Detection and Segmentation of Brain Lesion using Feature vector Extraction in MRI

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ABSTRACT: Brain tumor or lesion is an abnormal growth of brain cells within the brain. Detection of brain Tumor is a challenging problem, due to complex structure of the brain. The automatic segmentation has great potential in clinical medicine by freeing physicians from the burden of manual labeling; whereas only a quantitative measurement allows to track and modeling precisely the disease. Magnetic resonance (MR) images are an awfully valuable tool to determine the tumor growth in brain. But, accurate brain image segmentation is a complicated and time consuming process. MR is generally more sensitive in detecting brain abnormalities during the early stages of disease, and is excellent in early detection of cases of cerebral infarction, brain tumors, or infections. In this research we put forward a method for automatic brain tumor diagnostics using MR images. This project presents an analytical method that enhances detection of brain lesion and to analyze automatically structure by training and classification of samples using unsupervised and supervised methods.

I. INTRODUCTION

Medical imaging is the technique used to create images of the human body for clinical or medical science that produce images of the internal aspect of the body. Magnetic Resonance Imaging (MRI) is one of the medical imaging techniques. MRI of brain is highly sensitive for detecting all forms of White Matter abnormalities. Non-specific changes in the White Matter appear frequently on MRI in elderly patients presenting with either stroke or cognitive impairment. In general, human brain consists of main components namely, White Matter (WM), Grey Matter (GM) as shown in Figure, Neuronal tissue containing mainly long, myelinated axons is known as White Matter. Closely packed neuron cell bodies form the Grey Matter. Grey Matter is in grey color because of the grey nuclei that comprises the cells. Myelin is responsible for the white appearance of White Matter. White Matter Lesions (WMLs) are commonly found in patients with Multiple Sclerosis (MS), Cerebrovascular Disease (CVD), stroke, and other neurological disorders.

It is believed that the total volume of the lesions and their progression relate to the aging process as well as disease process. Therefore, quantification of White Matter Lesions is very important in understanding the aging process and diagnosis and assessment of these diseases.
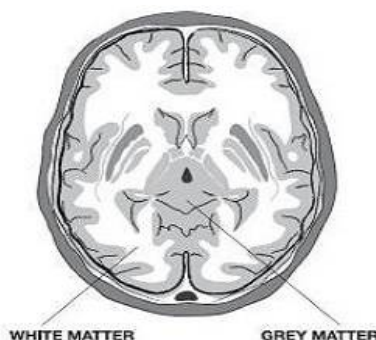
Here, we present a novel method to automatically detect brain lesions from a T1-weighted 3D MRI. The proposed method combines the advantages of both unsupervised and supervised methods.

Though unsupervised segmentation was a de-facto standard for MRI segmentation early on, recently MRI segmentation literature has favored fully supervised techniques such as Dictionary Learning and Atlas-based techniques. But, the benefits of unsupervised techniques e.g., no need for large amount of training data and better potential of handling variability in anatomy and image contrast, is more evident with emerging MR modalities [1-4].

II. LITERATURE SURVEY

For coming on conclusion we have studied different earlier proposed system which is in use but having different limitations while detecting brain lesion;

- Geostastical fuzzy c-means clustering(GFCM)
- The spatial intensity in homogeneity.
- Recursive modified Automatic Lesion Identification (ALI) procedure.
- Fast bounding box algorithm.
- A fully unsupervised motion & sparse based segmentation (UMSS) method.

1. Seghier et al. proposed clustering models are derived by extending the objective functions of FCM and Possibilistic clustering with a Geostatistical (Spatial) model. These algorithms are applied to real magnetic resonance images and is shown to be more robust to noise and other artifacts than competing approaches. MS lesions present different characteristics from lesions in elderly individuals there are many clustering models to determine the accuracy but those methods are not directly applicable to predict the accurate lesions because of the decreased contrast between White Matter and Grey Matter in elderly people. .This technique is used to generalize to include a spatial penalty on the membership functions. Clustering techniques are sensitive to initialization and are easily trapped in local optima[1].

