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DEEP MACHINE LEARNING FOR BRAIN MRI CLASSIFICATION

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Abstract

Deep learning is a subdivision of machine learning that employs computation models made of several layers to learn features from data with different levels of abstraction. Implementation of these models has led to a startling improvement in areas such as visual object recognition, drug discovery, and genomics. This paper presents a deep learning algorithm, based on a convolution neural network to classify brain MRI into five classes. The designed model achieves a test accuracy of 97.5% demonstrating the potential of deep learning in automated disease diagnosis. A standalone application has also been developed to display the classifier output and activations of convolution and ReLu layers.

Keywords:

Deep Learning, Convolution Neural Network, Machine Learning, MRI

1. INTRODUCTION

Medical imaging techniques such as MRI have been used in the diagnosis and treatment of ailments for the past couple of years. Interpretation of these medical images has more often than not relied upon human experts such as doctors and radiologists. However, with machine learning coming into play, the situation has improved dramatically. Some of the machine learning algorithms that have played a key role in medical imaging research include Support Vector Machine, K-Nearest Neighbours and Random Forest algorithms. Although these machine learning techniques have demonstrated great potential, only a few have been able to achieve clinical efficiency mainly due to the fact that they rely on a set of predefined features [1] – [18].

A major challenge that arises due to this issue is the inability of one to choose the right features to correctly model a problem. The learning process is also restrained to a specific template, with a set of predefined features hence once the features are altered, the whole training operation has to be repeated all over again. Deep learning techniques such as convolution neural networks allow one to circumvent the issue of manual feature extraction as the algorithms learn directly from raw input data. This has, in turn, resulted in improved performance of algorithms to the extent of exceeding human accuracy. This work applies a Convolution neural network (CNN) with a Directed acyclic graph (DAG) architecture to differentiate between the following brain MRI classes: Normal, Alzheimer, Tumour, Autism and Multiple Sclerosis.

2. RELATED WORKS

In recent years, deep learning has made a significant leap in the identification and classification of patterns in brain MRI images. Brosch [12] developed a deep belief network based on manifold learning for Alzheimer disease (AD) detection for from brain MRI images.

Liu et al. [14] suggested a multimodal stacked autoencoder that made use of zero masking strategy to classify binary images of MRI and PET for early AD detection. This model achieved a classification accuracy of 87.76%. Deep learning models such as Stacked Autoencoders, Deep Belief Networks, and Deep Boltzmann Machines take their inputs in vector form. However, when dealing with medical images, the structural information among neighbouring pixels is very important. Vectorization of these images eventually damages such information. The design of CNNs allows them to make use of the structural information due to the fact that they take their input as images [4].

Seetha [15] proposes a CNN based classifier to distinguish between tumour and non-tumor images. A comparison is also made between the designed model and a deep neural network (DNN). The CNN model achieves a 97.5% accuracy while the accuracy of the DNN is 94% thus demonstrating the effectiveness of CNNs in image classification.

Mohsen et al. [16] implemented Fuzzy C Means (FCM) to separate healthy and tumour regions of the brain A multilevel Discrete Transform was then applied across the input images to extract features. Finally, DNN was used to classify the brain MRI into tumour and non-tumour classes. This technique yielded an accuracy of 96.97%. However, the model had a very high degree of complexity.

Havaei et al. [17] proposed a cascaded architecture to classify brain MRI whereby, a two-path CNN was trained and its parameters fixed. The already trained model was then used in the cascaded architecture. The best performance of their three architectures submitted to the BRATS 2013 brain tumour challenge was obtained by concatenation the feature maps of the last layer of the first network with the inputs of the second network.

3. METHODOLOGY

The Fig.1 illustrates the steps taken to classify brain MRI into five classes.

3.1 DATASET ACQUISITION

The proposed CNN model is trained and tested using brain MRI images obtained from the following sources: Cancer Imaging Archive, Harvard Medical School Brain Atlas Database, The Brain Web and Autism Imaging Data Exchange Database. The compiled dataset is made up 825 brain MRI with 132 normal, 114 Multiple Sclerosis, 69 Alzheimer, 114 brain tumour and 396 Autism images. Fig.2 shows sample images from each of the 5 classes.

