AUTOMATED LESION DETECTION ON MRI SCANS USING HYBRID METHOD

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Abstract- Automatic segmentation of brain tumor using computer analysis aided diagnosis in clinical practice but it is still a challenging task, especially when there are lesions needing to be outlined. In the applications of image-based diagnosis and computer-aided lesion detection, image segmentation is an important procedure. Accurate and precise detection of brain lesions on MR images (MRI) is paramount for accurately relating lesion location to impaired behavior. In this paper, we present a novel method to automatically detect brain lesions from a T1-weighted 3D MRI. We have form a hybrid method combining the advantages of both unsupervised and supervised methods. In our system we basically used hybrid method this allows us to construct an initial lesion probability map. Then, we perform non-rigid and reversible atlas-based registration to refine the probability maps of gray matter, white matter, external CSF, ventricle, and lesions. These probability maps are combined with the normalized MRI to construct three types of features, with which we use supervised methods to train three support vector machine (SVM) classifiers for a combined classifier. Finally, the combined classifier is used to accomplish lesion detection.

Index Terms: Lesion detection, Magnetic resonance imaging (MRI), Unsupervised and supervised methods.

1. INTRODUCTION

Accurate and precise detection of brain lesions on MR images (MRI) is paramount for accurately relating lesion location to impaired behavior. In this paper, 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. Accurate detection of lesions in the brain is critical to both clinical practice and neuropsychological research. For example, every year more than 795,000 people in the United States suffer a new or recurrent stroke (http:// www.strokeassociation.org) and the identification and analysis of the brain lesions resulting from a stroke can help understand the lesion-deficit relationship, predict patient diagnosis and prognosis and chart the development of brain pathology over time. In the past two decades, Magnetic Resonance Imaging (MRI) has become a reliable and increasingly popular technique for identifying brain damage and pathologies. To study brain lesions using MRI, the first step is to accurately detect the lesion from different-modality MRIs (e.g. Diffusion-weighted imaging, T1-MRI, FLAIR, or T2- MRI).

Traditionally, the gold standard for lesion detection relied on manual delineation by one or more trained neurologists/radiologists creating a binary lesion mask [5]. These methods show high reliability (e.g. 0.86–0.95) between raters [4, 6]. However, manual labeling is laborious and subjective. In recent years, several automated methods have been developed for brain lesion detection [7–13]. However, automated brain lesion detection from MR images is still a very challenging problem, particularly when only the T1-MRI is available. First, it is sometimes difficult to separate the lesion from the surrounding tissues that is relatively structurally intact based only on image intensity since the intensities of the lesion and healthy tissues may be similar, not to mention that the intensity of the lesion may not be homogeneous. Second, lesions are often non-rigid and complex in shape and vary greatly in size and position across different patients. Therefore it is difficult to construct a compact and informative geometric ‘prior’ to guide lesion detection.

1.1 Detail Problem Definition

A hybrid method for lesion detection on MRI scans is proposed to help normalize the patient MRI with lesions and initialize/refine a lesion probability map. In the supervised component, we extracted three different-order statistical features from both the tissue/lesion probability maps obtained from the unsupervised component and the original MRI intensity. Three support vector machine classifiers are then trained for the three features respectively and combined for Final voxel-based lesion classification.

1.2 Problem Statement

Magnetic Resonance (MR) brain image uses approach organization and dissection. Image preprocessing is a processing step for transforming a source image into a new image alike the source image. Feature extraction a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. The algorithms used in these systems are divided into three tasks: extraction, selection and classification. Currently all the method which area available for lesion detection on MRI scans are either supervised or unsupervised, some methods are combinations of supervised and unsupervised techniques but all this methods were having some disadvantages which needed to be overcome, so to overcome this we proposed a novel hybrid method for lesion detection on T1-weighed MR

1.3 Need of proposed system

Lesion detection and segmentation are challenging tasks due to the complexity and large variations in the anatomical structures of human brain tissues. Segmentation allows for extraction of certain regions to provide further information during other stages of quantitative assessment. Accurate segmentation of the brain is the basis for calculating important information; for example, size, compactness, and volume of the lesion.

