BRAIN TUMOR DETECTION AND CLASSIFICATION USING CONVOLUTION NEURAL NETWORK

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Abstract

Brain tumors are the most common and dreadful ailment that reduces the lifespan of the human in a greater scale. There are various imaging techniques such as Computed tomography, Ultrasound imaging, Magnetic Resonance Imaging that are being used in detecting the tumor in various body parts. Automatic defects detection in magnetic resonance images is very vital in lots of diagnostic and therapeutic applications. In Magnetic resonance images, the quantity of information is too much for manual interpretation and analysis. Because of high quantity records in Magnetic Resonance images and blurred barriers, tumor segmentation and type identification is very difficult. In the past few years, brain tumor segmentation in magnetic resonance imaging (MRI) has turned out to be an emergent research region inside the discipline of medical imaging system. Therefore there is a need for a trusted and automatic classification technique that is essential for reducing the human death rates. The computerized brain tumor classification could be very tough task in massive spatial and structural variability of surrounding area of brain tumor. In this paper we introduce a system which is an automatic brain tumor detection technique using a convolution neural network to boost the accuracy and yield and reduce the diagnosis time. Accurate detection of size and location of brain tumor performs a essential role in the prognosis of tumor. MRI images, the input which are forwarded to the convolution neural network to detect and classify the brain tumor type.

Keywords: brain tumor detection, convolution neural network, magnetic resonance imaging (MRI).

I. INTRODUCTION

Brain consists of millions of cells, which is the most vital organ of the human body. The abnormal growth of the cells in the brain skull is called a brain tumor. There are two basic types of brain tumors, the primary and the secondary tumors. The primary tumor is sub-divided into benign and malignant. The benign is the type of tumor that spreads rarely and the growth of these type of cells are slow and has specific boundaries. Benign can become a threat to life if it is located at certain area. Whereas the malignant are usually called the brain cancer yet they do not satisfy the definition of cancer since they do not grow or spread to other organs other than brain or spine. The secondary type of tumor starts as a cancer and then spread to the brain[1].

With the advances in imaging systems, diagnostic imaging has become an necessary tool in medical field today. X-ray angiography, magnetic resonance angiography, magnetic resonance imaging, and other different imaging modalities are heavily utilized in medical practice. Such images provide related information about the patient. While the size and volume of the medical images required the automation of the diagnosis method is being increased, the trendy advances in computer technology and reduced prices have made it feasible to develop such systems. Brain tumor detection from the medical reports forms an important step in fixing several sensible applications consisting of diagnosis of the tumors and registration of affected person's images obtained at distinct times. Tumor segmentation algorithms are the key additives of automated radiological diagnostic systems. Segmentation techniques range relying at the imaging modality, utility domain, technique being automatic or semi- automatic, and other specific factors. While a few techniques employ pure intensity-based pattern recognition techniques such as thresholding followed by connected component analysis, a few other methods apply specific tumor models to extract the tumor contours [2].

Medical image segmentation algorithms and techniques can be divided into six main categories, pattern recognition techniques, model-based approaches, tracking-based approaches, artificial intelligence-based approaches, neural network-based approaches, and miscellaneous tube-like object detection approaches [3]. Digital image processing, the manipulation of images by means of computer, is relatively latest development in terms of man's historic fascination with visual stimuli. In its quick records, it is been implemented to almost each type of images with varying degree of success.

A breakthrough in constructing models for image classification came with the invention that a Convolutional Neural Network (CNN) will be used to regularly extract higher level representations of the image content [4]. Instead of preprocessing the data to derive features like textures and shapes, a CNN takes just the image's pixel facts as input and learns a way to extract those features, and in the end infer what item they constitute. The CNN receives an input characteristic map, a three-dimensional matrix in which the size of the primary and second dimensions corresponds to the length and width of the image in pixels. The size of the third dimension is three, that is the three channels of a color image(red, blue, and green).

II. RELATED WORKS

Image processing is a complicated task when it comes to medical images. Though there are many ways by which it could be done there are two major steps involved in processing a medical image. The primary step is preprocessing by which the image becomes suitable for the further operations. This step involves noise reduction and filtering of the images. The segmentation and other operations to find the size and location of the tumor forms the next step. The following methods are the major methods that were used for the classification of brain tumor.

A. Classification Using K-Means

In this method before applying the k- means the Magnetic Resonance image is first converted to binary form and then the noise removal takes place. There are different types of filters that can be used for the noise reduction such as Median Filter, Adaptive Filter, Averaging Filter, Gaussian Filter, Un-sharp masking filter [5]. The median filter is a non-linear filter which removes the unwanted signals from the image. This filter performs well against the impulse noises. The adaptive filter is a linear filter and removes impulse noise. The average filter is a linear and low-pass that is used for smoothing the images. The gaussian filter removes the fine details that are basically present in the image. The un-sharp masking filter generally is a sharpening function that is used to enhance the edges of the image. After the noise reduction process the clustering process is done for the segmentation of the Magnetic Resonance images.

