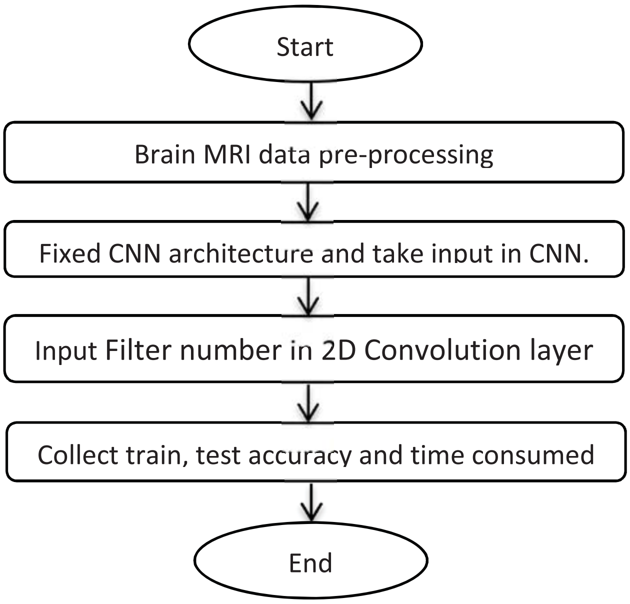

Fig. 2 Block diagram to collect result for different values of filter number

In first step, we fixed 10 filters and 10 epochs to find out effects of filter size with stride. We trained CNN for different filter size and convolution stride one after another and performed three trials for each combination. We have collected train accuracy, test accuracy, and consumed time for corresponding combination. Then we have taken best one result for each combination of filter size and stride to show in result section. We have used square and rectangular filters with smaller and larger stride than convolutional filter size. Block diagram of research work's first step given in Fig. 1.

In second step, we have selected some efficient combination of filter size and stride first. Then fixing filter size, stride and iteration number we have changed only filter number from 10 to 60 with increment 10. At last, we have collected train accuracy, test accuracy, and consumed time for corresponding combination and showed in result section. Block diagram of this step given in Fig. 2.

IV. Description of Implementation

A. Software

MATLAB R2016a is minimum requirement for easiest implementation of Convolutional neural network in Matlab. Some functions are developed in this version to implement CNN whose performance reduce time and labour. We have used MATLAB R2017a for implementing our research.

B. Brain MRI Dataset

We have collected two datasets. One for normal brain MRI images another for Low Grade Gliomas (LGG) and High Grade Gliomas (HGG) [5]. We have created a dataset of normal 200 and LGG 200 images for our research work.

1) IXI Dataset: This is an open source brain image dataset of different MRI data of around 600 healthy and normal persons. The link of this dataset is declared in [13]. We have collected 3D brain MRI T2 raw data of 578 persons from their website. We have selected 50 people randomly from these persons. For our dataset we taken 200 middle slices of brain from 50 persons.

2) BRATS 2015: This is also an open source data for Low Grade Gliomas (LGG) and High Grade Gliomas (HGG) [5]. Reference [14] presented website for this dataset. BRATS2015_Training folder contains 220 HGG patients and 54 LGG patients image of different MRI technique. We have selected 20 patients randomly for both LGG and HGG group. Then we have taken 200 LGG and 200 HGG affected slices for T2 MRI images.

C. Network Architecture

1) Image Input Layer: This is the first layer of convolutional neural network. Input data number depends on image size and dimension. If an image is 200*150*3 then the input data number will be 90,000 for single image. If the image dimension is X*Y*D then we can express by below equation-

$$Input\ data\ number = X \times Y \times D \quad (1)$$

2) Convolution Layer: Second layer of convolutional neural network is 2D convolution layer. In this layer all input image is convolved with a filter matrix and output of convolution layer is called feature map or activation map. If image is expressed by I(x, y), filter is expressed by F(x, y), invert then shifting of filter is F(-u+x, -v+y), the convolution output will be defined by below equation.

$$(I * F)(x,y) = \sum_{u=-\propto}^{\propto} \sum_{v=-\propto}^{\propto} I(u,v) * F(-u+x, -v+y) \quad (2)$$

Output of convolution layer is a matrix that represents where an identical feature is active in input matrix indicating filter activation. The output matrix number (feature number) will be same as the number of filter taken for convolution.

3) Filter Size, Number and Depth: Filter also called kernel which is a matrix that represent feature such as-curve, edge, shape etc. [2]. Bigger filter size represents bigger shape but it can convolve in lower number with input image. Therefore, the convolution output will be lower size. Different filter produce different feature map. Increased number of filters will produce larger number of feature map. Depth of filter depends on the depth of matrix to be convolved with filter. A filter may be square or rectangular shape. For easiest understanding and less complexities we used square and rectangular filter of odd number greater than 2.

