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Faster Way of Brain Tumor Detection from Scratch MRI Images

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Abstract— Deep learning is exceptionally mainstream and yet, it was confined by its demand for a lot of information and tremendous time for training. On the other hand, MRI is one of the most popular imaging modalities and broadly used for diagnosis. Deep learning application in MR images is not a new thing, but as always it is confined by the typical limitations of deep learning. This research introduces a quicker method of classification that combines image processing and deep learning to figure out how to characterize MR (Magnetic Resonance) images. Here, the brain tumor is considered as the case of interest due to its awfulness where image processing is used to resize the images and deep neural network is used to train the model according to their features in a very short time. In a nutshell, it can be said that it is a super-fast process of tumor detection, which requires around 1 second of time to deal with 212 images. And it provides an average accuracy of around 72.66% without any kind of difficult preprocessing methods such as the application of filter or noise reduction, etc. Here the total procedure will be discussed briefly.

Index Terms— Brain, CNN (Convolutional Neural Network), Hemorrhage, Image Classification, MRI (Magnetic Resonance Imaging), ReLU (Rectified Linear Unit), Tumor.

1 Introduction

THE Brain Cancer is considered one of the most common and dangerous types of cancer. In 2018, the number of new cases of brain cancer is around 296,851, and deaths in this year are around 241,037 [1].

Cancer might start from a carcinogenic mutation and soon become a tumor and day by day it grows so fast and takes a hideous look. Time is very critical for a cancer patient because of its faster-growing capacity, but the treatment process involves several steps that take too much time for patients and causes trouble for everyone involved in this process. So, here automation process of tumor detection can greatly assist by reducing the time and trouble for everyone.

1.1 Magnetic Resonance Imaging (MRI)

MRI is a painless, noninvasive diagnostic imaging modality which is very popular for detecting small lesion because of its enhanced CNR (Contrast to Noise Ratio). Strong magnetic field gradient and radio waves are used here to produce an image that is used to observe the anatomical and physiological structure of the human body.

MRI gives comprehensive pictures of soft tissues that's why MRI has great popularity in detecting several brain abnormalities such as infection, multiple sclerosis, injury, tumor, and dementia, etc.

1.2 Deep Learning

Deep learning is a branch of machine learning where images, text or sound is used for training a model and that model learns to perform classification tasks directly from that images, text, or sound. In deep learning, the term "deep" refers to the number of layers in the implemented neural network. Here, as much as the number of layers increases, the network becomes deeper. Old-fashioned neural networks contain only 2 to 3 layers, while deeper neural networks might contain hundreds of layers. Nowadays, deep learning is used in several sectors of regular life and industry.

2 Prior Works

The objective of this research is to only detect the brain tumor faster, not to identify its type, texture or size, etc. There are different ways to classify tumors using MRI images. Combining conventional and perfusion MRI a computer-assisted classification method is used for differential diagnosis and the scheme consists of many steps like region-of-interest definition, feature extraction, feature selection, and classification [2].

CAD systems of human brain MRI images are still an open problem. A hybrid intelligent machine learning technique is based on the computational methods – the feedback pulse-coupled neural network for image segmentation, the discrete wavelet transform for feature extraction, the principal component analysis for reducing the dimensionality of the wavelet coefficients, and the feed-forward back-propagation neural network to classify inputs into normal or abnormal [3].

To classify the brain tumor type using Convolutional Neural Networks (CNN) is one of the most common ways, but the shortcoming of it is that it needs a large amount of training data and cannot properly handle input transformations. To

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overcome these a brand new architecture Capsule Networks (Caps Nets) are used which require far less training data than CNN, which is the case for processing medical image datasets including brain Magnetic Resonance Imaging (MRI) images [4]. The feature extraction is the process that represents a raw image in its reduced form and facilitates decision making like pattern classification. This concept is used by a group of researchers to address the problem of classifying MR images. The technique has been carried out over a larger database and is more robust and effective. PCA and Linear Discriminant Analysis (LDA) was applied to reduce the number of features used. As a comparison of nonlinear techniques vs. linear techniques, the Support Vector Machine (SVM) classifier is used [5]

For classification of MR images, a hybrid technique with three stages – feature extraction, dimensionality reduction, and classification is used by some people. The features related MRI images are obtained by using discrete wavelet transform (DWT), to reduce image principle component analysis (PCA) is used and lastly, for classification, two classifiers have been developed – the first based on feed-forward back propagation artificial neural network (FP-ANN) and the second based on k-nearest neighbor [6]. For detecting the brain tumor image processing of the MRI images is important. One of the important steps of image processing is the segmentation of the images. In MRI images the segmentation is commonly done using CNN (convolutional neural networks). For brain tumor segmentation in MRI images intensity normalization as a preprocessor step together with data augmentation is very effective as a brain tumor is highly variable in their spatial localization and structural composition [7].

