Brain Image Segmentation using Machine Learning for Detection of Tumor

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Abstract -*In the field of medical image processing, brain tumor detection and segmentation using MRI Scan has become one of the most important and challenging research areas . The treatment planning is a key stage to improve the quality of life of affected patients. Magnetic Resonance Imaging(MRI) produces large amount of data that prevents manual segmentation in a reasonable time. So, automatic and reliable segmentation methods are required. Automatic segmentation becomes a challenging problem because of large spatial and structural variability among brain tumors make. Hence there is high demand for an efficient and automatic brain tumor detection and segmentation using brain MR images to overcome errors in manual segmentation. So in current days a number of methods have proposed by research. But still efficiency is not high due to the complexities in this process. So this project focuses on improving efficiency for brain tumor detection and segmentation using Machine Learning Techniques. Our method uses different techniques like Supervised Learning, Unsupervised Learning and Deep Learning to improve efficiency. After importing the scanned MRI images, preprocessing is done using image filtering and intensity normalization technique. The patch extraction process is used to extract images of three different channels(RGB Channels). Our method aims to provide Real Time Brain Image Segmentation Using Machine Learning.*

***Key Words*: Brain Tumour, Machine Learning, Deep learning, MRI.**

1. INTRODUCTION

Tumor is an uncontrolled growth of cancer cells in any part of the body. Tumors are of different types and have different characteristics and different treatments. At present, brain tumors are classified as primary brain tumors and metastatic brain tumors. The former begin in the brain and tend to stay in the brain, the latter begin as a cancer elsewhere in the body and spreading to the brain. Brain tumor segmentation is one of the crucial procedures in surgical and treatment planning. Brain tumor segmentation using MRI has been an intense research area. Brain tumors can have various sizes and shapes and may appear at different locations. Varying intensity of tumors in brain magnetic resonance images (MRI) makes the automatic segmentation of tumors extremely challenging. There are various intensity based techniques which have been proposed to segment tumors on magnetic resonance images.

Texture is one of most popular feature for image classification and retrieval. The multifractal texture estimation methods are more time consuming. A texture based image segmentation using GLCM (Gray-Level Co-occurrence Matrix) combined with AdaBoost classifier is proposed here. From the MRI images of brain, the optimal texture features of brain tumor are extracted by utilizing GLCM. Then using these features AdaBoost classifier algorithm classifies the tumor and non-tumor tissues and tumor is segmented. This method provides more efficient brain tumor segmentation compared to the segmentation technique based on mBm and will provide more accurate result. Tumor is the abnormal growth of the tissues.

A brain tumor is a mass of unnecessary cells growing in the brain or central spine canal. Brain cancer can be counted among the most deadly and intractable diseases. Today, tools and methods to analyse tumors and their behaviour are becoming more prevalent. Clearly, efforts over the past century have yielded real advances. However, we have also come to realize that gains in survival must be enhanced by better diagnosis tools. Although we have yet to cure brain tumours, clear steps forward have been taken toward reaching this ultimate goal, more and more researchers have incorporated measures into clinical trials each advance injects hope to the team of caregivers and more importantly, to those who live with this diagnosis. Magnetic Resonance Imaging (MRI) has become a widely-used method of high-quality medical imaging, especially in brain imaging where MRI's soft tissue contrast and non-invasiveness are clear advantages. An important use of MRI data is tracking the size of brain tumor as it responds treatment. Therefore, an automatic and reliable method for segmenting tumor would be a useful tool. MRI provides a digital representation of tissue characteristics that can be obtained in any tissue plane. The images produced by an MRI scanner are best described as slices through the brain. MRI has the added advantage of being able to produce images which slice through the brain in both horizontal and vertical planes. This makes the MRI-scan images an ideal source for detecting, identifying and classifying the right infected regions of the brain.