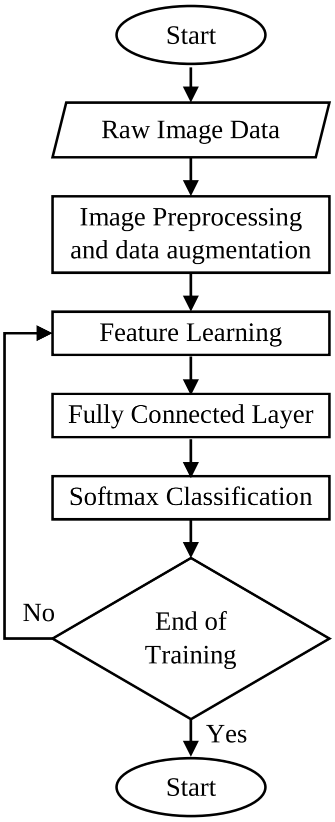


Fig.1. Overall Experimental Process

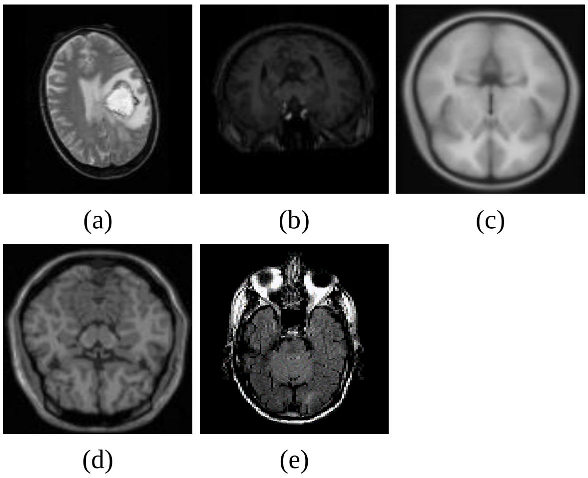


Fig.2. Sample Images (a) Tumour (b) Autism (c) Normal (d) Multiple Sclerosis (e) Alzheimer

3.2 IMAGE DATA PRE-PROCESSING AND DATA AUGMENTATION

The images in the compiled dataset have a large deviation in size. Prior to network training, the images are down-sampled to a fixed resolution of 50×50×1. Resizing also helps in reducing the computational complexity of the deep learning model. To prevent the deep learning model from overfitting, the following data augmentation techniques are performed: reflection in the vertical direction, reflection in the horizontal direction, rotation and horizontal shear.

3.3 NEURAL NETWORK IMPLEMENTATION

The designed convolution neural network architecture consists of 17 layers as shown in Fig.3.

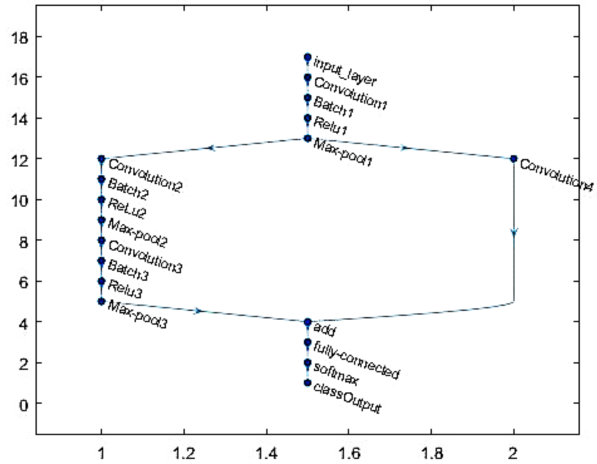


Fig.3. Neural Network Structure

The input layer has a resolution of 50×50×1 which is equal to the size of the input image where 1 indicates that the input image is a single channel image.

The first convolutional layer adopts 16 convolution filters each of size 3×3. These filters are applied across the input image which is then followed by an element-wise multiplication between each of the element in the filters and the input at the location of the filters. These elements are then summed up to obtain 16 feature maps at the corresponding position of the input tensor. This operation can be summarised as:

$$\left(I*K\right)_{ij}=\sum_{m=0}^{k_1-1}\sum_{n=0}^{k_2-2}I\left(i-m,j-n\right)K\left(m,n\right) \tag{1}$$

$$\left(I*K\right)_{ij}=\sum_{m=0}^{k_1-1}\sum_{n=0}^{k_2-2}I\left(i+m,j+n\right)K\left(-m,-n\right) \tag{2}$$

where,

I is the input image and

K is the kernel of dimensions $k_1 \times k_2$.