4) Receptive field, Stride and Padding: Receptive field is the different portion of image where filter convolve. If the filter size is f*f then the receptive field size will be also f*f. A filter slides over the input image to produce convolutional output. Stride is the number of pixels that a filter shifts in next step after convolution. If an image is n*m size and we take a filter of j*k, stride of s*s and padding of [p, q] then the convolution output size will be defined by below equation.

$$[\mathrm{Row}, \mathrm{Column}] \; = \; \left[\frac{\mathrm{n}-\mathrm{j}+2\mathrm{p}}{\mathrm{s}}+1, \frac{\mathrm{m}-\mathrm{k}+2\mathrm{q}}{\mathrm{s}}+1\right] \quad (3)$$

It is clear from above equation that the output size will be lower than input size and may be fraction. If the output is fraction the lower integer will be counted. If anyone wants the input and output size will be same he/she has to use zero padding outside the input image. For stride [1, 1] padding will be determined by below equation-

$$(Row\ padding, Column\ padding) = \left(\frac{j-1}{2}, \frac{k-1}{2}\right) \quad (4)$$

Here, filter size is j*k. To get lower spatial dimension and less overlap in receptive field we used larger stride but not more than filter dimension.

5) Rectification Linear Unit (ReLU) Layer: If a filter has negative pixel value then the convolution output may be negative. Negative value has no significance without representing lowest activation in image. Therefore, we need to rectify these values. This layer provides non-linear output to the next layer. Researcher normally use sigmoid and tanh function for non-linear output but rectification process is better because of its computational efficiency [2]. In our work, this layer changes all negative values of convolution layer output to zero. The equation is given below, where i and j indicate the point of matrix and x is the value of that point.

$$F_{i,j}(x) = max(0, x) \quad (5)$$

6) Polling Layer: Polling layer is used for reducing data and controlling network over-fitting. Polling layer also named as down-sampling layer and there are different options such as- average polling, max-polling and L2-norm polling etc. We used max-polling method in our system. For max-polling a filter of any size and stride of same size is taken and transverse on whole matrix. Maximum value is taken from each filter size from sub-region of matrix.

7) Fully-connected layer: Output data of polling layer is a 2D cascade matrix. Number of 2D matrix is equivalent to convolutional layer filter number. 2D matrixes transfer to 1D matrix in this layer then feed to classification layer.

8) Classification Layer: This layer is the last layer of CNN that classify images depends on the information collected from fully connected layer. Anyone needs to declare class number for classification.

9) Training Algorithm: CNN train and update it's weights and biases in different layer by Stochastic Gradient Descent with Momentum that is back propagation algorithm using train option parameter's information.

V. RESULTS AND DISCUSSIONS

At the time of CNN training, convolution filters get scope to fit for maximum accuracy for training data but CNN use updated filters for testing different image. To choose effective CNN architecture with effective filter size, filter no. and stride anyone should consider 50% contribution of test accuracy and 30% contribution of train accuracy and 20% contribution of consumed time duration. We presented our 1st step's results in table and highlighted effective combination to implement 2nd step. Results of 2nd step's listed in table 2.

TABLE I

RESULT FOR DIFFERENT FILTER SIZE AND STRIDE BUT FOR FIXED 10 FILTERS AND 10 EPOCHS

Filter Size	Convo Stride	Time Cons	Train Accu	Test Accu
3*3	2	51.84	98.6	98.3
3*3	4	31.7	94.6	91.7
3*3	9	22.78	96.1	91.7
3*5	3	38.64	99.3	98.3
3*5	4	30.62	97.9	96.7
3*5	10	25.96	94.3	93.3
4*4	3	43.09	99.3	95.8
4*4	4	31.21	94.8	96.2
4*4	10	23.9	92.5	94.2
4*4	16	21.77	81.8	75
5*5	4	36.46	100	99.2
5*5	10	25.5	93.6	94.2
5*5	15	21.73	91.8	88.3
6*6	5	29.81	97.1	95.8
6*6	10	25.47	97.1	95.8
6*6	15	24.05	94.6	87
6*8	5	31.25	98.9	99.2
6*8	10	24.75	97.1	97.5
6*8	15	23.21	86	88.7
7*7	3	41.06	99.3	99.2
7*7	5	31.25	98.9	99.2
7*7	7	16.72	99.3	98.3
7*7	9	26.17	98.6	97.5
7*7	15	23.87	93.6	94.5
7*7	20	22.37	88.6	92.5
10*10	3	48.06	99.6	97.5
10*10	10	26.82	97.9	99.2
10*10	15	23.8	98.2	98.3
10*10	20	21.81	91.4	90.8
10*10	30	19.7	94.6	88.3
10*10	40	18.86	85	80
10*10	50	17.77	75.7	70.8
20*20	10	24.65	98.3	97.1
20*20	20	22.92	97.5	96.7
20*20	25	20.91	95.4	92.5
20*20	30	21.07	95.7	95
20*20	40	20.18	92.9	94.2
20*20	50	19.75	91.8	89.2
30*30	10	28.8	96.5	97.5
30*30	20	28.6	97.5	98.3
30*30	30	21.5	96.8	97.5
30*30	40	18.7	90.7	88.3
30*30	50	21.2	96.4	95.8
30*30	60	16.8	88.9	90.8
30*30	70	20.5	93.9	91.7
30*30	80	16.9	89.6	90.8
30*30	90	13.7	91.1	90.8
40*40	30	20.1	99.3	95
40*40	40	17.5	97.1	95.8
40*40	60	16.8	92.1	90.2
50*50	50	15.8	95	93.3
50*50	100	17	91.8	86.7
60*60	60	20.2	90.4	90
60*60	120	20.7	88.2	92.5