Many approaches have been proposed by various researchers to deal with MRI images. To improve the efficiency of lesion detection a hybrid method is needed which will cover the disadvantages of the existing system. In our system we basically used hybrid method this allows us to construct an initial lesion probability map. Then, we perform non-rigid and reversible atlas-based registration to refine the probability maps of gray matter, white matter, external CSF, ventricle, and lesions. These probability maps are combined with the normalized MRI to construct three types of features, with which we use super- vised methods to train three support vector machine (SVM) classifiers for a combined classifier. Finally, the combined classifier is used to accomplish lesion detection.

1.4 Scope and Objectives

1. To automatically detection lesion on MRI scans with speed and accuracy.
2. To study brain lesions using MRI.
3. To separate the lesion from the surrounding tissues
4. Decrease time complexity for speed search

1.5 Application

1. For fast MRI analysis
2. To assist medical specialist in lesion detection.

2. LITERATURE SURVEY

Various algorithms and methods which are already available for lesion detection on MRI scans but each method has some advantages and disadvantages. In this section we will study the existing systems.

2.1 Study of existing systems

1. Unsupervised myocardial segmentation for cardiac MRI

Though unsupervised segmentation was a de-facto standard for cardiac MRI segmentation early on, recently cardiac 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 cardiac MR modalities. For example, CP-BOLD is a new MRI technique that has been shown to detect ischemia without any contrast at stress but also at rest conditions. Although CP-BOLD looks similar to standard CINE, changes in myocardial intensity pat- terns and shape across cardiac phases, due to the hearts motion, BOLD effect and artifacts affect the underlying mechanisms of fully supervised segmentation techniques resulting in a significant drop in segmentation accuracy. In this paper, we present a fully unsupervised technique for segmenting myocardium from the background in both standard CINE MR and CP-BOLD MR. We combine appearance with motion information (obtained via Optical Flow) in a dictionary learning framework to sparsely represent important features in a low dimensional space and separate myocardium from background accordingly. Our fully automated method learns background-only models and one class classifier provides myocardial segmentation. The advantages of the proposed technique are demonstrated on a dataset containing CP-BOLD MR and standard CINE MR image sequences acquired in base- line and ischemic condition across 10 canine subjects, where our method outperforms state-of-the-art supervised segmentation techniques in CP-BOLD MR and performs at- par for standard CINE MR. This work has shown that unsupervised methods can still deliver state-of-the-art performance even for standard CINE MR. The proposed algorithm does not exploit the spatio temporal information across cardiac phases and doing so by introducing graph-based formulation should increase performance in future extensions. UMSS can be an effective tool in challenging datasets where inter-acquisition variability prohibits the effectiveness of supervised segmentation strategies. Finally, such post-processing tools are expected to be instrumental in advancing the utility of emerging cardiac MR imaging techniques, e.g., CP-BOLD MR, towards clinical translation.

2. Detection and segmentation of brain tumor from MRI Images

Brain tumor is an abnormal intracranial growth caused by cells reproducing themselves in an uncontrolled manner. Curing cancer has been a major goal of medical researchers for decades. The early detection of cancer can be helpful in curing the disease completely. While most of the natural cells are getting old or damaged, they disappear and new cells are replaced with them. Sometimes, this process goes wrong and new cells are produced when body does not need them and the old and damaged cells don't disappear. Therefore, the illimitable and incontrollable increase of cells causes the brain tumor creation. Normally, the anatomy of brain tumor can be examined by MRI scan. MRI provide accurate visualize of anatomical structure of tissues. MRI is a one type of scanning device, which use magnetic field and radio waves. Now a days, image segmentation play vital role in medical image segmentations. The segmentation of brain tumor from magnetic resonance images (MRI) is an important task. Manual segmentation is one of the techniques for finding tumor from the MRI. In segmentation method First is pre-processing level where the extra parts which are outside the skull and don't have any helpful information are removed and then by applying the fast bounding box (FBB) algorithm, the tumor area is displayed on the MRI images. We are developing a project on Brain tumor which detects and segments the MRI images which help us to understand the tumor present in the brain. Relevance of these approaches is the direct medical application for segmentation and edge detection. We have reviewed the techniques of the MRI image enhancement in terms of tumor pixels detected. We have studied several digital image processing methods and discussed its requirements and properties in brain tumor detection. This paper gives enhanced information about brain tumor detection and segmentation. The marked area is segmented and the assessment of this tool from the radiologist, whom the project is concerned with, is positive and this tool helps them in diagnosis, the treatment procedure and state of the tumor monitoring.

