ROBUST BRAIN MAGNETIC RESONANCE IMAGE SEGMENTATION FOR HYDROCEPHALUS PATIENTS

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Abstract - *Brain magnetic resonance segmentation for the detection of hydrocephalus is a demanding work. Encoding the variation of the brain anatomical structures of different individuals for manual analysis is difficult. The task becomes even more challenging when the brain image data from many hydrocephalus patients are considered, which often have large deformations. The manual process performs through domain specialists is more complex and time consuming. Numerous works exist for hydrocephalus detection but still, there is a need for a fast and efficient technique with less complexity. We propose a novel strategy to solve the segmentation problems for hydrocephalus MR and CT images. With the success of deep learning, supervised segmentation approaches built on 3D convolution neural networks (CNNs) have produced accurate segmentation results at high speed. By their very nature, hydrocephalus can appear anywhere in the brain ventricles and have almost any kind of shape, size, and contrast. We are using NN classifier to obtain the result. Our method integrates the image convolution, features extraction, and classification methods. The databases are utilized for hydrocephalus detection. The output of the proposed system illustrates that it effectively classifies the abnormal and normal brain region.*

Key Words: Hydrocephalus, Magnetic Resonance Imaging (MRI), Neural Networks (NN), Discrete Wavelet transform (DWT).

1. INTRODUCTION

Image processing is used to determine the hydrocephalus in human body. To enhance the image experiments of detecting the tumor part in our body. In this paper, we present a automatic brain hydrocephalus segmentation method based on Neural Networks (NNs). We are using NN classifier to obtain the results. Neural network have 3 basic layers which transform the information of each pixel through each node. Those three layers are input layer, hidden layer, output layer. These layers are working depending upon the theory of human neuron. The diagnosis follows these stages, pre-processing of input images, feature extraction, and classification. Here, the preprocessing is done using Gaussian filtering technique ,the given image by eliminating the noise and filtering the image.

The feature extracting involve extracting statistical features. Finally, the KNN classifiers are employed to classify the given image as normal or abnormal. The experimental results evaluate the performance of the proposed model in terms of sensitivity and classification rate. That means we will get the accuracy results very fast.

1.1 DIGITAL IMAGE PROCESSING

The identification of hydrocephalus part in brain would probably start with image processing techniques such as noise removal, followed by feature extraction to locate lines, regions and possibly areas with certain textures. Since images are defined in two dimensions digital image processing may be modeled in the form of multidimensional systems. The generation and development of digital image processing are mainly affected by factors such as : the development of computers; the development of discrete mathematics , the demand for a wide range of applications in environment like diagnosis etc.

1.2 Technical process in Hydrocephalus detection

Hydrocephalus is the accumulation of fluid in the ventricles deep within the brain. The excess fluid layer increases the size of the ventricles and puts pressure on the brain, thereby the size of the skull becomes abnormal. Cerebrospinal fluid normally flows through the ventricles and spinal column. But the pressure of excess cerebrospinal fluid associated with hydrocephalus can damage brain tissues and cause a range of impairments in brain function.

Automatically detecting the tumour or cancer or enlargement of ventricles is important in diagnostic and therapeutic applications.. In MR images, the amount of data required to detect the hydrocephalus is too much for manual interpretation and analysis. Because of insufficient data in MR images and blurred boundaries, tumour segmentation and classification of hydrocephalus affected part is very hard. This work has introduced one automatic brain hydrocephalus detection method to increase the accuracy and yield and decrease the diagnosis time. During past few years, brain hydrocephalus detection and segmentation especially for children under 7 years in magnetic resonance imaging (MRI) has become an important research area in the field of medical imaging system. Accurate detection of size and location of brain hydrocephalus plays a vital role in the diagnosis of hydrocephalus. The diagnosis follows these stages, pre-processing of input images, feature extraction, and classification. After equalization and convolution of image, the features are extracted based on discrete wavelet transformation (DWT). In the last stage, Neural Network (NN) are employed to classify the Normal and abnormal brain.

1.3. Processing and Segmentation

Image Acquisition is to acquire a digital image. Magnetic resonance images are scanned images. Scanner produces a 2D image.

Image enhancement is one of the basic step of digital image processing. Basically, the idea behind enhancement techniques is to bring out detail that is blurred, or simply to highlight diminished features of interesting an image. These techniques are used to enhance the intensity of the scanned image.