Image processing of MRI can also be done by the fuzzy clustering means (FCM), which is an unsupervised clustering algorithm. The FCM and FFCC both are the segmentation techniques with results that the radiologists find acceptable. To detect the tumor without mistake a fuzzy classification method and asymmetry analysis method can be compared and for segmentation refinement, a deformable model constrained by spatial relations can be used [6],[8]. An automatic segmentation and labeling system of brain tumors in MRI images that integrates knowledge-based (KB) techniques with multispectral analysis that is potential in effectively segmenting glioblastoma-multiform tumors without the need for human supervision and has potential for segmenting tumor for therapy planning. The KB paradigm allows processing tools for the existing system and also easy integration of new domain information when MRI data are considered [9]. Different types of brain tumors need different treatments, some tumors keep enhancing with time. To separate non-enhancing brain tumors from the enhancing ones a group of people introduced an automated segmentation method with three weighted images for each axial slice through the head. A fuzzy clustering algorithm is used for initial segmentation and final tumor segmentation integrated domain knowledge and image processing are used [10].

3 METHOD

Image processing and deep learning combination is a very common and popular way to analyze medical images. Multiple studies of machine learning and image processing are available which have already introduced an automation system in different sectors of medical imaging. But most of them are time-consuming and fuzzy, but some of them are very efficient with good accuracies. Here, in this paper, a faster method of tumor detection is introduced.

3.1 Preparing Dataset

The maximum process of image classification with deep learning takes several difficult preprocessing steps. This process includes easy steps of preprocessing. They are-

Data Collection. Grayscale MR Images were collected from a well-known hospital Ahsania Mission Cancer and General Hospital, Dhaka and Kaggle dataset.

Data Conversion (DICOM to PNG). Here, the images collected from the hospital were all in DICOM (Digital Imaging and Communication in Medicine) file format. But for the model images of the PNG file format is acceptable. So, using "DICOM Converter" DICOM file formats are converted into PNG (Portable Network Graphics) file format. And the dataset collected from Kaggle Dataset was already in PNG file format, so no conversion was needed in that case.

Resizing and Channel Addition. Here, for this system, the required size of images is 32 × 32 × 3, where 32 × 32 is the number of pixels in height and width of each and every image and 3 is the number of channels. Collected images had various sizes. So, images were resized by using 'Image Resizer' in 32 × 32 pixel size. After that, it was expanded with additional channel producing images of the size 32 × 32 × 3 by using a Python programming language code.

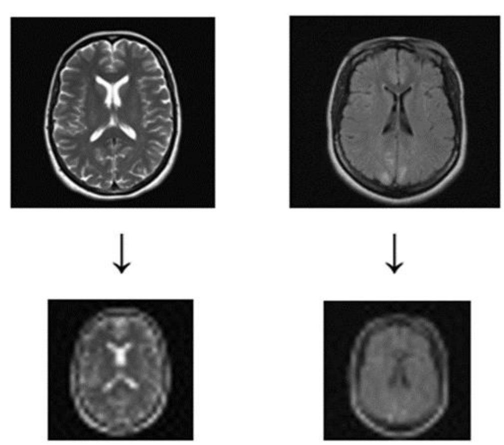

Fig. 1. Conversion of Images from random size to *32 × 32* by using 'Image Resizer'

3.2 Image Classification

Deep neural network is constructed inspired by the biological nervous system. As it is known that a deep neural network directly learns from data because it contains several layers for directly processing the data and learn from it. Where each layer contains numerous hidden interconnected layers with an input and an output layer. Each of these hidden layers uses the output of the previous layer as its input as they are interconnected via neurons or nodes.