3. Automated detection of white matter lesions in MRI brain images

Using spatiofuzzy and spatio probabilistic clustering models White Matter Lesions (WMLs) are small areas of dead cells found in parts of the brain. In general, it is difficult for medical experts to accurately quantify the WMLs due to decreased contrast between White Matter (WM) and Grey Matter (GM). The aim of this paper is to automatically detect the White Matter Lesions which is present in the brains of elderly people. WML detection process includes the following stages: 1. Image preprocessing, 2. Clustering (Fuzzy c-means clustering (FCM), Geostatistical Possibilistic clustering (GPC) and Geostatistical Fuzzy clustering (GFCM)). The proposed system is tested on a database of 208 MRI images. GFCM yields high sensitivity of 90The proposed Fuzzy c-means clustering, Geostatistical Possibilistic clustering and Geostatistical Fuzzy c-means clustering methods are used for automatic detection of WMLs in brains of elderly people. The incorporation of the geostatistical estimate variance into the objective functions of fuzzy clustering and possibilistic clustering algorithms is relatively a simple and effective procedure for implementation and can be further explored using various advanced kriging systems in multivariate geostatistics. Experimental results using the MRI data of elderly individuals shows the advantages that Geostatistical Fuzzy c-means clustering is the best and effective approach for extracting White Matter

Lesions. More accurate results are obtained by GFCM whereas GPC and FCM provide more false positives in brain image and they are less sensitive to noise. Experimental results over datasets show that GFCM is efficient and can reveal very encouraging results in terms of quality of solution found.

4. Automated identification of brain tumors from single MR images based on segmentation with refined patient specific priors

Brain tumor scan have different shapes or locations, making their identification very challenging. In functional MRI, it is not unusual that patients have only one an atomically image due to time and Financial constraints. Here, we provide a modified automatic lesion identification (ALI) procedure which enables brain tumor identification from single MR images. Our method rests on (A) a modified segmentation-normalization procedure with an explicit extra prior for the tumor and (B) an outlier detection procedure for abnormal voxel (i.e., tumor) classification. To minimize tissue misclassification, this segmentation-normalization procedure enquires prior information of the tumor location and extent. We therefore propose that ALI is run iteratively so that the output of Step B is used as a patient-specific prior in Step A. We test this procedure on real T1- weighted images from18 patients, and the results were validated in comparison to two independent observers' manual tracings. The automated procedure identified the tumors successfully with an excellent agreement with the manual segmentation (area under the-ROC curve=0.970.03).The proposed procedure increases the edibility and robustness of the ALI tool and will be particularly useful for lesion-behavior mapping studies, or when lesion identification and/or spatial normalization are problematic. The success of the tumor identification was validated in comparison to manual segmentation which is the current gold standard approach. We also show how tumor identification, in some patients, improved with the new recursive-ALI approach compared to the standard ALI approach. The recursive ALI procedure that we propose here will be particularly useful for studies of lesion-behavior mappings with large samples of patients. It may also have potential uses for surgical or diagnostic purposes. Recursive ALI procedure was able to identify tumors at the correct location in all the patients irrespective of the type, size or location.