K-means is a simple and unsupervised learning algorithm that solves the clustering problem. Clustering is nothing but the grouping of the image pixels according to the intensity values. This grouping is of two types, hard clustering and the soft clustering. Hard clustering is where the data points belong to one cluster and k-means is a hard clustering methodology[6]. The important part of this k-means clustering is defining the k-centroid for each cluster[7]. These k-centroids has to be placed cleverly since the results may vary according to the location. Therefore these centroids are placed far away from each other after which every point in the data are associated with the nearest centeroid. Then the new centroids are recalculated and the previous step is repeated. A loop is generated by which the centroids change their locations progressively until there are no more changes. Finally this method aims at minimizing the squared error function. The features are then extracted by the Non-subsampled Contourlet Transform after the segmentation process. After the features are extracted, they are used to train the Support Vector Machine to classify the images [6].

The drawbacks of this method are the prediction of the k value is difficult, the different initial cluster partitions results in different clusters, and it is difficult to work with clusters of different data size and density.Maintaining the Integrity of the Specifications

B. *Classification Using Fuzzy C-Means*

Clustering techniques are very miscellaneous. In case 1, the data are grouped to separate the datum that belongs to a definite cluster. In case 2, the data are clustered to assign different degrees of membership to multiple clusters in which the data will be associated to an appropriate membership value. The next is the Hierarchical clustering which works by unioning the two nearest clusters. Here each datum is considered as a cluster and each are iterated to get the output clusters. The last case is the fuzzy c-means clustering methodology. Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to multiple clusters. It is frequently used in pattern recognition.

The working of this algorithm involves assigning the membership to each cluster by computing the distance between the cluster center and the data point and the summation of the membership is calculated using iterations [7]. The main objective is to find the minimal Euclidean distance between the data and cluster center [8]. The main concepts involved in fuzzy clustering are fuzzy deviation, variance and cardinality of the fuzzy cluster, separation, validity index and partition index of the cluster.

The fuzzy c-means clustering for brain tumor segmentation involves various stages. The first is preprocessing of images, in this stage the pixels having extra-cranial region are separated to apply median filtering and then enhanced images are transferred into a new ordered data collection. The next stage is segmentation in which the Euclidean distance is computed between the center cluster and the data through various iteration after which the image from the previous clustering is binarized. The segmentation is carried out using the threshold segmentation and level-set contour detection. The last stage is the classification and validation which is carried out by generating the curve using Receiver Operating Characteristic (ROC) analysis [9]. The fuzzy c-means also uses multi-objective clustering to maximize the global compactness and fuzzy separation. Though this system gives better result for overlapped data set better than k-means algorithm, it has some drawbacks namely Euclidean distance measures of unequal underlying factors, more number of iterations to compute the lower value of β in-order to achieve better results.

C. *Classification Using Discrete Wavelet Transformation*

Discrete wavelet transform (DWT) is a mathematical tool for feature extraction. It includes choosing scales and positions based on powers of two, named as dyadic scales and positions. It has two functions namely scaling and wavelet functions to capture both frequency and location information.

This framework has various stages namely preprocessing phase, feature extraction phase and segmentation phase. The preprocessing phase has various stages namely normalization, skull stripping, median filtering after the pre-process. The pre-processing is done to remove the untoward noises to achieve better efficiency. The image is converted into standard sized grey scale images. Then the image median filter is applied and the image is enhanced with image enhancement techniques such as image filtering to provide good results [10]. Then the skull scripting is done to remove the unwanted substances in the image. The next stage is image feature extraction which involves various features like contrast, correlation, energy and homogeneity. The contrast is used for measuring the amount of nearby changes in an image and to restore the contrast between the pixel and the neighboring pixels. Correlation is used to measure the dark tone conditions in an image which gives the negative and positive correlations.

The similarity between the pixels is measured by homogeneity. The increase in homogeneity increases the image value. The last stage is the segmentation which is the method for dividing the source image into different region having similar intensities images. Haar wavelets are used for one or two level wavelet decomposition [11]. Each level has a threshold value from 1 to N to filter the signal. When it comes to fine analysis of images the discrete wavelet algorithm becomes computationally intensive. The discretization becomes less efficient due to redundancy of data.

III. PROPOSED SYSTEM

To deal with the disadvantages of the previous works, bionic convolutional neural networks are proposed to decrease the number of parameters and adapt the network structure in specifically to view tasks. Convolutional neural networks are normally composed of set of layers that may be grouped by their functionalities.

