Classification of Pituitary Tumor and Multiple Sclerosis Brain Lesions through Convolutional Neural Networks

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Abstract: Automatic classification of Brain Tumor and brain Lesions has become a very important step in the field of medical image analytics. The machine learning/Deep learning approaches are playing a tremendous role in the field of medical imaging classification, due to the drastic changes in the field of computing power and image analytics techniques. The deep learning, which is the subfield of machine learning, is playing the major role in the automatic classification of Magnetic Resonance Images (MRIs) having various brain abnormalities. Convolutional Neural Networks are widely used for the classification and detection of various brain disorders. In this research paper, Convolutional Neural Networks are designed with considering various learning parameters for the classification of Multiple Sclerosis Brain Lesions and Pituitary Tumor. In the proposed research, T1-weighted Contrast-enhanced Magnetic Resonance images are preprocessed with various image-preprocessing approaches such as to resize the images, to convert the images into suitable image format so that the experimental work can be performed with deep learning in the Matlab environment. The experiment is conducted with the dataset of Multiple Sclerosis and Pituitary Tumor each of having 718 and 930T1-weighted MRI images respectively. The experimental results we achieved 99.7% classification accuracy of pituitary Tumor, and 99.2% accuracy of Multiple Sclerosis brain Lesions. The average accuracy of both classifications is 99.55%. The precision of the classification of Pituitary Tumor is 99.7, recall value is 99.7 and the f1_score of the classification is 99.7%. Similarly, the precision of the classification of Multiple Sclerosis Brain Lesions is 99.15%, the recall value is 99.15%, and the f1_score is 99.15%. The purposed approach of the Convolutional Neural Network architecture exhibited outstanding performance as compared to other research outcomes.

Keywords: Brain Tumor, Multiple Sclerosis Brain Lesions, machine learning, Deep learning, Convolutional Neural Networks, brain disorders.
INTRODUCTION

Brain Tumor and Multiple Sclerosis both are considered very dangerous diseases related to the brain [1]. The Pituitary tumor inside the pituitary gland affects the functioning of the brain. The pituitary gland is a very important organ in the human body; it plays a central role in the growth of body, metabolism, and reproductive function. The pituitary Tumors patients are increasing very rapidly all across the world. More than 14,120 patients are diagnosed in the United States, last one year as reported by the World Health Organization [2]. A pituitary tumor is generally benign but causes other mental damage as compared to other brain tumors [3]. Multiple sclerosis (MS) is a leading disabling disease related to the brain and spinal cord (Central Nervous System). In this disease, the human immune system attacks the myelin sheath, a protective cover for nerve fibers. The damage due to Multiple sclerosis causes communication problems between the human brain and other body parts. The disease can cause permanent damage to the nerves. Early detection of the disease can help for improvement [5]. The advancement of the latest technologies such as machine learning and deep learning are playing a major role in analyzing the large medical imaging datasets by providing the important supporting tools for the classification and prediction of various brain abnormalities [3]. The Convolutional Neural network is one of the machine learning approaches that substantially performed outstanding results in the classification of medical images [3]. The various machine-learning methods for image classification and disease detection are applied in MRI image analytics to provide additional support and opinions to radiologists [3].

In this research work, the “Convolutional Neural Network” [15, 16, 17], model is proposed for the classification of Pituitary Tumor and Multiple sclerosis brain lesions. The model is built and trained considering the various hyper-parameters. The size of the input images, size of the image dataset, and the number of categories of the images are very important parameters. The Convolutional Neural Network is trained with setting Hyper-parameters such as learning rate, dropout factor, number of Convolutional layers, etc. The paper is organized into five sections such as introduction, literature review, proposed research methodology, experimental results, and the conclusion with future work. In the literature review section, related research work carried out by the academicians, and researchers have explored with research the outcomes. In the research methodology, proposed research approaches are explored with considering the concepts of Convolutional Neural Networks (CNNs) and image preprocessing techniques. An experimental setup with detailed implementation approaches is explored in the results and analysis section. Finally, the conclusion section highlights the research outcome with future research directions.