5. A Review of Fully Automated Techniques for Brain Tumor Detection From MR Images

Radiologists use medical images to diagnose diseases precisely. However, identification of brain tumor from medical images is still a critical and complicated job for a radiologist. Brain tumor identification form magnetic resonance imaging (MRI) consists of several stages. Segmentation is known to be an essential step in medical imaging classification and analysis. Performing the brain MR images segmentation manually is a difficult task as there are several challenges associated with it. Radiologist and medical experts spend plenty of time for manually segmenting brain MR images, and this is a non-repeatable task. In view of this, an automatic segmentation of brain MR images is needed to correctly segment White Matter (WM), Gray Matter (GM) and Cerebrospinal Fluid (CSF) tissues of brain in a shorter span of time. The accurate segmentation is crucial as otherwise the wrong identification of disease can lead to severe consequences. Taking into account therefore said challenges, this research is focused towards high- lighting the strengths and limitations of the earlier proposed segmentation techniques discussed in the contemporary literature. Besides summarizing the literature, the paper also provides a critical evaluation of the surveyed literature which reveals new facets of research. However, articulating a new technique is beyond the scope of this paper. Image segmentation is extensively used in numerous biomedical-imaging applications, e.g., the quantitation of tissue volumes, study of anatomical structure, diagnosis, localization of pathology, treatment planning and computer-integrated surgery. As diagnosis tumor is a complicated and sensitive task; therefore, accuracy and reliability are al- ways assigned much importance. Hence, an elaborated methodology that highlights new vistas for developing more robust image segmentation technique is much sought.

6. Computer-Assisted Segmentation of White Matter Lesions in 3D MR images, Using Support Vector Machine

Brain lesions, especially White Matter Lesions (WMLs), are associated with cardiac and vascular disease, but also with normal aging. Quantitative analysis of WML in large clinical trials is becoming more and more important. In this paper, we present a computer-assisted WML segmentation method, based on local features extracted from multi-parametric Magnetic Resonance Imaging (MRI) sequences, i.e. T1-weighted (T1-w), T2-weighted (T2-w), proton density-weighted (PD), and Fluid attenuation inversion recovery (FLAIR) MR scans. A Support

Vector Machine (SVM) classifier is first trained on expert-defined WMLs, and is then used to classify new scans. Subsequent post processing analysis further reduces false positives by utilizing anatomical knowledge and measures of distance from the training set. Cross- validation on a population of 45 patients from 3 different imaging sites with WMLs of varying sizes, shapes and locations tests the robustness and accuracy of the proposed segmentation method, compared to the manual segmentation results from two experienced neuro radiologists. the problem of WML segmentation, based on integrating multiple MR acquisitions and training a nonlinear pattern classification algorithm to recognize imaging profiles that are representative of a brain lesion. By combining 4 types of MR acquisition protocols, namely FLAIR, T2, PD and T1, a multi-variant imaging signature is constructed for every image voxel, and is subsequently evaluated by a nonlinear pattern classifier. Results that agree well with human experts were obtained. One of the challenges we faced during the development of the segmentation method was that the number of lesion training voxels that we had available were dramatically smaller than the number of training voxels for healthy tissue, since lesions constitute a very small percentage of the entire brain

2.2 Comparison of existing systems with proposed System

All the existing system which we have studied are having some AWS, to over the dis- advantages of the existing system we present a novel method to automatically detect brain lesions from a T1-weighted 3D MRI. We have form a hybrid method combining the advantages of both unsupervised and supervised methods. In our system we basically used hybrid method this allows us to construct an initial lesion probability map. Then, we perform non-rigid and reversible atlas-based registration to refine the probability maps of gray matter, white matter, external CSF, ventricle, and lesions. These probability maps are combined with the normalized MRI to construct three types of features, with which we use supervised methods to train three support vector machine (SVM) classifiers for a combined classifier. Finally, the combined classifier is used to accomplish lesion detection.

3. PROPOSED SYSTEM ARCHITECTURE

The main purpose of this project is to get novel automated procedure for lesion detection from T1-weighted MRIs by combining both an unsupervised and a supervised component. In the unsupervised component, we proposed a method to identify lesion hemisphere to help normalize the patient MRI with lesions and initialize a lesion probability map. In the supervised component, we extracted three different order statistical features from both the tissue/lesion probability maps obtained from the unsupervised component and the original MRI intensity. Three support vector machine classifiers are then trained for the three features respectively and combined for final voxel-based lesion classification. To Propose an intelligent classification technique to identify normal and abnormal slices of the magnetic resonance human brain images(MRI).To propose an hybrid technique consists of four sequential stages; pre- processing, feature extraction, and classification and dimensionality reduction for image classification accuracy improvement.