Most of the current conventional diagnosis techniques are based on human experience in interpreting the MRI-scan for judgment; certainly this increases the possibility to false detection and identification of the brain tumor. On the other hand, applying digital image processing ensures the quick and precise detection of the tumor. One of the most effective techniques to extract information from complex medical images that has wide application in medical field is the segmentation process. The main objective of the image segmentation is to partition an image into mutually exclusive and exhausted regions such that each region of interest is spatially contiguous and the pixels within the region are homogenous with respect to a predefined criterion. The cause of most cases is unknown. Risk factors that may occasionally be involved include: a number of genetic syndrome such as neurofibromatosis as well as exposure to the chemical vinyl chloride, Epstein-Barr virus, and ionizing radiation[15].

Magnetic resonance imaging (MRI) is the prime technique to diagnose brain tumors and monitor their treatment. Different MRI modalities of each patient are acquired and these images are interpreted by computer-based image analysis methods in order to handle the complexity as well as constraints on time and objectiveness. In this thesis, two major novel approaches for analyzing tumor-bearing brain images in an automatic way are presented: Multi-modal tissue classification with integrated regularization can segment healthy and pathologic brain tissues including their sub- compartments to provide quantitative volumetric information. The method has been evaluated with good results on a large number of clinical and synthetic images. The fast run-time of the algorithm allows for an easy integration into the clinical work flow.

An extension has been proposed for integrated segmentation of longitudinal patient studies, which has been assessed on a small dataset from a multi-center clinical trial with promising results. Atlas-based segmentation with integrated tumor-growth modeling has been shown to be a suitable means for segmenting the healthy brain structures surrounding the tumor. Tumor-growth modeling offers a way to cope with the missing tumor prior in the atlas during registration. To this end, two different tumor-growth models have been compared. While a simplistic tumor growth model offered advantages in computation speed, a more sophisticated multi-scale tumor growth model showed better potential to provide a more realistic and meaningful prior for atlas-based segmentation. Both approaches have been combined into a generic framework for analyzing tumor-bearing brain images, which makes use of all the image information generally available in clinics. This segmentation framework paves the way for better diagnosis, treatment planning and monitoring in radiotherapy and neurosurgery of brain tumors[11]

2. EXISTING SYSTEM

Segmenting brain tumors is a very difficult task. In the first consideration, there is a large class of tumor types that have a variety of shapes and sizes. The appearance of a brain tumor at different locations in the brain with different image intensities is another factor that makes difficulties in automated brain tumor detection and segmentation. Many techniques have been proposed for the automatic brain tumor detection and segmentation in recent years such as thresholding based, region growing based, clustering based, neural network based, K-means clustering, fuzzy c-means (FCM) and fuzzy c-means strategy is integrated withHNN[3].

The existing system describes a novel algorithm for interactive multilabel segmentation of N-dimensional images. Given a small number of user-labelled pixels, the rest of the image is segmented automatically by a Cellular Automaton. The process is iterative, as the automaton labels the image, user can observe the segmentation evolution and guide the algorithm with human input where the segmentation is difficult to compute. In the areas, where the segmentation is reliably computed automatically no additional user effort is required. Results of segmenting generic photos and medical images are presented. Our experiments show that modest user effort is required for segmentation of moderately hard images. The existing systems take an intuitive user interaction scheme-user specifies certain image pixels (we will call them seed pixels) that belong to objects that should be segmented from each other[18].

The task is to assign labels to all other image pixels automatically, preferably achieving the segmentation result the user is expecting to get. The task statement and input data is similar to and, however the segmentation instrument differs. Our method uses cellular automaton for solving pixel labelling task. The method is iterative, giving feedback to the user while the segmentation is computed. Proposed method allows (but not requires) human input during labeling process, to provide dynamic interaction and feedback between the user and the algorithm. This allows to correcting and guidance of the algorithm with user input in the areas where the segmentation is difficult to compute, yet does not require additional user effort where the segmentation is reliably computed automatically. One important difference from the methods based on graph cuts is that seeds do not necessarily specify hard segmentation constraints. In other words - user brush strokes need not to specify only the areas of firm foreground or firm background, but instead can adjust the pixels state continuously, making them 'more foreground' or 'a little more background' for example.