The output of the convolution layer whose resolution is 50×50×16 is then fed into a batch normalization layer that normalizes each input channel across a mini-batch. This allows each layer within the network to learn features by itself with a little more independence from the other layers. A Relu activation function is then applied to the extracted features, mapping them to values defined by:

$$f(z) = \max(0,z) \tag{3}$$

where,

z is the input and

$f(z)$ is the output.

This operation helps introduce invariance to data coupled with computationally efficient representation.

To reduce the dimensionality of extracted feature maps from the first convolution layer, a max-pooling operation is performed.

Firstly, the feature maps are divided into several rectangular regions of the same size. Max-pooling operation then outputs the maximum value of each patch from the feature map and discards the rest. The max-pooling window is a 2×2 matrix while the subsampling step size, also known as stride is 2 hence, the max-pooling layer outputs a feature map of resolution 25×25×16. This operation facilitates faster convergence rate by selecting superior invariant features which improve the generalization performance of the deep learning model.

The output of the first max-pooling layer is then fed into the second convolution layer which is characterized by 32 kernels that in turn produces 32 feature maps. These features are then normalized, passed through the second ReLu activation and downsampled using the second max-pooling layer whose output is of size 12×12×32. The third convolution layer has 64 kernels, therefore, its output feature map is of size 12×12×64. This feature map is then downsampled to a resolution of 6×6×64 by the third max-pooling layer.

The fourth and final convolution layer enables parameter gradients to flow more easily from the output layer of the earlier layers of the deep learning model. Afterwards, the generated feature maps are converted into a one-dimensional vector and fed into the fully connected layer for classification. The output layer has 5 softmax neurons that correspond to the 5 categories of brain MRI images.

The softmax classifier defines a mapping function f that takes the input data and maps it to a set of labels through a dot product of the input x and a weight matrix W:

$$f(x_i,W) = Wx_i \tag{4}$$

The softmax function enables one to predict the discrete probability distribution over the classes. It does this by taking an N-dimensional vector composed of real numbers and transforming it a real numbered vector whose elements range from 0 to 1 as shown in Eq.(5).

$$p_i = \frac{e^{a_1}}{\sum_{k=1}^{N} e^{a_k}} \tag{5}$$

where a denotes the scoring function of the form $a = f(x_i,W)$

The number of feature maps, kernel size, and stride for the alternating convolution and max-pooling layers is shown in Table.1.

Table.1. Neural network parameters

Layer	Feature maps	Kernel Size	Stride
Input layer	1	-	-
Convolution1	16	3×3	1
Max-pool1	16	2×2	2
Convolution2	32	3×3	1
Max-pool2	32	2×2	2
Convolution3	64	3×3	1
Max-pool3	64	3×3	2
Convolution4	64	3×3	1

To optimize the convolutional neural network, "Adam" optimization algorithm with an initial learning rate of 0.001 is used. This algorithm calculates an adaptive learning rate for various distinct parameters using first and second-order moments of gradients.

The training process includes the forward and backpropagation summarized as follows.

Step 1: Random initialization of weights

Step 2: Image data forward pass

Step 3: Calculation of output layer error with reference to the desired output

Step 4: Weights update through backpropagation algorithm

Step 5: Repetition of step 2 to step 4 until the point of minimum error

For each training step, a mini-batch of 32 images from is sampled from the training set $\{x^{(1)},\ldots,x^{32}\}$ with the corresponding targets y^i and then the back-propagation algorithm is used to compute the gradient $g \leftarrow= \frac{1}{m}\nabla_{\theta} L\left(f\left(x^i;\theta\right), y^{(i)}\right)$ of the loss function. This is followed by an update of the first moment $s \leftarrow \rho_1 s + (1-\rho_1 s)g$ and second moment $s \leftarrow \rho_2 s + (1-\rho_2 s)g \odot g$ estimate. The bias of the first moment $\breve{s} \leftarrow \frac{s}{1-\sigma_1^l}$ and the second moment $\breve{r} \leftarrow \frac{r}{1-\sigma_1^l}$ are then corrected. Finally, the weight update is computed and applied. Once the CNN network is trained, it is used to extract high-level features from brain MRI images.

4. TESTING AND PERFORMANCE EVALUATION

To test the performance of the deep learning model, the image data is divided into training, validation, and testing set as illustrated in Table.2 below. After every 5 training iterations, the model is tested against the validation set and the validation accuracy computed. Finally, the trained model is fed with a new set of test images and the test accuracy evaluated.