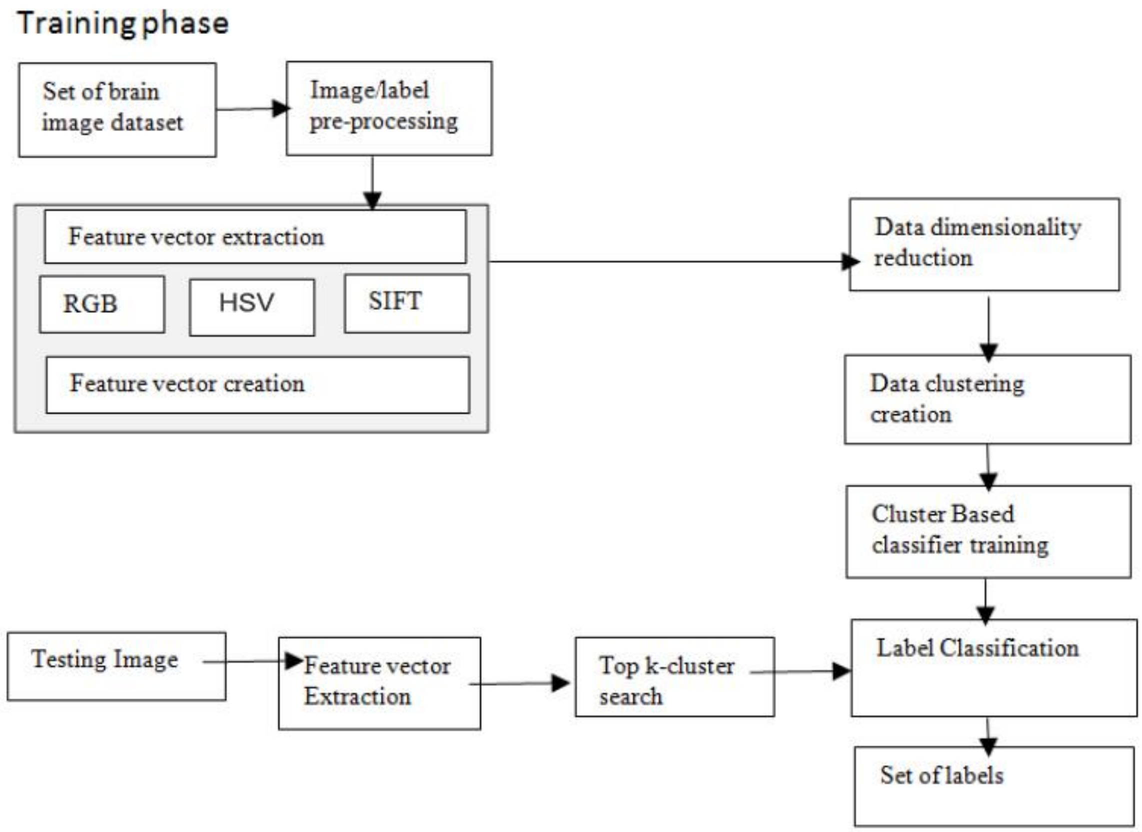

Figure 1. Automated lesion detection on MRI using Hybrid method

Initially MRI images of the brain are given as input to the system. Preprocessing is done on input dataset images where the image labels are process. Next step is feature vector extraction in which the SIFT and RGB features are extracted and the feature vector is created. Data dimensionality is reduced for data cluster creation. Cluster based classifier training is done. After that the test image is given input to the system of which the features are extracted and then the label classification is done and set of labels are given as output.