Segmentation procedures partition an image into its constituent objects for easy indentification. In general, autonomous segmentation is one of the most difficult tasks in digital image processing. Deep learning is a type of machine learning in which a model learns to perform classification tasks directly from images, text or sound. Deep learning is usually implemented using neural network architecture. The term deep refers to the number of layers in the network, the more the layers, the deeper the network. Traditional neural networks contain only two or three layers, while deep networks can have hundreds.

A deep neural network combines multiple non-linear processing layers, using simple elements operating in parallel. It is inspired by the biological nervous system, and consists of an input layer, several hidden layers, and an output layer. The layers are interconnected via nodes, or neurons, with each hidden layer using the output of the previous layer as its input. Using this training data, the network can then start to understand the object's specific features and associate them with the corresponding category. Each layer in the network takes in data from the previous layer, transforms it, and passes it on. The network increases the complexity and detail of what it is learning from layer to layer. Deep learning is extremely data hungry. This is one of the main limitations that the field is currently facing, and performance grows only logarithmically with the amount of data used.

2. PROPOSED METHODOLOGY

With the advances in imaging technology, diagnostic imaging has become an indispensable tool in medicine today. X-ray angiography (XRA), magnetic resonance angiography (MRA), magnetic resonance imaging (MRI), computed tomography (CT), and other imaging modalities are heavily used in clinical practice. Such images provide complementary information about the patient. While increased size and volume in medical images required the automation of the diagnosis process, the latest advances in computer technology and reduced costs have made it possible to develop such systems.

Brain hydrocephalus detection on medical images forms an essential step in solving several practical applications such as diagnosis of the hydrocephalus and registration of patient images obtained at different times. Segmentation algorithms form the essence of medical image applications such as radiological diagnostic systems, multimodal image registration, creating anatomical atlases, visualization, and computer-aided surgery

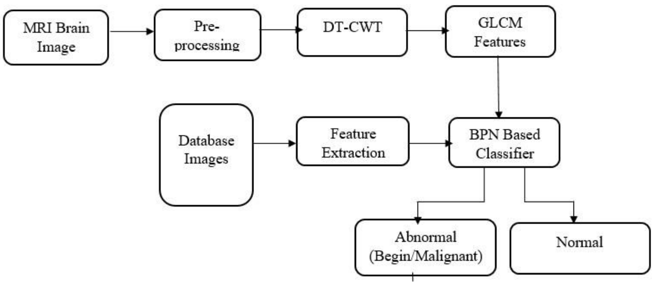
Hydrocephalus segmentation algorithms are the key components of automated radiological diagnostic systems. Segmentation methods vary depending on the imaging modality, application domain, method being automatic or semi-automatic, and other specific factors. There is no single segmentation method that can extract vasculature from every medical image modality. While some methods employ pure intensity-based pattern recognition techniques such as threshold followed by connected component analysis, some other methods apply explicit hydrocephalus models to extract the hydrocephalus contours. Depending on the image quality and the general image artifacts such as noise, some segmentation methods may require image preprocessing prior to the segmentation algorithm. On the other hand, some methods apply post-processing to overcome the problems arising from over segmentation.

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.

Pattern recognition techniques are further divided into seven categories, multi-scale approaches, skeleton-based approaches, region growing approaches, ridge-based approaches, differential geometry-based approaches, matching filters approaches, and mathematical morphology schemes.

Clustering analysis plays an important role in scientific research and commercial application. This thesis provides a survey of current hydrocephalus segmentation methods using clustering approach and provides both early and recent literature related to hydrocephalus segmentation algorithms and techniques.

3. DESIGN AND IMPLEMENTATION



Step1 : Input Image

Input: MRI and CT images of brain

Output: stored in array format

The input image is in DICOM format this image can be convert into JPEG format and resize the image, because the image is having more size, it requires more time for segmentation process and less picture quality. So the size should be resized. The input images for this work using Brain (MRI) images received from diagnosis hospitals.

Step 2: Preprocessing

Input: stored input image

Output: analyzed image

Preprocessing is used to improve the quality of an image. Every image has contained some salt and pepper noise having some blurriness. To remove the noise and blurriness' using Median filter.

Step 3: Median filter

Input: analyzed image

Output: filtered image

The median filter is a sliding window spatial filter, it replaces the center value of an window with the median of all the pixel .Due to changing the median of all the values through the center value it remove the noise and preserve the edges of an image, its one type of smoothening technique. It improves the quality of an image. There is alteration in contrast, it doesn't alter boundaries and unrealistic values are not created near edges.

Step 4: Segmentation process

Input: filtered image

Output: segmented image using DWT

DWT used to detect the tumor in brain (MRI) and lung (CT) images. The both algorithms is used to segment the tumor from brain and lung images. The image can be segmented thoroughly and finally obtained the image into segments.