2. Gondal & Khan et al. Proposed the spatial intensity inhomogeneity induced by the RF coil poses a foremost problem to perform an automated analysis of MRI data. Such inhomogeneities make the application of both traditional intensity-based classification of MR images and advanced techniques (like nonparametric and multichannel methods) extremely difficult. The most probable reason for this anomaly could be linked with the fact that the intensity inhomogeneities that appear in MR images produce spatial changes in tissue statistics, such as mean and variance [2].

3. Seghier et al. proposed an automated lesion identification (ALI) method that can operate on a single an atomical image This procedure defines a lesion as a set of a typical voxels identified as outliers in gray and white matter tissue images .This method rests on two innovations:(A)optimization of the unified segmentation normalization algorithm with the addition of an extra "tissue class prior" that explicitly models the presence of a typical tissue, and(B) a fuzzy clustering outlier detection procedure that identifies a typical tissue in both normalized gray and white matter, by comparing the patient's tissue image, voxel by voxel, against a group of normal subjects' tissue images. Recursive ALI procedure is a fuzzy set indexing the degree of abnormality at each voxel of the brain. It is very good accuracy tumors differed in type, size & location [3].

4. Shivani P et al. proposed fast bounding box (FBB) algorithm for Imaging plays a central role in the diagnosis of brain tumors. The parts on which immediate changes in grey tones occur in the images are called edges. Edge detection techniques transform images to edge images benefiting from the changes of grey tones in the images. As a result of this transformation, edge based brain segmentation image is obtained without encountering any changes in physical qualities of the main image. By applying the fast bounding. The individual feature contributions to the criterion value do not change strongly in relation in different subsets. When used with computationally demanding non-recursive criterion functions with higher than linear computational complexity [4].

5. Mukhopadhyay et al. proposed UMSS method w.r.t. state-of-the-art methods, to demonstrate its effectiveness for myocardial segmentation. Note that our method outperforms all supervised methods from current literature in both baseline and ischemia cases of CP-BOLD MR, whereas yields state-of-the-art results for both baseline and ischemia cases of standard CINE MR. for segmenting 2D cardiac MR image sequence. This technique is better handling of variability in image contrast to do manual intervention.

III. OBJECTIVE & SCOPE OF PROPOSED SYSTEM

We introduce a novel automated procedure for lesion detection from T1-weighted MRIs by combining both an unsupervised and a supervised component. In the unsupervised component, we developed new approaches to identify the lesioned hemisphere and used it to help normalize the patient MRI with lesions i.e.

1.	To Propose an intelligent classification technique to identify normal and abnormal slices of the magnetic resonance human brain images(MRI)
2.	To propose an hybrid technique consists of four subsequent stages; namely, dimensionality reduction, preprocessing, feature extraction, and classification for image classification accuracy improvement
3.	Propose system will use an Automatic image segmentation
4.	Propose system will work as Automatic segmentation of brain tumor using computer analysis aided diagnosis in clinical practice
5.	It will work as image classification system and to develop a fully automatic algorithm for accurately detecting lesions from T1-MRI scans in chronic stroke patients

IV. PROPOSED SYSTEM

The proposed method detects lesions on T1-weighedMR images by two sequential components: an unsupervised component to construct an LPM, followed by a supervised component to detect the final lesion areas.

The unsupervised component consists of four sequential steps:

1) Detection of lesion-hemisphere and enantiomorphic normalization that normalizes the input T1-weighted MRI into a standard space,

2) Comparing the normalized MRI to a group of normalized healthy controls and identifying an initial probability map of the lesion (LPM) by using the fuzzy clustering pipeline (FCP)

3) Amending the template probability maps of GM, WM, external CSF and ventricle using the initial LPM, and

4) Refining the LPM and constructing the probability maps of GM, WM, external CSF and ventricle from the input (normalized) MRI by mapping to the amended template.

Note that, in Step3, a new amended template, including four tissue probability maps, needs to be constructed for each input T1-weighted MRI separately. The supervised component also consists of four sequential steps

5) At each voxel, extracting zero-order, 1st-order, and 2nd-order statistical features from the probability maps of GM, WM and external CSF and the refined LPM resulted from the unsupervised component, and the original T1-weighted MRI;

6) Training three binary SVM classifiers that recognize each voxel to be part of lesion or not, by using the three types of statistical features, respectively.