4. MATHEMATICAL MODEL

Mathematical model is a description of a system using mathematical concepts
and language. The process of developing a mathematical model is termed mathematical modeling. Let S be the system or application.
let S be the system define as
S=fI1,D,N,F,Fd,Qg,
I1=Set of input images,
I=fi1,i2......ing,
O=O is the set of output images,
o=fo1,o2,o3...okg,
N=N is the set of KNN of query Q,
N=fN1,N2.....Nk,g
F=F is the image features of SIFT, HSV, color,
F=ff1,f2.....fn,g
Fd=Fd is the set of feature after data dimensionality reduction,
Fd= ffd1,fd2.......fdn,g
function f1=this function read set of images as input as apply feature extraction

algorithm, F1(I)(i1,i2,......in)(f1,f2,....fn)F,
function f2=this function read set of images features and apply data dimensionality reduction,
F2(F)(f1,f2,......fn)(fd1,fd2,....fdk)Fd k<n,
k=number of images after Dm reduction,
function f3this function read Fd set of images and apply classification SVM training,
F3(fd)(fd1,fd2.........fdk)SVMT,
function f4=this function read query image and extract feature of query,
f4()(FqFq) function F5=this function record query image and classifier train data and output

top k close neighbor images of current image,
F5(T,Fq)(t1,t2........tn)(Fq)q1,q2...qk,
O=set of classified image of current query image.

5. ALGORITHM DETAILS

a. Support Vector Machine

Mathematical equation in Support Vector Machine
Input/output sets X, Y
Training set (x 1, y 1),..., (x m, y m)
Generalization: given a previously seen x ∈ X, find a suitable y ∈ Y.
i.e., want to learn a classifier: y = f (x, α), where α are the parameters of the function.
For example, if we are choosing our model from the set of hyper planes in R n, then we have:

$$f(x, \{w, b\}) = \text{sign}(w \cdot x + b).$$

b. KNN algorithm steps:-

1. Find k most similar users (KNN).
2. Order the label application with increasing ranking, rating and review.
3. Identify set of application, C, Visited by the group of user together with their frequency.
4. Recommend the top N- most frequent items in C that the active user visited or not.

KNN Pseudo code:

Procedure: KNN (Q, d, Sim, Dmin)

Input: Q is search hierarchy on the input location.

1. For search location l do
2. User location Ul for l in Q
3. For Ul ϵ l find Sim
4. Each nearest neighbor finds out using rating.
5. Calculate Dmin from selected rating to Ul
6. For sort all result do
7. Display results
8. End for
9. End for
10. End for

c. SIFT ALGORITHM

SIFT (Scale Invariant Feature Transform) algorithm proposed by Lowe in 2004 [6] to solve the image rotation, scaling, and affine deformation, viewpoint change, noise, illumination changes, also has strong robustness. The SIFT algorithm has four main steps: (1) Scale Space Extrema Detection, (2) Key point Localization, (3) Orientation Assignment and (4) Description Generation. The first stage is to identify location and scales of key points using scale space extreme in the DoG (Difference-of- Gaussian) functions with different values of σ, the DoG function is convolved of image in scale space separated by a
constant factor k as in the following equation.

D(x, y) = (G(x, y, k) – G(x, y) × I(x, y)………………………………………….(1)

Where, G is the Gaussian function and I is the image.

Now the Gaussian images are subtracted to produce a DoG, after that the Gaussian image subsample by factor 2 and produce DoG for sampled image. A pixel compared of 3×3 neighborhood to detect the local maxima and minima of D(x, y, σ).

In the key point localization step, key point candidates are localized and refined by eliminating the key points where they rejected the low contrast points. In the orientation assignment step, the orientation of key point is obtained based on local image gradient. In description generation stage is to compute the local image descriptor for each key point based on image gradient magnitude and orientation at each image sample point in a region centered at key point these samples building 3D histogram of gradient location and orientation; with 4×4 array location grid and 8 orientation bins in each sample. That is 128-element dimension of key point descriptor.

Construction Of SIFT Descriptor Figure 1 illustrates the computation of the key point descriptor. First the image gradient magnitudes and orientations are sampled around the key point location, using the scale of the key point to select the level of Gaussian blur for the image [6]. In order to achieve orientation invariance, the coordinates of the descriptor, then the gradient orientations are rotated relative to the key point orientation. Figure 1 illustrated with small arrows at each sample location on the left side.