This gives more versatile control of the segmentation from the user part and makes the process tolerable to inaccurate paint strokes. As we have already emphasized in the introduction, our hope is to stir up the research community, motivating to search new ideas in the field of cellular automata and evolutionary computation and applying them to interactive image segmentation. We expect that results exceeding our current can be obtained. However, our current method can already compete with elegant achievements of graph theory. In this section we will try to compare current top performing methods with ours and point out advantages and disadvantages of our scheme. We take four methods - Graph Cuts, GrabCut, Random Walker and GrowCut and compare them by several criteria: segmentation quality, speed and convenience for the user. Accurately speaking, the methods differ seriously by the amount of information that they extract from the image. Grab Cut uses most information - it computes the evolving color statistics of foreground and background and takes into account color difference between neighboring pixels. Graph Cuts differs in using color statistics collected from the user-specified seeds only, computed before the segmentation start. Random Walker uses only intensity difference between neighboring pixels. Our current Grow Cut variant also does not take advantage of object color statistics, however it can be easily extended to maintain regions color statistics and use them in automaton evolution. The performance of described photo editing methods was evaluated in (except for the intelligent paint)[12].

The authors have clearly shown, that methods based on graph cuts allow achieving better segmentation results with less user effort required, compared with other methods. One of the few drawbacks of the graph-based methods is that they are not easily extended to multi-label task and the other is that they are not very flexible - the only tunable parameters are the graph weighting and cost function coefficients. For example, additional restrictions on the object boundary smoothness or soft user-specified segmentation constraints cannot be added readily. As for the intelligent paint, judging by the examples supplied by the authors, the advantage of their method over the traditional 'magic wand' is in speed and number of user interactions. As it appears from the algorithm description and presented results, it is unlikely that intelligent paint would be capable of solving hard segmentation problems[4].

Precise object boundary estimation is also questionable, because the finest segmentation level is obtained by initial tobogganing over segmentation, which may not coincide with actual object borders. Speaking about medical images, the best performing method is random walker (judging by the provided examples). It leaves behind both watershed segmentation and region growing behind in quality and robustness of segmentation. The quality of segmentation comparable to is graph cuts, but random walker is capable of finding the solution for number of labels However, it is rather slow and its implementation is not an easy task. Also, method extension to achieve some special algorithm properties (i.e. controllable boundary smoothness) is not straightforward. It should be mentioned, that multi-labelling tasks can be solved by min-cut graph algorithms, but no attempt to apply this multi-labelling method to interactive image segmentation is known to us.The process is iterative, asthe automaton labels the image, user can observe the segmentationevolution and guide the algorithm with human input where the segmentation is difficult to compute[6].

Disadvantages:

- This method was limited to enhancing tumors with clear enhancing edges.
- This method works with two labels only - object and background.
- One of the few drawbacks of the graph-based methods is that they are not easily extended to multi- label task.
- The other is that they are not veryflexible
- The only tunable parameters are the graph weighting and cost function coefficients.

3. PROPOSED SYSTEM

This System basically several techniques of machine learning to improve the efficiency of determination of brain tumor and segmentation.Here we feed the system with both image and textual date(mainly to aid image data).

Input Data undergoes following stages:

i) Data Preprocessing
ii) Data Cleaning
iii) Data Visualisation

Once the dataset is rich it is split into training and testing set in the ratio 80:20 using train-test split from scikit learn from sklearn.model_selection import train_test_split X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42)

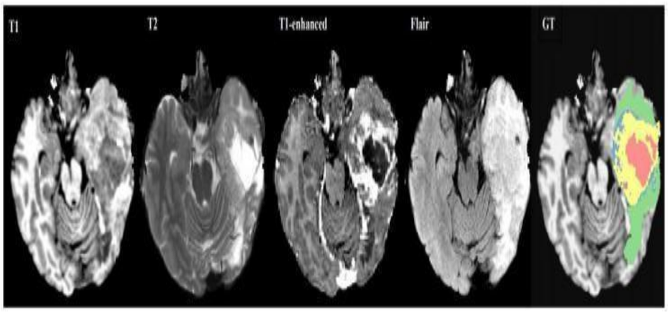
Then any model is chosen which is based on complexity of input data and trained with that data from sklearn.linear_model import LinearRegression reg = LinearRegression()

reg.fit(X,y)