❖ Cons and Accu in the table stands for consumed and accuracy

TABLE II

RESULT FOR DIFFERENT FILTER SIZE AND NUMBERS BUT FOR FIXED STRIDE AND 10 EPOCHS

Filter Size	Convo Stride	Filter No.	Time Cons	Train Accu	Test Accu
3*3	2	10	10	99.3	98.3
3*3	2	20	18	98.9	96.7
3*3	2	30	25	96.1	97.5
3*3	2	40	33	96.4	97.5
3*3	2	50	40	99.6	99.2
3*3	2	60	47	99.6	99.2
3*5	3	10	6	99.3	99.2
3*5	3	20	9	97.5	95.8
3*5	3	30	12	98.6	96.7
3*5	3	40	16	98.9	99.2
3*5	3	50	21	98.9	98.3
3*5	3	60	24	98.9	97.5
4*4	3	10	6	97.5	97.5
4*4	3	20	9	97.5	96.7
4*4	3	30	13	97.9	99.2
4*4	3	40	17	99.6	98.3
4*4	3	50	20	97.5	96.7
4*4	3	60	24	98.6	99.2

Filter Size	Convo Stride	Filter No.	Time Cons	Train Accu	Test Accu
6*8	5	10	4	99.6	98.3
6*8	5	20	6	98.9	98.3
6*8	5	30	7	96.4	95.8
6*8	5	40	8	99.6	100
6*8	5	50	10	98.6	100
6*8	5	60	10	100	99.2
7*7	5	10	4	99.3	99.2
7*7	5	20	5	97.1	96.7
7*7	5	30	7	100	99.2
7*7	5	40	8	98.6	95.8
7*7	5	50	9	99.3	99.2
7*7	5	60	10	99.3	100
10*10	10	10	3	98.6	95.8
10*10	10	20	4	97.9	95
10*10	10	30	4	98.6	97.5
10*10	10	40	5	98.9	99.2
10*10	10	50	6	100	99.2
10*10	10	60	6	100	99.2

Filter Size	Convo Stride	Filter No.	Time Cons	Train Accu	Test Accu
20*20	10	10	3	97.5	96.3
20*20	10	20	4	98.6	99.2
20*20	10	30	5	98.6	98.3
20*20	10	40	5	99.3	99.3
20*20	10	50	5	99.3	95.8
20*20	10	60	6	99.3	98.2
20*20	10	60	5	99.3	99.2
30*30	20	10	3	96.3	94.9
30*30	20	20	3	97.1	95.8
30*30	20	30	4	98.2	97.5
30*30	20	40	4	98.2	94.2
30*30	20	50	5	100	99.2
30*30	20	60	5	98.9	99.2
40*40	30	10	3	93.2	91.7
40*40	30	20	4	94.2	93.6
40*40	30	40	6	92.8	92.3
40*40	30	60	7	95.6	94.8

❖ Cons and Accu in the table stands for consumed and accuracy

A) Research Outcomes:

1. If convolution strides increase, CNN accuracy will decrease. However, with increase of stride, the convolution output complexity will decrease. It is not good practice to consider stride more than twice of filter length because accuracy show below 90% on larger strides.
2. For filter size 3*3 to 10*10 accuracy varies from 90.8 to 99.2 and 20*20 to 60*60 accuracy varies from 86.7 to 98.3 with respect to different stride size.
3. Square filter is better than rectangular filter because convolution stride is same for horizontal and vertical transverse. For rectangular filter in any stride it will overlap or create gap in the time of convolution.
4. Large number of feature has good impact in ordinary Neural Network but in CNN, impact is negligible. Moreover, large number of feature (larger number of filter for CNN) will produce more complexities and make waste of time.

VI. CONCLUSION

As we worked with software implementation so we added a brief discussions about CNN architecture to represent the working procedure. Description of CNN architecture will help to understand step-by-step network's output. Taking different values for convolution layer's filter size, number and convolution stride we have collected CNN training and test accuracy and consumed time duration. Depends on collected results we described research outcomes in section IV. We have tried to build up a direction for the researchers who are interested with CNN for their different works instead of only brain MRI image.

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