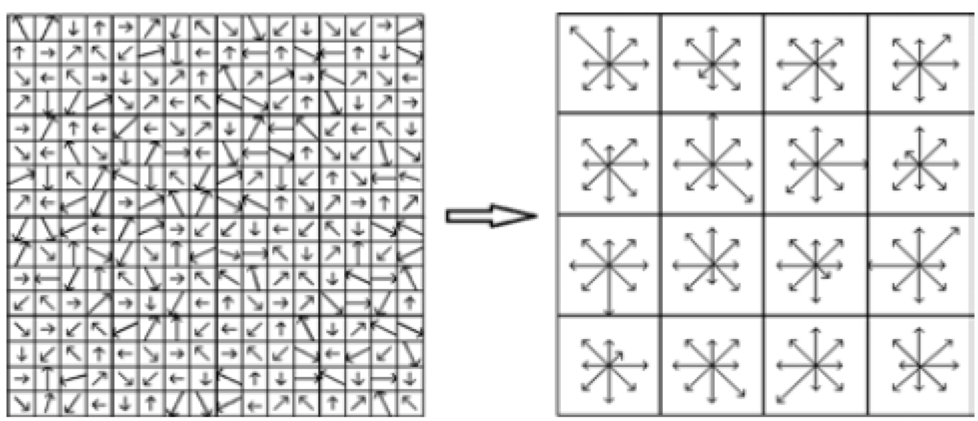

Figure 2. SIFT Descriptor Generation

d. SURF ALGORITHM

SURF (Speed Up Robust Features) algorithm, is base on multi-scale space theory and the feature detector is base on Hessian matrix. Since Hessian matrix has good performance and accuracy. In image I, x = (x, y) is the given point, the Hessian matrix H(x, σ) in x at scale σ, it can be define as

H(x, σ) = $\boldsymbol{Lx(x,\sigma)\ Lxy(x,\sigma)\ Lyx(x,\sigma)\ Lyy(x,\sigma)}$ **…………………………………(2)**

Where Lxx (**x**, σ) is the convolution result of the second order derivative of Gaussian filter $2\partial x$ 2 (σ) with the image I in point **x**, and similarly for Lxy (**x**, σ) and Lyy (**x**, σ).

SURF creates a "stack" without 2:1 down sampling for higher levels in the pyramid resulting in images of the same resolution. Due to the use of integral images, SURF filters the stack using a box filter approximation of second-order Gaussian partial derivatives [3]. Since integral images allow the computation of rectangular box filters in near constant time. In Figure 2 Show the Gaussian second orders partial derivatives in y-direction and xy-direction.

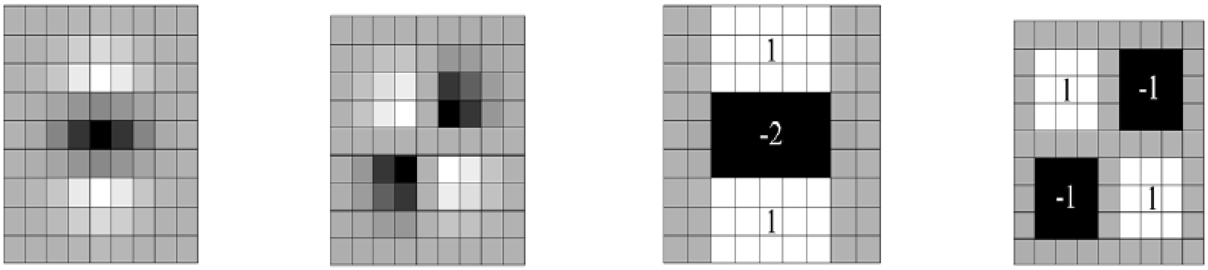

Figure 3.The Gaussian second orders partial derivatives in y-direction and xy-direction [4].

In descriptors, SIFT is good performance compare to other descriptors. The proposed SURF descriptor is based on similar properties. The first step consists of fixing a reproducible orientation based on information from a circular region around the interest point. And second construct a square region aligned to the selected orientation, and extract the SURF descriptor from it. In order to be invariant to rotation, it calculate the Haar-wavelet responses in x and y direction shown in figure.