Table.2. Dataset Split

Category	Training Set	Validation Set	Test Set
Normal	70	18	44
Multiple Sclerosis	61	15	38
Tumour	61	15	38
Autism	212	52	132
Alzheimer	37	9	23

4.1 MATLAB BASED STANDALONE APPLICATION

The Fig.4 shows the MATLAB based standalone application. By pressing the load and classify button, an MRI image is displayed on the axis and then fed into the trained model which in turn gives a prediction. The popup-menu displays the activations of convolution and ReLu layers for the classified image.

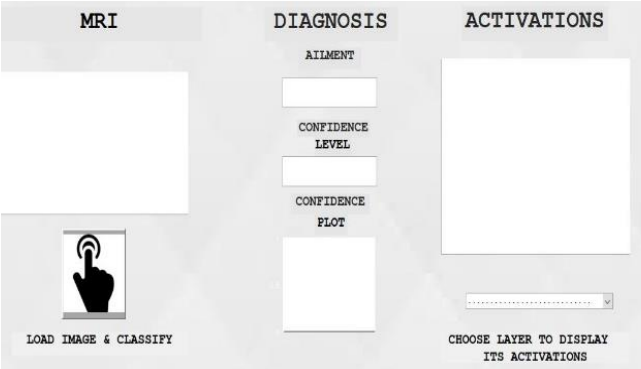


Fig.4. Standalone Application

5. RESULTS AND ANALYSIS

5.1 DATA AUGMENTATION

The Fig.5 illustrates the effect of data augmentation on the training set images. Augmenting these images helped increase the diversity of training data which in turn implicitly regularized the model and improved its generalization.

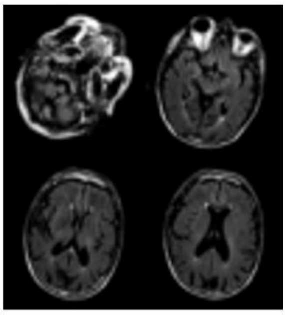


Fig.5. Sample Augmented Images

5.2 TRAINING

The Fig.6 illustrates the training process. The training and validation accuracies increase with each iteration while the mini-batch training and validation losses decrease with time. Furthermore, the model achieves a final validation accuracy of 92.73%.

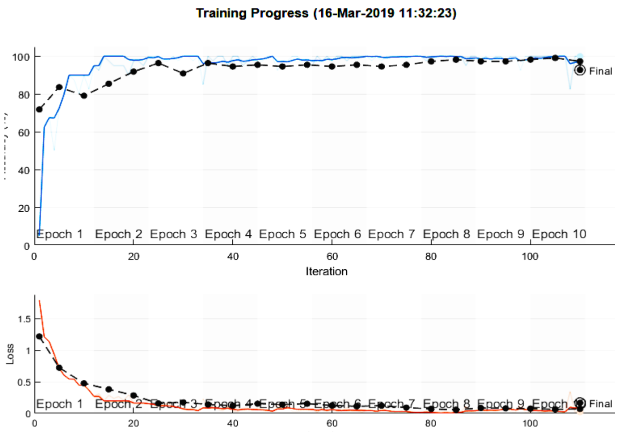
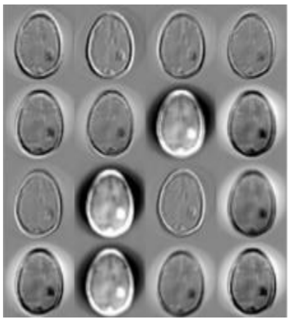


Fig.6. Training Progress

5.3 FEATURE EXTRACTION

The Fig.7 demonstrates the activations of the convolutional and ReLu layers. The white pixels constitute strong positive activations while the black pixels constitute strong negative activations. The ReLu layers discard the negative activations thus only positive activations are used in the subsequent layers.

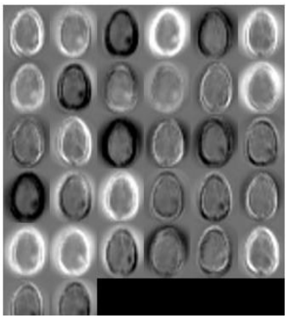


(a)

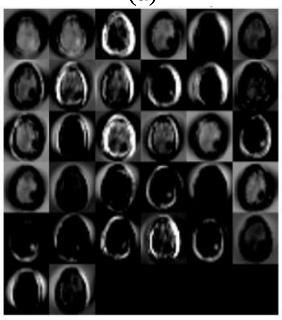
(b)

Fig.7. Neural network activations (a) first convolution layer (b) first ReLu layer

The Fig.8 shows the activations of the second convolution and ReLu layers. The extracted features are more complex as one moves deeper into the network.



