Detection of Brain Tumors Using Transfer Learning Features and Machine Learning Techniques

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***Abstract*- This paper proposes a Magnetic Resonance Imaging (MRI) based brain tumor image detection using Convolutional Neural Network (CNN) based deep learning method. In modern days, checking the huge number of MRI images and finding a brain tumor manually by a human is a very tedious and inaccurate task. It affects the proper medical treatment of the patient. Again, it is hugely time-consuming task as it involves a huge number of image datasets. The proposed an algorithm to segment brain tumors from 2D MRI by a convolutional neural network which is followed by traditional classifiers and deep learning methods and Transfer learning method for feature extraction. A CNN based model will help the doctors to detect brain tumors in MRI images accurately, so that the speed in treatment will increase a lot.**

***Keywords*- 2D Magnetic Resonance brain Images (MRI), Convolutional Neural Network, Wiener filter, Fuzzy c-means.**

I. INTRODUCTION

Brain tumor is a deadly disease and its classification is a challenging task for radiologists because of the heterogeneous nature of the tumor cells. Recently, computer-aided diagnosis-based systems have promised, as an assistive technology, to diagnose the brain tumor, through magnetic resonance imaging (MRI). In recent applications of pre-trained models, normally features are extracted from bottom layers which are different from natural images to medical images [1].Neural networks (NN) perform classification by learning from data and do not use rule sets. NN generalize using previous data and learn from past experience. They perform well on difficult, multivariate, non-linear and noisy domains, such as brain tissue segmentation, where it becomes more difficult to use decision trees, or rule-based systems [2].Traditional brain tumor segmentation methods such as probability theory, kernel feature selection, belief function, random forests, conditional random fields and support vector machines have achieved a great success in recent years. However, brain tumor segmentation is still a challenging task, especially in the case of missing some modalities [3].The challenge of segmentation on missing modalities is to learn a shared latent representation, which can take any subset of the image modalities and produce robust segmentation. To effectively learn the latent representation of individual representations, a novel brain tumor segmentation network to deal with the absence of imaging modalities [4].On the contrary, instead of the step-by-step process like ML, DL forms an entire network inspired by a biological neural network in order to perform the entire process of ML. Throughout the hierarchical structure of data movement, each level transforms the data it receives into more abstract data to be fed to the next level. DL employs different kinds of classifiers including RNN, CNN, Boltzmann machine, and autoencoders [5].In general, these methods take advantage of only local information for each pixel and do not include the shape and the boundary information. Many researchers use a wide range of techniques based on segmentation to solve the problem of localizing and analysing the characteristics of a brain tumour [6].In current clinical practice, the segmentation is still relied on manual delineation by human operators. Moreover, reproducible results are difficult to achieve even by the same operator [7].Brain tumor comprises of various biologic tissues; only single kind of MRI cannot give whole information related to anomalous tissues. Joining distinctive complementary information upgrade the segmented region of tumors. The segmentation strategies have been entirely effective especially in the improvement stages of infected tissues [8].A stacked classifier was used to determine if an image contains tumors. Meanwhile, image pre-processing is used to construct an image of the human body’s anatomical structure, as explained in and MRI images are used to locate tumor cells in a diseased human brain [9].The features are extracted using the principal component analysis (PCA) and the classification is performed using Probabilistic Neural Network (PNN). The features are extracted using principal Component Analysis (PCA) and then Back-Propagation Neural Network is used as a classifier to classify MRI brain images as normal or abnormal [10]. Generative Adversarial Networks (GANs) synthesize realistic/diverse additional training images to fill the data lack in the real image distribution; researchers have improved classification by augmenting data with noise-to-image. [11].The accurate cell detection in histopathological images has attracted a wide range of interests recently. A brief summary on nuclei detection and segmentation. Distance transform based methods have been used to detect seeds (cells) in clustered objects. However, it may not work well for tightly or densely clustered cells [12].

The proposed an algorithm to segment brain tumors from 2D Magnetic Resonance brain Images (MRI) by a convolutional neural network which is followed by traditional classifiers and deep learning methods and use Transfer learning method for feature extraction. CNN based model will help the doctors to detect brain tumors in MRI images accurately, so that the speed in treatment will increase a lot.

The list below demonstrates how the paper is organised: Section I gives a description of the introduction. The proposed model and description are explained in Part II. The results are presented in Section III. In Section IV, the conclusion is presented.