7) Combining the three SVM classifiers into a single SVM classifier and applying the combined SVM classifier to detect the lesion voxels; and

8) Performing inverse normalization to get the lesions in the original T1-weighted MRI.

In this paper, we normalize the brain to the MNI standard space for lesion estimation, feature extraction and final lesion classification to make the parameter setting of proposed method insensitive to the different-size brains and different-resolution images .Besides the basic idea of combining the unsupervised and supervised components, we also make technical contributions in several of the steps.

Step 1), we automatically detect the lesion hemisphere and only use the healthy hemisphere for enantiomorphic normalization. This step improves the accuracies of enantiomorphic normalization and the final lesion detection.

In Step 2), we extend the FCP to construct the initial LPM.

In Step 3), we amend the template probability maps with segmentation of the four brain tissues and refine the initial LPM, which will be elaborated.

Step 4) simply follows the six-tissue unified segmentation normalization (USN) pipeline.

Step 5): Feature extraction".

From Step 5) to Step 7), we apply statistical feature based supervised learning algorithm to further improve the lesion detection accuracy.

Step 8) first follows the inverse normalization in SPM8 and then binarizes the lesion likelihood map into a binary lesion mask.

With the availability of high precision MRI scanners helps in automatic clinical analysis of human brain for tumor detection. Cerebral cortex extraction from brain MR images is a challenging task due to its highly convoluted complex structures.

In this paper we first extract cerebral cortex from MRI using morphological approach. Next we segment gray and white matters using a Density based Segmentation/clustering (DenSeg) technique. We use publicly available IBSR datasets for experimentations and validation against manually segmented samples. A prototype java tool is developed based on the proposed method [5].