RELATED WORK

Many researchers and academicians are continuously working in the field of medical image analytics. Different types of methodologies and models are developed and deployed for the classification and detection of various brain disorders. Through the depth literature reviews, I came across the various research papers related to disease diagnosis through Convolutional neural networks using Magnetic Resonance Images (MRIs). The following research papers are more relevant to the proposed research work:

Sunanda Das et al. [1] proposed the Convolutional Neural Network (CNN) for the classification of different types of brain tumors, such as Glioma Tumor, Meningioma Tumor, and Pituitary Tumor. The researchers have performed the task of brain tumor classification using 3064 T1 weighted contrast-enhanced MRI images. The CNN model was trained using a series of Convolutional and pooling operations. The MRI images are resized and Convolutional operations are performed with Convolutional filters/kernel of variable size to generate a feature map. Accuracy of up to 94.39% was achieved after evaluating the model on test datasets with 28.16% loss. The precision of 88%, 94%, and 98% was achieved for Glioma Tumor, Meningioma Tumor, and Pituitary Tumor respectively.

Melika Maleki, M. Teshnehlab, and M. Nabavi [5] developed the fully automated process of extracting features from magnetic resonance images (MRI) of multiple sclerosis. Based on the
extracted features, multiple sclerosis disease was classified. The authors proposed the Convolutional Neural Network for the extraction of features from MRI images and the multilayer neural network for the classification of two classes such as normal and Multiple sclerosis. The outcomes of the research shown that CNNs approaches for the classification are more efficient and accurate without using the image segmentation approach. The authors achieved the classification accuracy as 92.93, sensitivity as 96.12, and specificity as 97.57.

Mostafa Salem et al. [6] proposed the fully Convolutional Neural Network for the detection of multiple sclerosis lesions in T2-w MRI images. The author's proposed network was trained using four image modalities such as T1-w, T2-w, PD-w, and Fluid Attenuated Inversion Recovery (FLAIR) with a gradient descent optimization approach. The authors trained the network with 3-dimensional 32X32X32 patches with a step size of 16x16x16 were extracted from follow-up images and baseline images of the four input modalities. The researchers detected the new lesions with a mean Dice Similarity coefficient value as 83%, the true positive rate for the detection as 83.09% and, false-positive detection rate as 9.36%. Further, they found that larger patch sizes did not significantly improve the performance. Increasing the size of patches requires more computational power and processing memory.

3 RESEARCH METHODOLOGY

This part of the research paper focused on the research methodology that is used to classify the Pituitary Tumor and Multiple Sclerosis Brain Lesions. The classification is performed with the following steps: The most important part of the research is the suitable data collection for practical implementation. Choosing a suitable dataset decides the performance of the implemented modal. The second step is the image preprocessing used for enhancing the quality of the raw images data by performing various data transformation techniques. The third step of the methodology is the selection of Convolutional Neural Network architecture with suitable hyper-parameters for the efficient execution accurate classification of the Brain Tumor and MS lesions. The research methodology is based on the design and implementation of a Convolutional Neural Network suitable for classifying the Magnetic Resonance Images with considering the various learning parameters. Various CNNs architectures were proposed by the researchers with classification accuracies, not more than 95 or 96%.

A. Data Collection and Description of Data

The Pituitary tumor dataset collected from [8] contains 930 T1-weighted contrast-enhanced images. The Pituitary images are collected from 233 patients. The Multiple sclerosis images are retrieved from [11], [12], [13], [14] contains 38 patients MRI images in TIFF format. The multiple sclerosis images are the collection of first and the second examination in 0 months and 6-12 months. Other images are retrieved online and combined with the Multiple Sclerosis images.

B. Preprocessing

Both the datasets are resized as 512x512-image size and converted into PNG image file format. The pituitary tumor dataset originally downloaded in the .mat file format is converted into PNG image file format. The datasets are kept in two different folders such as Pituitary and multiple sclerosis. The Pituitary and Multiple sclerosis images are shown in figure 1 and figure 2.
The datasets are divided into training and validation datasets containing 75% data for training and 25% data for validation. The total image data file are $(914+718) = 1632$ images. 1200 image files are used for training the Convolutional Neural Network model and the remaining 432 files are used for the validation of the model.

C. Pituitary Tumor and Multiple Sclerosis Brain Lesions Classification using CNN.

The Convolutional Neural Networks are trained to learn a set of features from the input images that can be used to classify new images data. Convolutional Neural Networks performance is tested in the field of brain MRI image analytics, specifically brain tumor/lesions classification and detection [6]. Convolutional Neural Network comprises the ability to extract and learning the features from large image datasets through the training process with gradient descent and computer vision approaches as compared to simple Artificial Neural Network. Through the design of Convolutional Neural Network layered architecture a series of Convolutional, batch normalization, ReLU, and max-pooling operations, followed by a fully connected layer, Softmax layer, and classification layer [1].