II. PROPOSED WORK EXPLANATION

The well-known CNN architectures using augmented MRI slices of brain tumor dataset by using adaptive wiener filter for pre-processing and fuzzy C means for segmentation. These pretrained CNN architectures are used to deploy the transfer learning techniques to extract the visual discriminative and rich features. Figure 1 clearly shows the proposed system. Finally, the visual patterns are classified using by CNN. The key elements of proposed framework are discussed in the subsections.

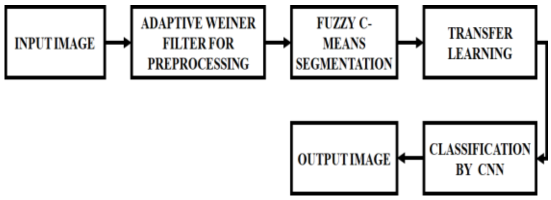

Figure 1: Proposed system

A. Adaptive wiener filter

Wiener filter is an excellent filter when it comes to noise reduction or deblluring of images. The Wiener filter is the MSE-optimal stationary linear filter for images degraded by additive noise and blurring. The main objective of Wiener filtering is to approximate the original image in such a way that the mean square error between the original and approximated image is minimized.

B. FCM Segmentation

Image segmentation is considered an important step in image processing. Fuzzy c-means clustering is one of the common methods of image segmentation. Fuzzy c-means clustering methods have great potential to extracting detailed features from image pixels. Fuzzy c-means (FCM) clustering is one of the important unsupervised learning algorithms. It requires knowledge of the initial details of some of the parameters, such as the number of clusters and the position of the centroid of the clusters, and its performance depends on the input parameters. The FCM algorithm assigns pixels to each category by using fuzzy memberships. Let (x_1, x_2... xn) denotes an image with N pixels to be partitioned into c clusters, where x_i represents multispectral (features) data. The algorithm is an iterative optimization that minimizes the cost function defined as follows:

$$J=\sum_{j=1}^{N}\sum_{i=1}^{c}u_{ij}^{m}\left\|x_j-v_i\right\| \quad (1)$$

Where u_{ij} represents the membership of pixel x_j in the ith cluster, v_i is the ith cluster centre and m is a constant. The parameter m controls the fuzziness of the resulting partition.

C. Transfer learning in CNN

The basic premise of transfer learning is simple: take a model trained on a large dataset and transfer its knowledge to a smaller dataset. For object recognition with a CNN, freeze the early convolutional layers of the network and only train the last few layers which make a prediction. CNNs comprehensively trained on the large scale well-annotated ImageNet may still be transferred to make medical image recognition tasks more effective. Collecting and annotating large numbers of medical images still poses significant challenges. On the other hand, the mainstream deep CNN architectures (e.g., AlexNet and GoogLeNet) contain tens of millions of free parameters to train, and thus require sufficiently large numbers of labeled medical images.

D. Classification by CNN

CNN is widely exploited in all types of medical image processing applications particularly in MRI brain tumor classification and segmentation. The proposed a simple CNN model, extracted the augmented MRI image data of 224 × 224 input size having RGB Color channels with a batch size of 32 through CNN model. Initially, a single 16 filters convolutional layer having a filter size of 3 × 3 is added. The reason for placing a small number of filters as 16 is to detect edges, corners, and lines. And then a max-pooling layer with 2 × 2 filter was added on it to get the max summary of that image, then it increased the number of convolutional layers and the number of filters to 32, 64, and 128, having the same filter size of 3×3. This combines these small patterns as the number of filters increases and finds bigger patterns like a circle, a square, etc. And an applied max-pooling layers on top of those convolutional layers to get the most of it. Figure 2 shows the layout of the proposed CNN architecture.