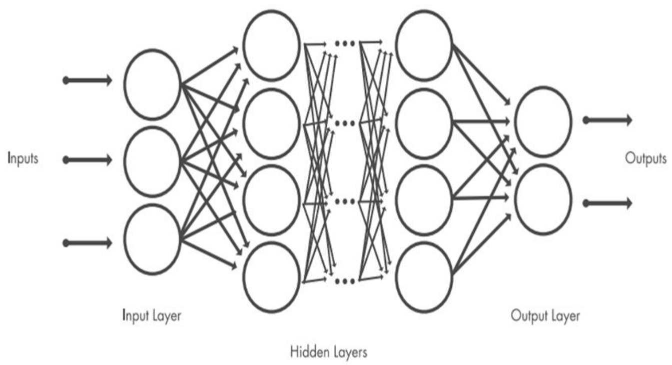

Fig. 2. Interconnected layers (uses the previous output as input)

These layers perform one of three types of operations on the data: convolution, pooling, or rectified linear unit (ReLU). Here a dataset containing two different categories (tumor and healthy) was labeled according to its content and used for training and testing. Using the training data, the deep learning network automatically learns to recognize the object by observing different features associated with that. Each layer observes the data and learn from them and passes it on to the next layer. As much as layer increases, the detail learning performance increases[11].

For deep neural networks, the time required for training is also a noticeable issue here. Previously developed deep learning algorithms take too much time (generally from several hours to days) to train. Which is really tiresome and the most important shortcoming of deep learning. It restrains the efficiency of the model. The processor and training algorithm play an effective role here. But here we have used a normal GPU but it didn't take too much time to train. So, it is clear that this algorithm is best for faster training which will be really a great initiative for the automation process in the medical diagnostic sector as a lot of data needs to be handled here.

Now, the number of used nodes in this system depends on the pixel size of the input image. Here, as the required pixel size is $32 \times 32 \times 3$, the number of nodes = $32 \times 32 \times 3 = 3072$.

And two different class of images are required, So, the number of output nodes = 2

So, used nodes for each hidden layer = 3072 – 2 = 3070.

So, the used network architecture looks like –

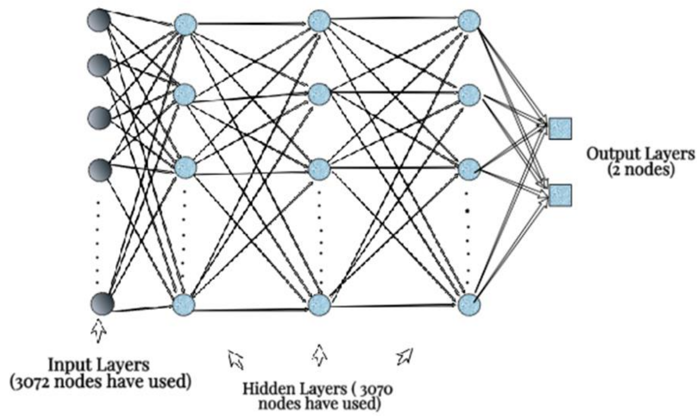

Fig. 3. Network architecture of layers of this model.

Here, a MATLAB code was used to build and train the total neural network. Two datasets were prepared for training and testing containing different sets of images (both tumor and healthy). The training set was used to familiarize the model with the two categories that were needed to classify. To load the training set containing MR images (both tumor and healthy) the command used in MATLAB is shown below –

```
categories = {'Tumor','Healthy'};
rootFolder = 'Training_set';
imds = imageDatastore(fullfile(rootFolder,
categories), ...
    'LabelSource', 'foldernames');
VarSize = 32;
```

As, the CNN based deep learning method was used for building and training the model the hidden layers performs three types of operations – convolution, pooling and rectified linear unit. In this model, 15 layers were used and all these layers were defined by giving relevant commands to the MATLAB. The next step is to train the model and for this the command used is given below –

```
[net, info] = trainNetwork(imds, layers,
opts);
```

Lastly, the network is needed to be tested, which is done by using new images that were not used before to train the network. For this, the testing dataset was used to classify the images and determine the accuracy of classification of the model.

Thus, using MATLAB the network to classify MR images of brain tumors and healthy brain images were trained. The total process flow can be shown in the figure below –

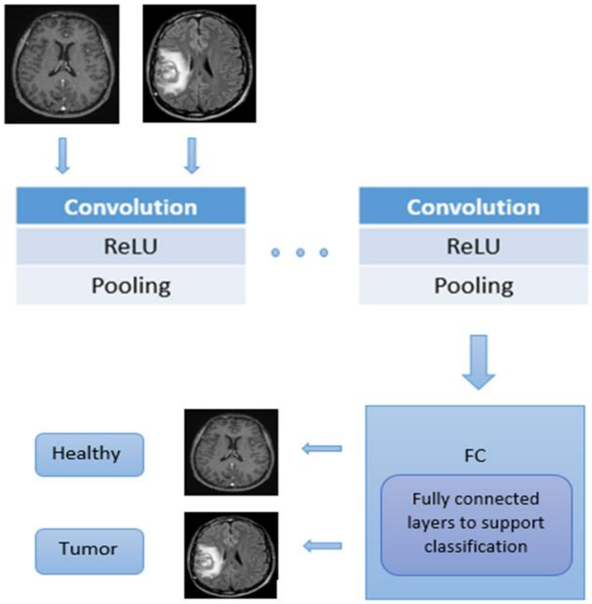

Fig. 4. Process of classifying tumor and healthy images by using several layers.