(a)



(b)

Fig.8. Neural network activations (a) second convolution layer (b) second ReLu layer

5.4 CLASSIFICATION

The Fig.9 shows the confusion matrix of the model. On feeding the trained model with new test data, 97.5% of the images are classified correctly with only 7 multiple sclerosis images being misclassified as tumour.

Fig.9. Confusion matrix

The rows of confusion matrix represent the predicted class while the columns represent the true class of the brain MRI image. The first five diagonal cells show the number of number and percentages of images correctly classified by the trained network. The column on the far right gives precision performance metric while the bottom row gives a performance metric known as recall. Four of the classes within our test data achieved a precision of 100% except for the tumour class which had a precision of 84.6%. These figures represent the proportion of positive identifications that was actually correct. Furthermore, all other classes except for multiple sclerosis had a recall of 100% which attained a recall of 81.6%. This represents the proportion of actual positives that were identified correctly.

The Fig.10 shows a sample tumour classification and activations of the first convolution layer of the classified image. The image has been classified as having a tumour with a probability of 0. 921084. The softmax layer makes its prediction based on class with the highest probability.

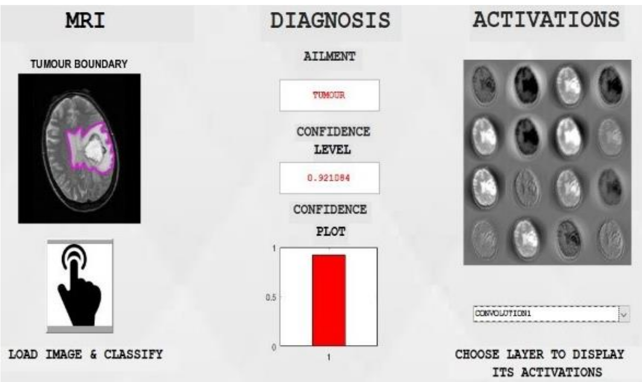


Fig.10. A sample brain tumour classification and activation of the first convolution layer

The Fig.11 shows a sample multiple sclerosis classification with a probability of 0.999110.

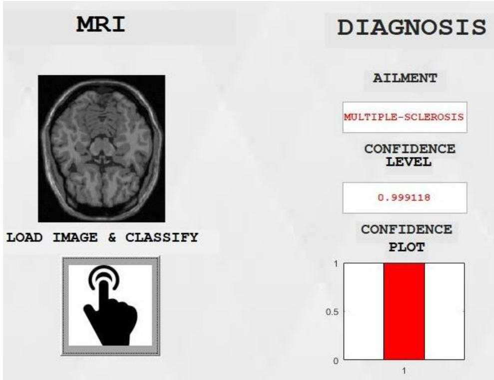


Fig.11. Multiple Sclerosis classification

A performance comparison between state-of-the-art methods and the proposed work is shown in Table 3. Based on our results the proposed work significantly outperforms the state-of-the-art methods in terms of accuracy. These results exemplify the efficiency of the proposed work.

Table.3. Overall Accuracy for different deep learning models

Article	Dataset	Number of Samples	Classes	Results
Maleki et al. [17]	Clinical trial	Train - 152 Val - 30 Test - 35	2	Accuracy - 96.1%
Brosch et al. [12]	Clinical trial	Train-250 Val - 50 Test - 75	2	Lesion-wise false positive rate - 62.5%
Q. Dou et al. [10]	Clinical trial	Train - 55 Val - 50 Test - 55	2	Sensitivity - 89%
Proposed Work	Cancer Imaging Archive, Autism Imaging Data Exchange Database	Train - 441 Val - 109 Test - 275	5	Accuracy - 97.5%

6. CONCLUSION

In this work, a novel brain classification method based on brain MRI and deep learning is proposed. We design a convolution neural network to identify and classify five different types of brain MRI images. The 2D CNN is able to automatically extract spatial and temporal features and find the most suitable one from which a reasonable classification was made. This deep learning model achieves a classification accuracy of 97.5%. In the future, a 3D convolution neural network can be implemented since it is more effective and less likely to omit the regions of interest in the MRI images. Furthermore, the training dataset can be expanded to include other MRI classes.

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