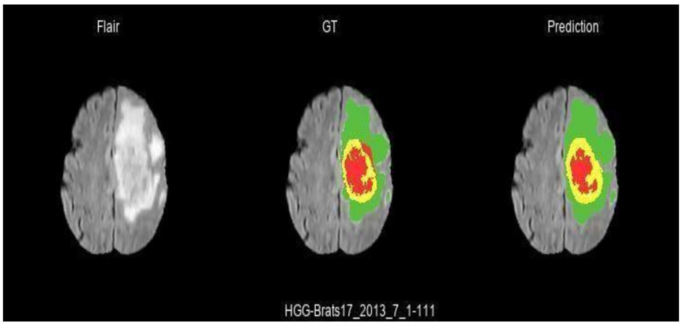
Then finally accuracy of prediction is measured .

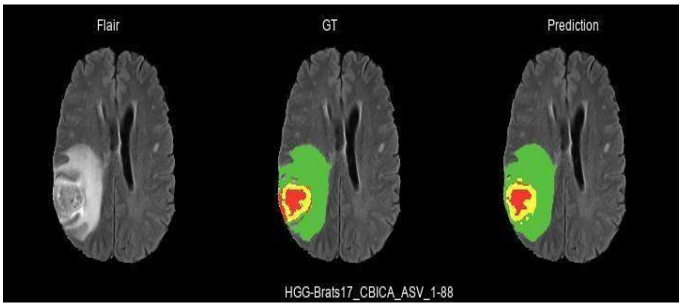
Advantages:

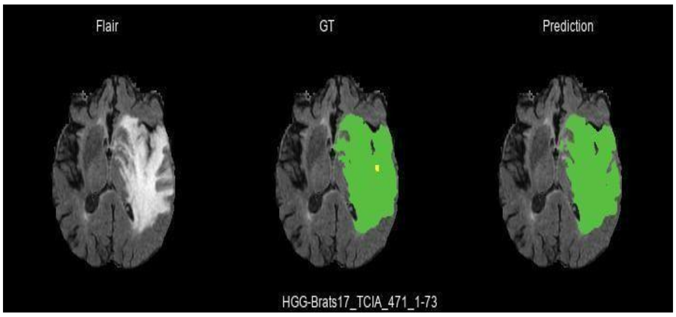
Real time Efficiency

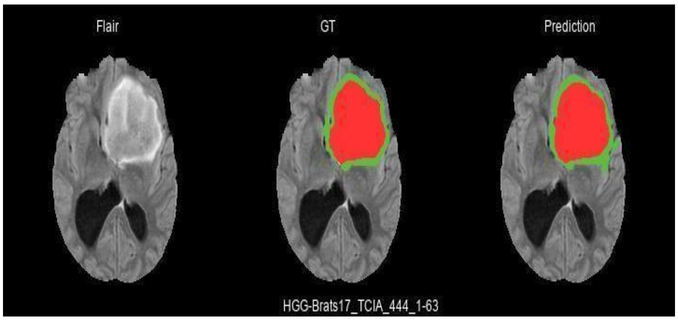


The slices in 4 modalities and ground truth labesls are as shown:

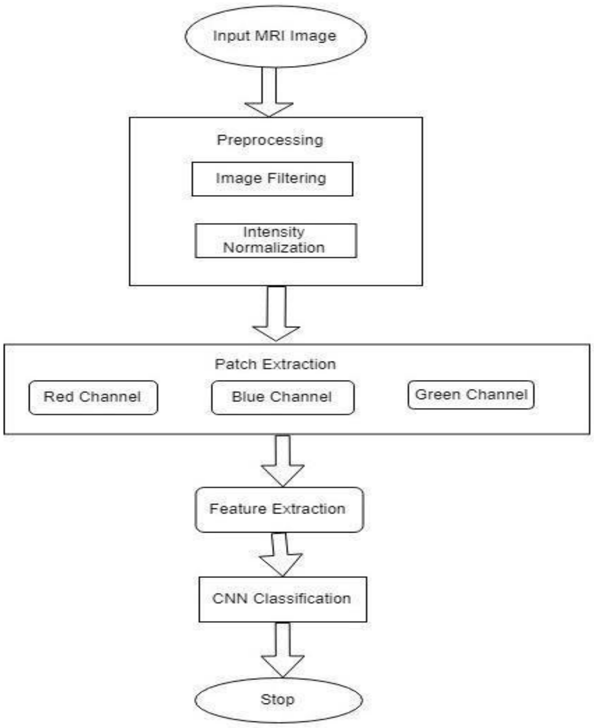








ARCHITECTURE DIAGRAM

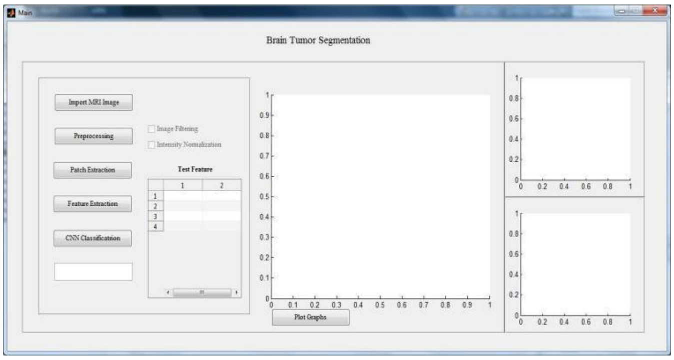


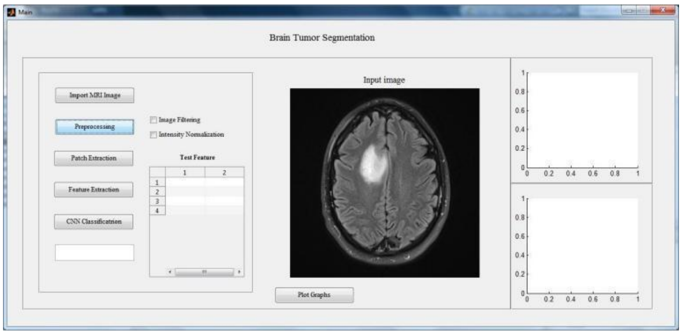
Real time data collected from Twitter, Kaggle, UCI, Data.gov.

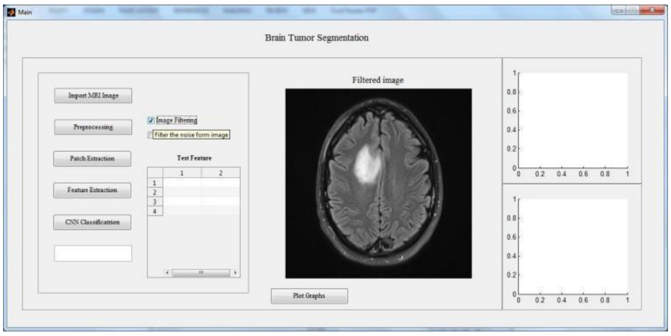
Collection of data is one of the major and most important tasks of any machine learning projects. Because the input we feed to the algorithms is data. So, the algorithms efficiency and accuracy depends upon the correctness and quality of data collected. So as the data same will be the output.