The convolution neural network the image is scalable and the convolution neural network takes the image pixels as input and learns the features and in the end classifies the image accordingly [12][13]. The convolution neural network comprises of several layers as in the fig.1 , the input layer, the convolution and rectified linear unit (RELU) which converts the given input image to several smaller segments and performs the element wise activation function, the pooling layer which is used for down sampling, and the fully connected layer which is the final learning phase that maps the extracted features to the necessary output.

In brain tumor classification the process is a two dimensional convolution. The filter in the convolution layer consists of the same number of layers as the input volume channels and the output volume has the same depth of the number of filters. The convolution layer requires four hyper parameters, the number of filters, their spatial extent, the stride, and padding. The stride is nothing but the number of shifts of the image pixels over the input matrix. Padding is of two types and is used when the filter does not fit the input image so either the image is padded with zeros (zero-padding) or the part that does not fit is discarded [14]. The RELU layer is the activation layer and is used to increase the non-linearity of the network without affecting the receptive fields of the convolution layer that results in faster training. The previous layer provides activation maps on which the non-linear down sampling is applied by the Pooling layer. The image pixels are mapped with the scores by the use of a score function in the pooling layer so that it identifies the image type correctly by mapping the scores with the filter applied. The output of the fully connected layer is a vector, which is then passed on to the softmax layer.

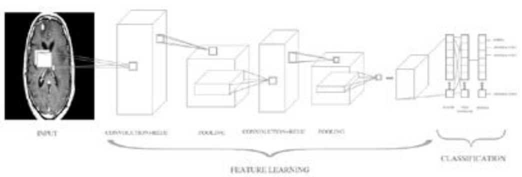

Fig.1. System Design

The classification of object using the probabilistic values is done in the softmax layer by applying activation function. The block diagram is given in fig.2 .

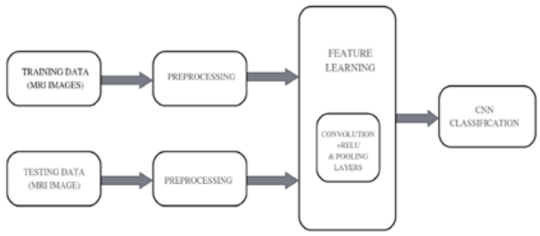

Fig.2. Block Diagram

The training data i.e. the magnetic resonance images are preprocessed and is forwarded to the convolution layer. The several layers of convolution plus RELU and the pooling layer finds a way to learn the features by filtering along with loss function. The proposed system classifies the brain magnetic resonance images into normal and abnormal. In abnormal condition the tumor is classified into five types. Once the model is trained it learns about all the types of brain images and has the capability to classify the input image. In the testing phase, the model is tested with the test data, the model learns the features and classifies its type. The end result is that the given image is normal or abnormal and if it is abnormal it shows the percentage of the type of abnormality and the percentage of normality.

Algorithm overview

Step1: Provide the input image (MRI image) into the convolution layer.

Step2: The parameters are chosen to apply filters accordingly and perform convolution.

Step3: Apply the RELU activation function.

Step4: Pooling is performed to reduce the dimension.

Step5: The steps 2 to 4 are repeated until satisfied.

Step 6: The output of the previous steps is fed into the fully connected layer.

Step 7: Softmax activation function is applied to the result of the fully connected layer and output the class after classification.

IV. RESULT AND DISCUSSION

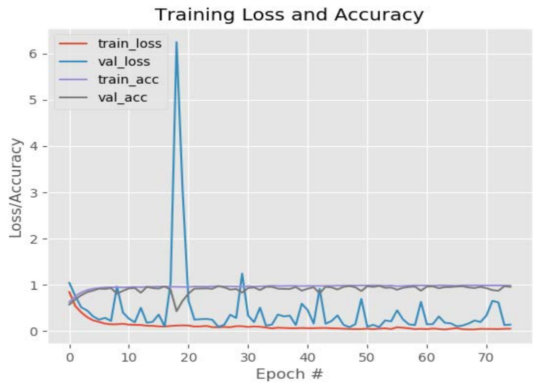

Fig.3. Accuracy Graph

The performance analysis is made by plotting the graphs of various metrics By analyzing the plotted graph, the performance of the system has been improved significantly.

V. CONCLUSION

The main aim of this paper is to provide an idea about a more efficient automatic image classification methodology for brain tumor classification. Conventionally tumor classification was done by using various methods such as K-Means clustering, Fuzzy C-Means algorithm, Support Vector Machine technique, Discrete Wavelet Transformation technique. The complexity and computation time for these methods is high as well as the accuracy is low. Therefore to increase the accuracy and to reduce computational time, Convolution neural network was used for classification. In this method the results are displayed as the given brain image is normal or abnormal and if abnormal its type and its percentage. The feature were extracted using CNN. The loss function is applied to obtain high accuracy.

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