V. BLOCK DIAGRAM OF PROPOSED SYSTEM

Training Phase
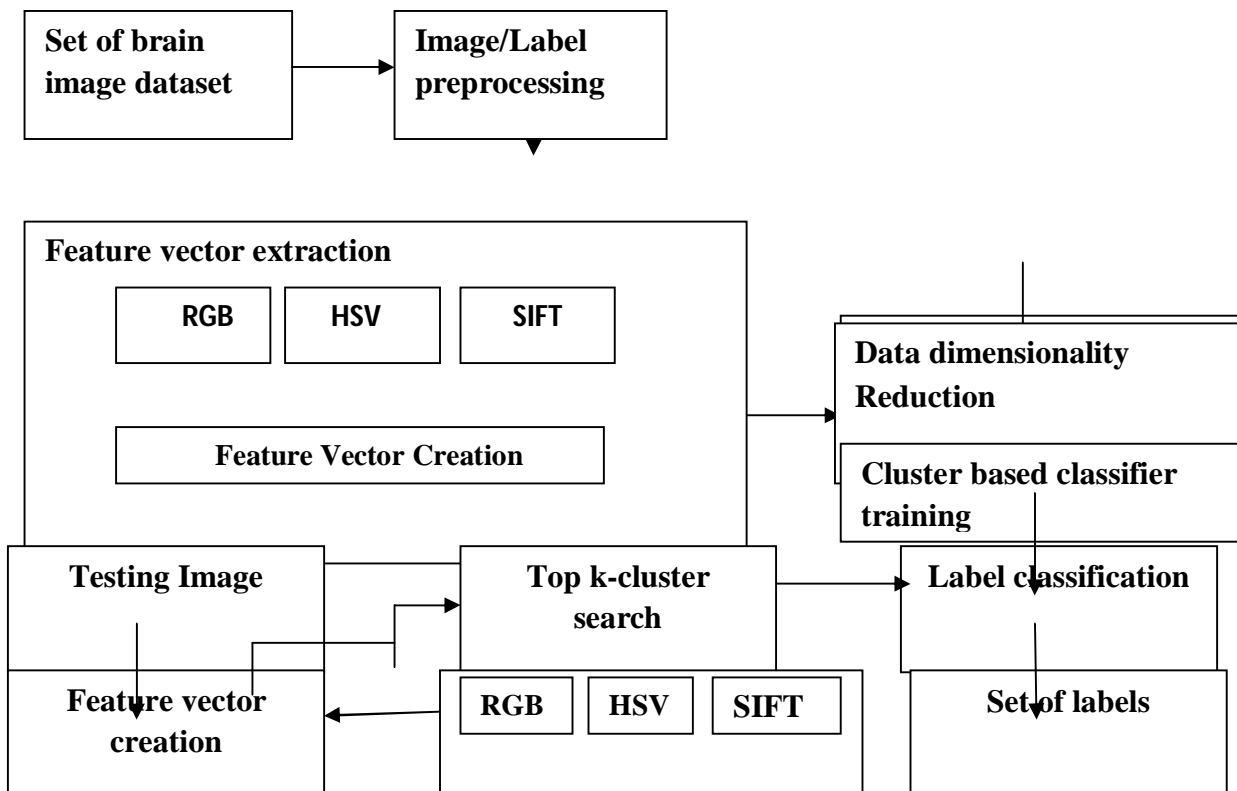
VI. PROPOSED ALGORITHM

We are mainly using following algorithm for overcoming different limitations of existing system and improving detection accuracy in Brain Lesion.

1. Feature Vector Creation Algorithm:
Step 1: Traverse through entire input image array.
Step 2: Read individual pixel color value (24-bit).
Step 3: Split the pixel color value into individual R, G and B 8-bit values.
Step 4: Make the color intensity range for each R,G,B color component of pixel into 10 bins i.e. 0-25, 25-50, 50-75….225-250.

Step 5: Read the color intensity value of R, G, B component of first pixel, increment the count of bin to which the intensity value belongs.
Step 6: Repeat the above step for each pixel.

2. Cosine Similarity Measurement

For getting exact image from database the similarity values between images are computed using cosine similarity formula:

$$\text{Cosine Similarity} = \frac{\sum_{i-1}^{t} x_i\, y_i}{\sqrt{\sum_{i-1}^{t} x_i^2}\ \sqrt{\sum_{i-1}^{t} y_i^2}}$$

Variable xi corresponds to vector of image x and yi for image y.

3. Naives bayes Classification:

It is a family of simple probabilistic classifiers based on applying Bayes' theorem with strong independence assumptions between the features.
The Bayes Theorm:

P(C/X) =P(C) P(X/C)/P(X)
P(C): Prior probability of class C having given image.
P(X): Prior Probability of training data X.
P(C/X): Probability of C given X.
P(X/C): Probability of X given C.
Input – Input Image, Class C, Trained dataset.
Output – Images which belongs to Class C.

Steps:-
Step 1: Extract the features of input image.
Step 2: Find out the probability P(C) of Class C that may contain the features of input image, called as prior probability.
Step 3: Find out the probability P(X/Ci), probability of occurrence of input image in given Class Ci, (Likelihood).
Step 4: Find out the probability P(X), probability of occurrence of input image among all classes. (Evidence).
Step 5: Find out the probability P (Ci/X), Probability of Class Ci that contain given input image X, is the possibility of that *X* can be labeled *Ci.*
Step 6: Repeat the step 2 to 5 for all Classes.
Step 7: Assign the label of class to Input image, who has the maximum posterior probability among all classes.

It does not require a-priori specification of number of clusters. As well as it is able to identify noise data while clustering. Mainly it fails in case of neck type of dataset. It does not work well in case of high dimensional data. DBSCAN algorithm fails in case of varying density clusters.

VII. CONCLUSION

Automated lesion detection on MRI scans using combined unsupervised and supervised methods is the direct medical application for segmentation and lesion detection. We have reviewed the techniques of the MRI image enhancement in terms of tumor pixels detected. This allows us to construct an initial lesion probability map by comparing the normalized MRI to healthy control subjects.

We have studied several digital image processing methods and discussed its requirements, advantages, limitations and properties in brain tumor detection .This paper gives enhanced information about brain tumor detection and segmentation. The marked area is segmented, To whom the project is concerned, is helpful and this tool facilitate them in diagnosis, the treatment procedure and state of the tumor supervising.

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