Step 5 : Feature extraction

Input: edge detected(segmented) image

Output: estimating features of image

The feature extraction is a major process in recognition applications and classifications, the texture based feature extraction is going on in this work, normally several texture based feature extraction classifications are there those are GLCM, LBP,SLBP... The gray scale invariant texture is measured and derived from definition of texture in local region. It is an efficient texture operator, it labels image pixels by the threshold process from the neighborhood of each pixel and represents in binary number. In this the tumor part is extracted from the lung and brain images, this is based on the texture and contrast of an image. Input cancer image (MRI/CT) Preprocessing Segmentation Using Classification with KNN Feature extraction Statistical values

Step 6 : Classification

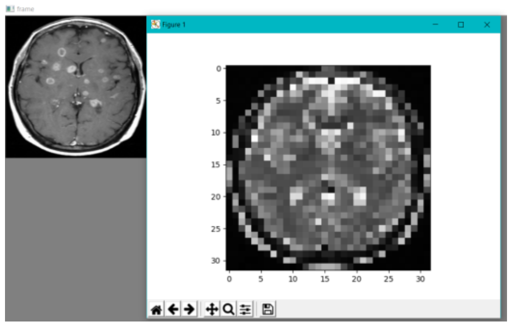
Input: trained dataset (features)

Output: classified as normal or abnormal image

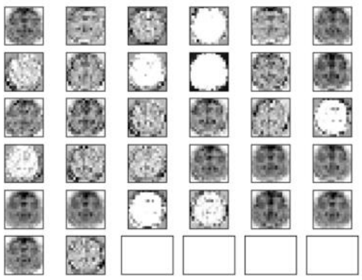
Normally the classification is used to classify that the image is normal or abnormal. NN is one type of classifier, the features and values of the tumor affected image and non tumor image is already placed in database, the intensity is also having in tumor affected image, the classifier compares the given image within the database if the tumor is identified while comparing the each pixels, it display the message box the tumor is affected, after completing the NN training.

4. OUTPUT ANALYSIS

Input is the scan report of the patient. The scanned image can be of either MRI or CT. In our proposed model MRI images are used as test images.



In-order to detect the affected region the input image is classified into various segments.

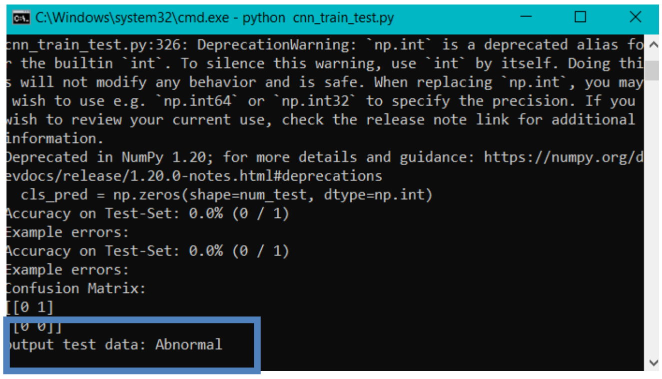


The scanned images undergoes image enhancement and restoration process this helps us identify the hydrocephalus affected area even in the beginning stage. The deep learning algorithm is fed with sufficient data to identify even small spots of damages in the brain. After the image is processed we will be able to view the enhanced image of the input image.

The deep learning algorithm classifies the image into various convoluted image. Convolution is employed to smooth, sharpen and enhance the intensity of the images. The convoluted image is compared and analysed with deep learning data set and thus the output is displayed as normal in case of not hydrocephalus affected and abnormal if the patient has hydrocephalus affected region.

5. OUTPUT ANALYSIS

In this study, we propose a feature matching method with learned local descriptors for predicting CT from MR image data. Thus the defects in the MRI images is identified with the help of image processing, in that the deep learning concept and CNN is used to identify the hydrocephalus in the image. In test image the features are extracted to classify the image. The same features will be extracted in the data set image, by these set of features we can classify the input image is normal or abnormal. Based on the training the convolutional neural network, the detection is achieved. The complexity is low. The computation time is also low meanwhile accuracy is enhanced compared to the existing systems. Further to improve the accuracy and to reduce the computation time, a convolution neural network based classification is introduced in the proposed scheme. Also python language is used for implementation. Image net database is used for classification. It is one of the pre-trained models. So the training is done for only final layer. Using this system we can identify the different stages in the hydrocephalus, based on the stage of the ventricle size such as normal, moderate and severe, further treatment can be proceeded based on the results.



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