In this research work, a Convolutional Neural Network is proposed with image input size $512 \times 512$. 8 filters/kernels of size $11 \times 11$ are used in the first Convolutional layer with stride $[1, 1]$ and padding $[1, 1, 1, 1]$. The process of stride slides the movement of the filter at each step horizontally as well as vertically. The proposed Convolutional Neural Network is designed with three Convolutional layers, Three ReLU layers, and three batch normalization layers and, three Max-pooling.
All the layers are finally connected with a fully connected layer, two-way softmax layer, and classification layer. The ReLU activation function is used for transforming the weighted input from the input node to the next output node as a positive input. The Rectified Linear Unit activation function is a piecewise linear function that is used to eliminate the negative values after Convolutional operation. This function has become the default activation function for many types of Convolutional Neural Networks. It is shown through the implementation of CNN that the ReLU activation function achieves comparatively better Performance.

The Rectified Linear Unit function can be defined as [15]:

\[
f_x = \max(0, wx + \text{bias})
\]

Where \(w\) is the weight and \(x\) as an input with bias value.

The Convolutional operation and max-pooling operation both are performed by CNN using the following two mathematical formulas:

\[
\text{Convolution-Layer-Output} = (W - F + 2P)/S + 1
\]

\[
\text{Maxpooling - Output} = (W - F_m + 2P)/S_m + 1
\]

Where \(W\) is the width of the image, the filter size is \(F\) and the stride is \(S\) and zero paddings are \(P\). we can choose either image height or width if the height and width are equal, otherwise, the calculation is performed with image height and width separately. In the case of Max-pooling, the filter size is \(F_m\) and stride is \(S_m\) as shown in equation 3. The image size in the proposed work is 512x512, so the image width and height both are equal. In this research paper, we took image size as 512x512, filter size as 11x11 with zero paddings as [1 1 1 1], and stride is [1 1] during the first Convolutional operation, the output of the Convolutional layer is \(((512-11+2))/1+1\), that is equal to 504, so we get 504x504x8 feature maps in the first Convolutional process. After the Convolutional and other operations, max-pooling is performed on the feature maps collected during the Convolutional process. Formula number (2) can be used for that purpose. Therefore, the output after the first max-pooling operation is:

\[((504-2+0))/2+1\], that is equal to 252, so we obtained 252x252x8 feature maps after the first max-pooling operation. The rest of the Convolutional and max-pooling operations are performed using the formula number (2) and (3).

The resulting output after the first Convolutional operation is 504x504x8. Batch Normalization operation is performed on the resulting output of the first Convolutional operation. This operation normalized the output within the range. ReLU Operation is performed to eliminate the negative values. The max-pooling operation with filter size 2x2 with stride [2 2] is performed on the first convolved output and the final output is generated as 252x252x8. In the second Convolutional operation, 16 filters of size 11x11 are applied to the input image size 252x252 to obtained the resulting image size is 244x244 with weights as 11x11x8x16 and bias as 1x1x16. The batch normalization and ReLU operation are also performed on the resulting output. Through the second max-pooling operation down-sampling is performed with a 2x2 filter size with [2 2] as stride. The resulting feature maps of size 122x122x16 are obtained. Through the third Convolutional operation with 32 filters/kernel of size 11x11, resulting feature maps of size 114x114x32 are generated with 11x11x16x32 weights and 1x1x32 Bias.

Through the third down-sampling process with 2x2 filter and [2 2] stride, feature maps are further reduced and resized as 57x57x32. Finally, 1x1x2 actions with 2x103968 weights are connected to a fully connected layer. The fully connected layer is further connected to softmax and classification to classify the Pituitary Tumor and Multiple Sclerosis brain lesions in the form of two classes.
D. Performance Evaluation of the Proposed CNN architecture.

The performance of the proposed Convolutional Neural Network for the classification of Pituitary Tumor and Multiple Sclerosis brain lesions is evaluated based on classification accuracy, Precision, Recall, and f1_score.

\[
\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{False Positive} + \text{False Negative} + \text{True Negative}}
\]

(4)

\[
\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}
\]

(5)

\[
\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}
\]

(6)

\[
\text{f}_{\text{score}} = \frac{2 \times \text{True Positive}}{2 \times \text{True Positive} + \text{False Positive} + \text{False Negative}}
\]

(7)

