International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 9 Issue 01, January-2020

A Modified Deep Convolutional Neural Network for Brian Abnormalities Detection

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***Abstract*—Cancer diagnosis is highly invasive, time consuming and expensive, there is an immediate requirement to develop a non-invasive, cost-effective and efficient tools for brain cancer characterization and grade estimation. Brain scans using magnetic resonance imaging (MRI), computed tomography (CT), as well as other imaging modalities, are fast and safer methods for tumor detection.. However, for analyzing brain tumor without human intervention is considered as a significant area of research because the extracted brain images need to be optimized using segmentation algorithm which should have high resilient towards noise and cluster size sensitivity problem with automatic region of Interest (ROI) detection. In this research, Deep Convolutional Neural Networks (DCNN) is one of the widely used deep learning networks for any practical applications. The accuracy is generally high and the manual feature extraction process is not necessary in these networks. However, the high accuracy is achieved at the cost of huge computational complexity. The complexity in DCNN is mainly due to: (a) Increased number of layers between input and output layers and (b) Two set of parameters (one set of filter coefficients and another set of weights in the fully connected network need to be adjusted. In this work, the second aspect is targeted to reduce the computational complexity of conventional DCNN. Suitable modifications are performed in the training algorithm to reduce the number of parameter adjustments. The weight adjustment process in the fully connected layer is completely eliminated in the proposed modified approach. Instead, a simple assignment process is used to find the weights of this fully connected layer. Thus, the computational complexity is significantly reduced in the proposed approach. The application of Modified DCNN (MDCNN) is explored in the context of Magnetic Resonance (MR) brain tumor image classification. Abnormal brain tumor images from four different classes are used in this work. This research pays its proficiency in the field of brain abnormality detection and analysis in health care sector without human intermediation.**

Keywords- DCNN, MDCN, Magnetic Resonance

I. INTRODUCTION

Deep learning approaches are one of the prime computational intelligence techniques used for medical imaging applications. Specifically, deep learning approaches are widely used for medical image classification which falls under pattern recognition applications. These deep learning based medical image classification approaches are normally employed in automated disease diagnostic systems. The main method among the deep learning approaches is the Deep Convolutional Neural Network (DCNN). The main advantage of DCNN is the high accuracy which is achieved with the help of many layers and automated feature extraction process. However, the high accuracy is achieved at the cost of high computational complexity. It is a well-defined concept that a system must be efficient in terms of accuracy and complexity for real time applications. Literature survey reveals several DCNN based research works for medical image classification applications.

Deep neural network-based brain tumor image classification is proposed in [1]. Three types of abnormal brain image category are used in this work. The conventional training process is used to classify images. The application of DCNN for Computer Tomography (CT) brain image classification is explored in [2]. The fusion of 2D CNN and 3D CNN is exploited in this work for performance enhancement of the conventional method. Early detection of Alzheimer is the focus of this work. DCNN is also used for Alzheimer disease detection in [3]. Positron Emission Tomography (PET) brain images are classified using DCNN for the disease detection process. Bi-level classification is carried out in this work. A software for deep learning based medical image processing is developed by Eli et al. [4]. Medical image classification is the prime focus of this work and it is open-sourcesoftware. A detailed survey on medical image analysis using deep learning approaches is given in [5]. The pros and cons of DCNN are discussed in detail in this work.

An improved deep learning approach based on human visual perception is proposed for image classification in [6]. The drawback of the conventional method and suggestions for improvement is available in this work. Deep autoencoder neural network-based functional MRI (f-MRI) brain image classification is proposed in [7]. This method is used for the accurate prediction of schizophrenia. Another survey on deep learning algorithms for biomedicine applications is available in [8]. DCNN and Deep Neural Networks are dealt in detail for various medical imaging applications. Several other deep learning architectures are also discussed in this work. A modified Deep Neural network for pattern recognition is implemented in [9]. The modifications are performed in such a way to reduce the number of training images. This method can be extended for any practical applications. Deep Residual Network based medical image classification is proposed in [10]. Four different types of abnormal categories are sued in this work. However, the complexity is quite high due to the large number of layers used in this work.

Autism disorder classification using Deep neural network is explored in [11]. Only bi-level (normal/abnormal) classification is carried out in this work. However, different stages of autism classification are necessary for practical applications. A modified DCNN is proposed in [12]. Modifications are done in such a way that large dataset is not necessary for training the proposed approach. Classification

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accuracy is used as the performance measure for analysing this method. Classification of multimodal medical images using deep convolutional neural network is proposed in [13]. This method also emphasizes on achieving high accuracy for the proposed approach. Glioma tumor classification and segmentation using deep convolutional neural network is illustrated in [14]. Five different DCNN based approaches are proposed in this work. Sensitivity and Specificity are the performance measures used in this work. Deep convolutional neural networks are also used for detection and diagnosis of seizures [15]. Deep convolutional neural networks for brain tumor detection is also explored in [16]. Grading of meningioma from MR images using deep convolutional neural network is developed in [17]. DCNN is also used for classification of other medical images [18]. Few modified deep neural networks for image classification are proposed in [19, 20].