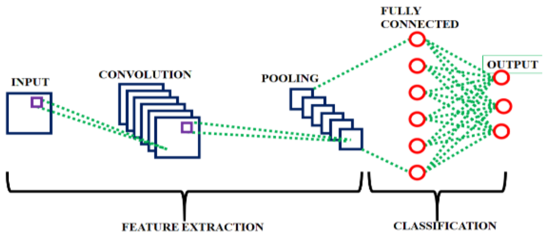

Figure 2: CNN architecture

The Rectified Linear Unit (ReLU) activation function is applied in each convolutional layer. An Activation function converts the input weighted sum into that node's output represented by Vinod and Hinton. Rectifier Linear unit function is often used in hidden layers of the convolutional neural network. Mathematically, ReLU is represented by

$$f(z)\max(0, z) \qquad (2)$$

Where z is the input when z is negative or equal to 0, it transforms the negative input to 0. When the input is greater than 0, then the output will be 1. So the derivative of ReLUs will be

$$f(z) = \begin{cases} 1, for\ z \geq 0 \\ 0, for\ z < 0 \end{cases} \qquad (3)$$

So if the input is 0 then that neuron is a dead neuron in ReLU function and it won't be activated.

III. RESULTS AND DISCUSSION

To justify the proposed model, steps of segmenting the tumor from 2D Brain MRI is illustrated in Figure 3. An accuracy of 92.42% is obtained using SVM and 94% of accuracy is achieved using CNN.

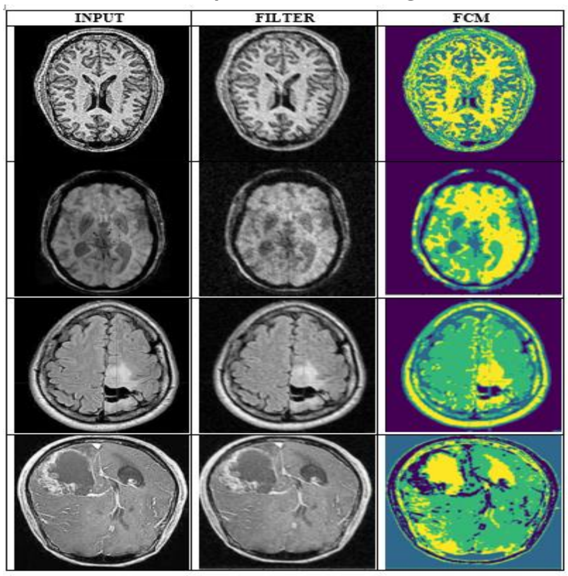

Figure 3: Output images

The above experiment results on the 5 input images indicates that the proposed network cannot only achieve a promising result on a complete modalities but also in the case of missing modalities. This model used an adaptive wiener filters, and it achieves better results. The fuzzy C means segmentation results are gradually improved when the proposed strategies are integrated, these comparisons indicate that the effectiveness of the proposed strategies. In addition, with all the proposed strategies, this proposed method achieve almost the same results with ground truth. Figure 4 shows the comparison of accuracy. SVM produces an accuracy of 92.42%, whereas CNN produces an accuracy of 94%.

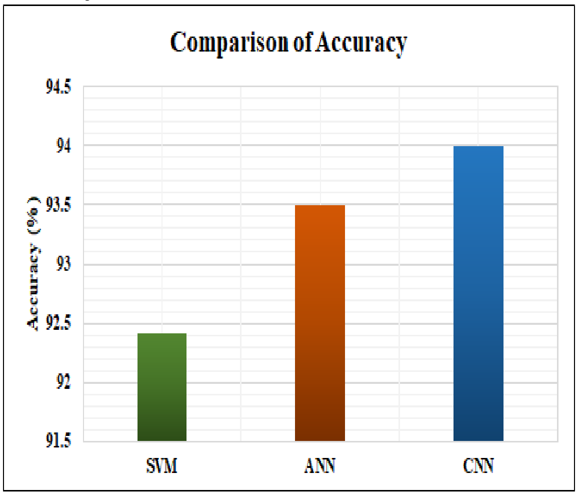

Figure 4: Comparison of accuracy

IV. CONCLUSION

In this paper detection of brain tumor using image processing is proposed. The proposed system is helpful in detection of brain tumors automatically. CNN is followed by conventional classifiers and deep learning techniques, are used in the proposed methodology to segment brain tumours from 2D MRI and apply Transfer Learning method for feature extraction. The speed of therapy will significantly rise with the use of the CNN based model, which will assist physicians in precisely identifying brain tumours in MRI scans. This proposed system identifies the abnormalities in the brain which is detected in the MR image. The system requires less training set and helps in faster detection of the tumors and provides accurate results. SVM and CNN both reach accuracy rates of 92.42%, and 94% respectively.

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