4 RESULT

For Different type and values of data provided different types of accuracies so here, giving a summary of required time and accuracies for different values of testing and training data.

TABLE 1
TRAINING DATASET WITH REQUIRED TIME AND ACCURACIES

Total Images	Training Set		Testing Set		Time (Sec)	Accuracy (%)
	Healthy	Tumor	Healthy	Tumor		
212	37	58	37	80	<1	71.57
212	31	78	43	60	<1	69.52
212	35	75	39	63	<1	74.60
212	36	70	38	68	<1	72.51
212	30	65	44	73	<1	70.19
212	40	68	34	70	<1	75.17
212	38	72	36	66	<1	75.04

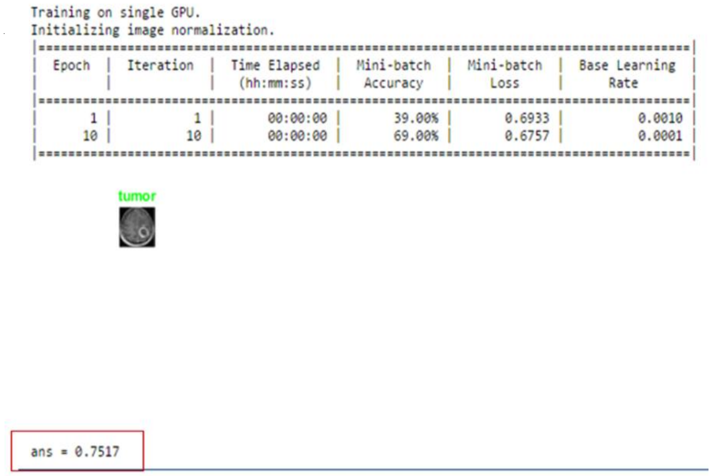

Fig. 5. Result with accuracy 75.17% and required time is always <1 second for MR images

Here, an average accuracy of 72.66% is obtanied, notwithstanding, the required time for preparing isn't even 1 second since totally, around 212 images had utilized. In this case, expanding the number of images increases the amount of required time, nevertheless, it still remains faster than most other approaches. Also, the advantage of the increasing number of images is the accuracy of the system also increases.

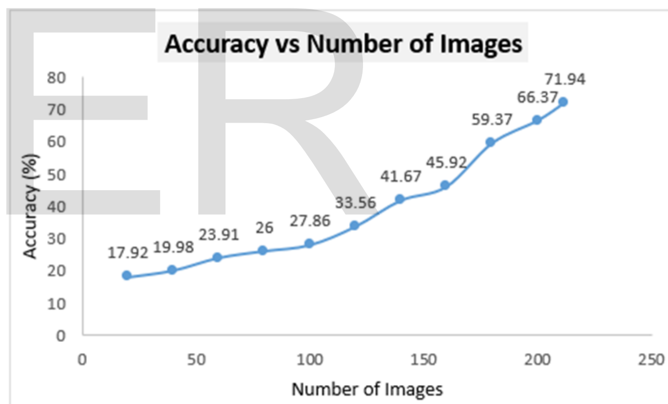

Fig. 6. Variation of accuracy with number of images

From fig. 8 it is obvious that with the increasing number of images, the accuracy rate of the system also increases significantly. So, by using a large number of images as input it is possible to get a satisfying number of accuracies.

5 CONCLUSION

Hereby, from the outcome, it is clear that a significant shortcoming of this model is low accuracy. Causes of low accuracy are- Too less data for training, Decreased quality of images in lower pixel values and Low power of GPU might decrease the accuracy. But it can be improved by considering these conditions. Here just 212 pictures are utilized which is truly unreasonably less for preparing a model.Increasing the number of images increases the accuracy but might affect the amount of time for both training and classifying. Here required time is around one second but the required time might increase in case of a larger amount of data. So, the future aim of this research is to observe the efficiency of this model for other imaging modalities and other diseases or abnormalities. Additionaly, observe the change in accuracy and time for different conditions, for instance, number and quality of images, the number of layers in the model, GPU, etc.

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