In this work, a modified DCNN is proposed for abnormal brain image classification. The modification is performed in the fully connected layer of conventional DCNN. The weights in the fully connected layer are estimated by an assignment process rather than the gradient descent mode of training used in conventional DCNN. This methodology reduces the computational complexity to a higher extent without compromising the accuracy. The restof the proposed MDCNN is same as that of the conventional DCNN. Experiments are conducted on real-time MR brain tumor images. The performance of the proposed approach is analysed in terms of accuracy and complexity.

II. METHODOLOGY

A CNN-based brain tumor segmentation method was proposed in . In this proposed method, three CNNs were used for training on multi-institutional data. Each CNN consisted of four convolution layers followed by two fully connected layers..Patching-based segmentation was used. The equal sized patches extracted from images were annotated into three classes: tumor patches, healthy patches surrounding the tumor and other healthy patches.The tumor images were further divided into five classes based on patient data i.e, class-0: normal, class-2: enhancing region, class-3: necrotic region, class-4: T1-abnormality, class-5: FLAIR abnormality, class-1: ground truth region based on combination of classes 2–5.

The goals for any computer-based automated analysis are as follows.

1. The algorithms must generate the reproducible results with the same accuracy on every run.
2. It should not be overwhelmed by volume of the data.
3. The use of graphical processing unit (GPU) and parallel algorithms speeds up the processing.
4. The automated tumor segmentation supports human expert, which in turn results in treatment planning and follow-up.
5. Such data can be captured at remote location and processed at a centralized location.

The conventional brain tumor segmentation methods suffer from following issues.

1. All such methods require user to extract features from the image and supply them to the method for segmentation.
2. The feature extraction depends on the expertise and knowledge of a user.
3. Moreover, handling the input with higher dimensions is tedious and difficult task.
4. All methods require prior belief about the relationship among image pixels, which may not hold out to be true yielding poor segmentation.
5. The methods use heuristics for parameter selection.
6. The methods may require extensive preprocessing before segmentation is applied.
7. Some of the methods have poor convergence.
8. Usually classification is done after the image is segmented.

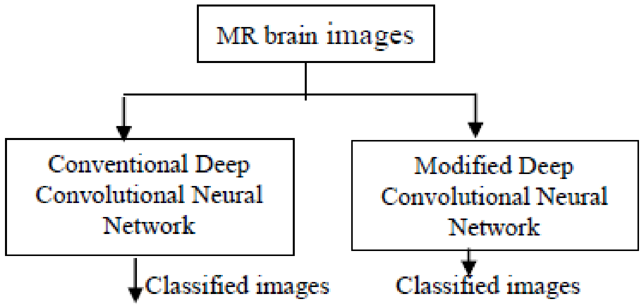

Figure 1: Proposed methodology

There are some automatic brain tumor grading methods which were proposed based on texture analysis using ML techniques Most of them use MRI (T1, T2, FLAIR, etc.). Recently many DL architectures (especially CNN) have shown remarkable performance in medical image analysis such as brain tumor segmentation and tissue classification on brain MRI. However, tumor grading utilizing DL methods is unexplored so far and there is a lot of research scope to explore further. We have provided a plausible solution for the tumor grading as shown in Figure.

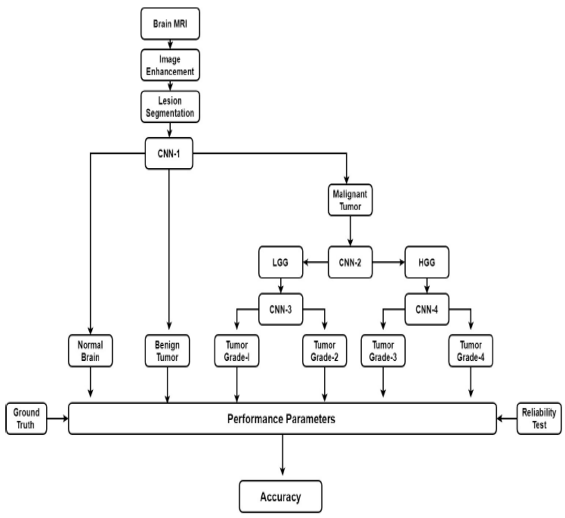

Figure 2: Brain tumour grading

The proposed methodology for classifying the brain tumors is as follows:

Step 1: Brain MRIs Dataset acquisition
Step 2: Image segmentation using Fuzzy C-means
Step 3: Feature extraction using discrete wavelet transform(DWT) and reduction using Principle component analysis (PCA) technique
Step 4: Classification using DCNN

V CONCLUSION

A modified deep convolutional neural network is proposed in this work for MR brain image classification. The proposed approach is analyzed in terms of accuracy andcomputational complexity. An approximate improvement of 3% is achieved with the proposed approach in comparison to the conventional CNN approach. A sufficient improvement in the True Positive Rate and True Negative Rate is also seen from the experimental results. In the proposed approach, the weights are not adjusted in the fully connected layer of the proposed approach. This reduces the computational complexity to high extent which makes it suitable for practical applications. Thus, an alternate for conventional CNN is proposed in this work which performs better than the conventional CNN.

ACKNOWLEDGMENT

The authors would like to thank the University authorities and the head of the department for their kind cooperation and valuable suggestions for the completion of the work.

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