4 EXPERIMENTAL SETUP AND RESULTS ANALYSIS

The model is implemented in the Matlab Environment using Matlab version R2020a with the help of Deep learning and computer vision approaches [18]. The Stochastic Gradient Descent Momentum (SGDM) optimizer, 128 epochs, and 30 iterations for validation frequency are used as a hyper-parameter during the training. SGDM is one of the powerful optimization algorithms generally used to train the Convolutional Neural Networks. The model is trained on Quadro P5000 GPU with 16GB GDDR5X GPU Memory, 2560 NVIDIA CUDA Cores, and 8.9 Teraflops Computing Power. Figure 3 shown below illustrates the training progress with training accuracy, validation accuracy, training loss, and validation loss. The outcomes of the Convolutional Neural Network during the training period are shown below in Table 1.

| Table 1 Convolutional Neural Networks. Layer wise Training outcomes |
| --- | --- | --- | --- |
| Name | Type | Activations | Learnable |
| 1. Input | Image Input | 512x512x1 | --- |
| 2. Conv1 | Convolutional | 504x504x8 | Weights 11x11x1x8 |
| 3. BatchNorm1 | Batch Normalization | 504x504x8 | Scale 1x1x8 |
| 4. ReLU | ReLU | 504x504x8 | --- |
| 5. MaxPool1 | Max Pooling | 252x252x8 | --- |
| 6. Conv2 | Convolutional | 244x244x16 | Weights 11x11x8x16 |
| 7. BatchNorm2 | Batch Normalization | 244x244x16 | Offset |
| Layer | Description | Operation | Output | Parameters |
|-------|-------------|-----------|--------|------------|
| 8     | Relu2       | ReLU      | 244x244x16 | -- |
| 9     | Maxpool2    | Max Pooling | 122x122x16 | -- |
| 10    | Convlayer3  | Convolutional | 114x114x32 | Weights 11x11x16x32 Bias 1x1x32 |
| 11    | BatchNorm3  | Batch Normalization | 114x114x32 | Offset 1x1x32 Scale 1x1x32 |
| 12    | Relu3       | ReLU      | 114x114x32 | -- |
| 13    | Maxpool3    | Max Pooling | 57x57x32 | --- |
| 14    | 2 Fully Connected Layer | Fully Connected | 1x1x2 | Weights 2x103968 Bias 2x1 |
| 15    | SoftmaxLayer | softmax | 1x1x2 | --- |
| 16    | Classification layer | Cross-entropy with classes ‘Mscerosis’ and ‘pituitary’ | Classification Output | - |

Figure 3. Execution Progress with training accuracy, validation accuracy, training loss, and validation loss

The confusion matrix is an important performance evaluation matrix used to depict the predicted classification results concerning actual values. Through the validation process, the confusion matrix is generated with predicted and actual classification results in the form of the Con-
fusion matrix as shown in figure 4. During the validation, 118 images of Multiple Sclerosis and 330 images of Pituitary Tumor are used for validation. We can that the proposed Convolutional Neural Network truly predicted 117 images belong to Multiple Sclerosis and 329 images are predicted as Pituitary Tumor. The validation process also creates a confusion matrix chart showing the true labels and predicted labels with predicted accuracy and miss classification accuracy. The rows of the confusion matrix depict true classes and columns depict the predicted class. The main diagonal and opposite diagonal cells represent correctly classified and incorrectly classified observations respectively [18].

A set of 53 images of Pituitary Tumor and Multiple Sclerosis are used for the testing of the classification model. The testing accuracy is printed above each image. Among the 50 testing images, some images with testing accuracy are printed above on each image, are shown in figure 6.

![Figure 4. Confusion Matrix for the Classification.](image)

![Figure 5. Confusion Chart for the Classification](image)

Table 2 Performance Evaluation Table
5 CONCLUSIONS

Accurately classifying brain disorders is a challenging task for healthcare experts. Deep learning approaches are proving to be effective and accurate methods of automatic brain tumors and lesions classification and detection. This research paper explored the deep learning approaches with the help of the Convolutional Neural Network to provide more accurate results for the classification of brain-related diseases. The 99.2% classification accuracy is achieved for the Multiple Sclerosis brain lesion classification and 99.7% classification accuracy is achieved for the classification of Pituitary Tumor. It is also found that classification accuracy is highly dependent on the quality of the image datasets. The model designed through the CNN approaches can be used to classify the unknown images of the tumors and lesions if the images are scanned with a high-quality MRI machine of 1.5 Tesla, 3 Tesla or higher intensities. As compared to the other classification model, our model for the brain tumor and Multiple Sclerosis brain lesion, classification has higher accuracy as shown in table 2. The model can be used for real-life applications if we have enough MRI images data related to Pituitary Tumor and Multiple Sclerosis. As a future scope, we can explore the research work in the domain of medical image processing applications for the detection of various brain-related disorders through transfer learning approaches as well as designing the large Convolutional Neural Networks.

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