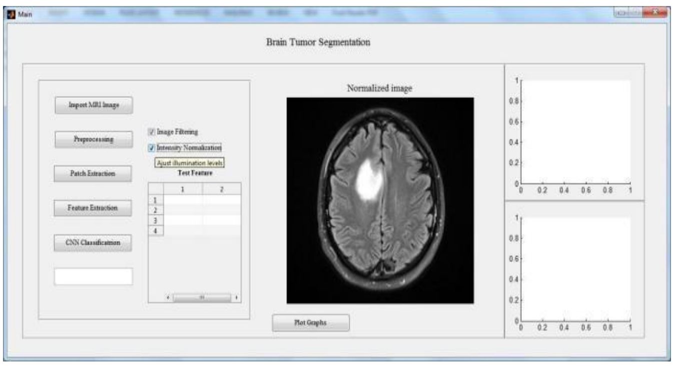
Finally after processing of data and training the very next task is obviously testing. This is where performance of the algorithms, quality of data, and required output al appears out. From the huge data set collected 90 percent of the data is utilized for training and 10 percent of the data is reserved for testing. Training as discussed before is the process of making the machine to learn and giving it to make further predictions based on the training it took. Where as testing means already having a predefined data set with output also previously labeled and the model is tested whether it is working properly or not and is giving the right prediction or not. If maximum number of predictions are right then model will have a good accuracy percentage and is reliable to continue with otherwise better to change the model.

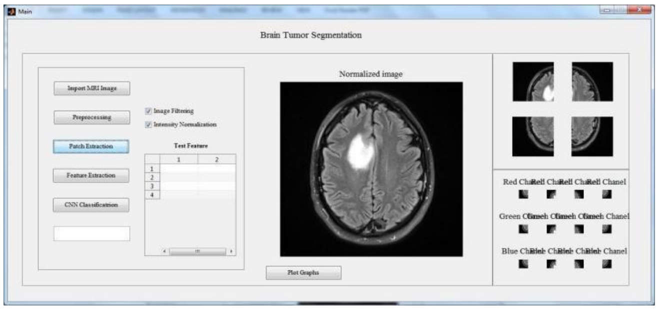
4. EXPERIMENTAL RESULTS

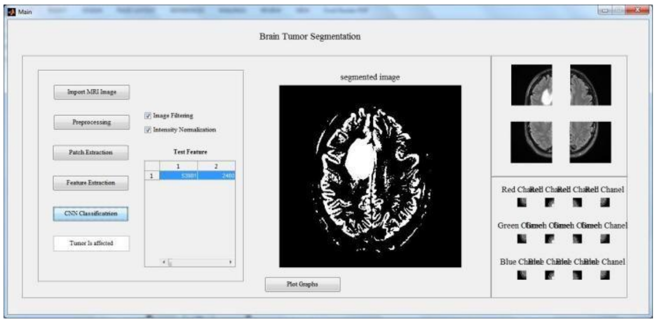


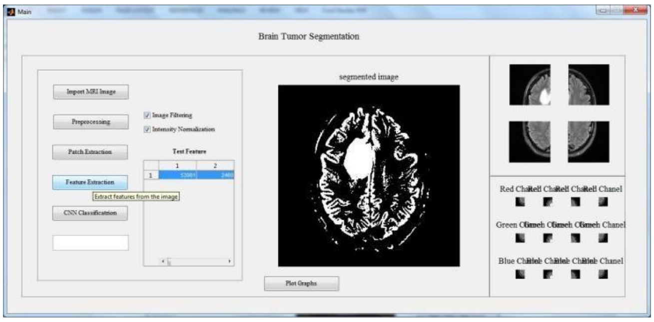












5. CONCLUSION

This paper has provided comprehensive overview of the state of the art MRI-based brain tumor segmentation methods. Many of the current brain tumor segmentation methods operate MRI images due to the non-invasive and good soft tissue contrast of MRI and employ classification and clustering methods by using different features and taking spatial information in a local neighborhood into account. The purpose of these methods is to provide a preliminary judgment on diagnosis, tumor monitoring, and therapy planning forth physician. Although most of brain tumor segmentation algorithms have relatively good results in the field of medical image analysis, there is a certain distance in clinical applications.

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