5. EXPERIMENTAL RESULTS

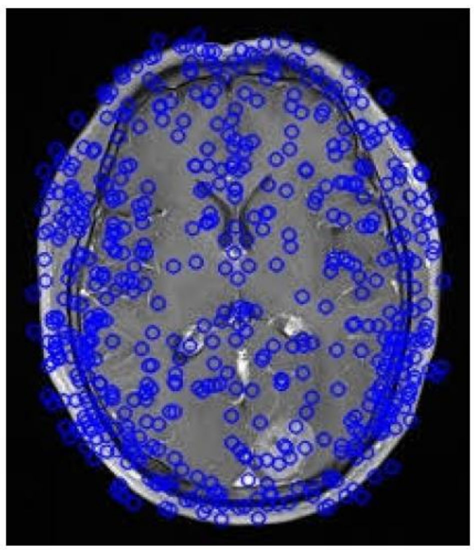

Figure 4 SIFT feature extraction

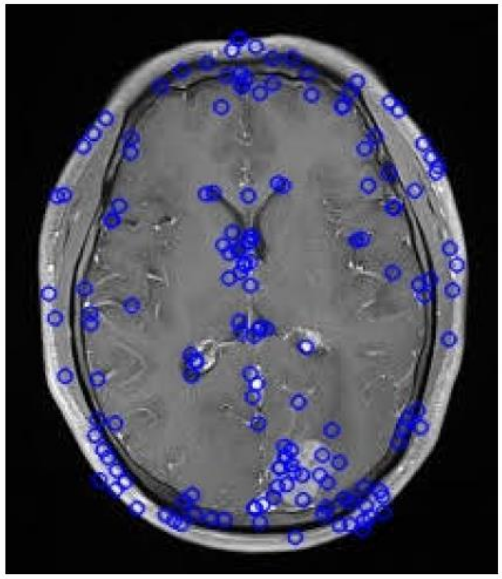

Figure 5 Surf feature extraction

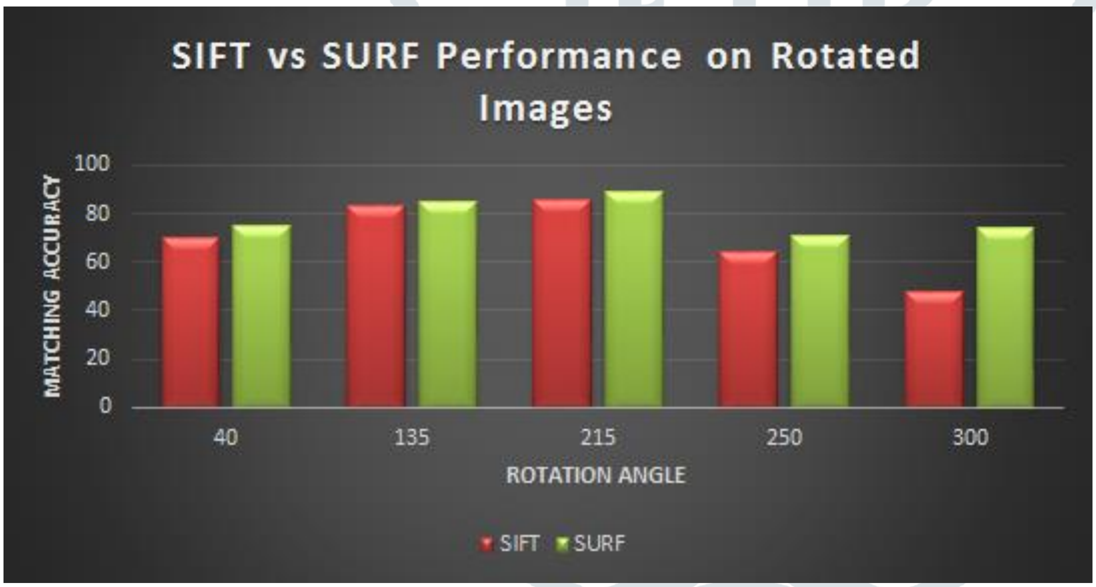

Figure 6. Performance accuracy of SURF and SIFT for rotating images

Table:01 Brain Image Clustering Accuracy

	No. of Images	**Clustering Accuracy**
Existing	**100**	**90%**
Proposed (Hybrid Approach)	**100**	**95%**

Performance accuracy of surf s better than sift for rotating images

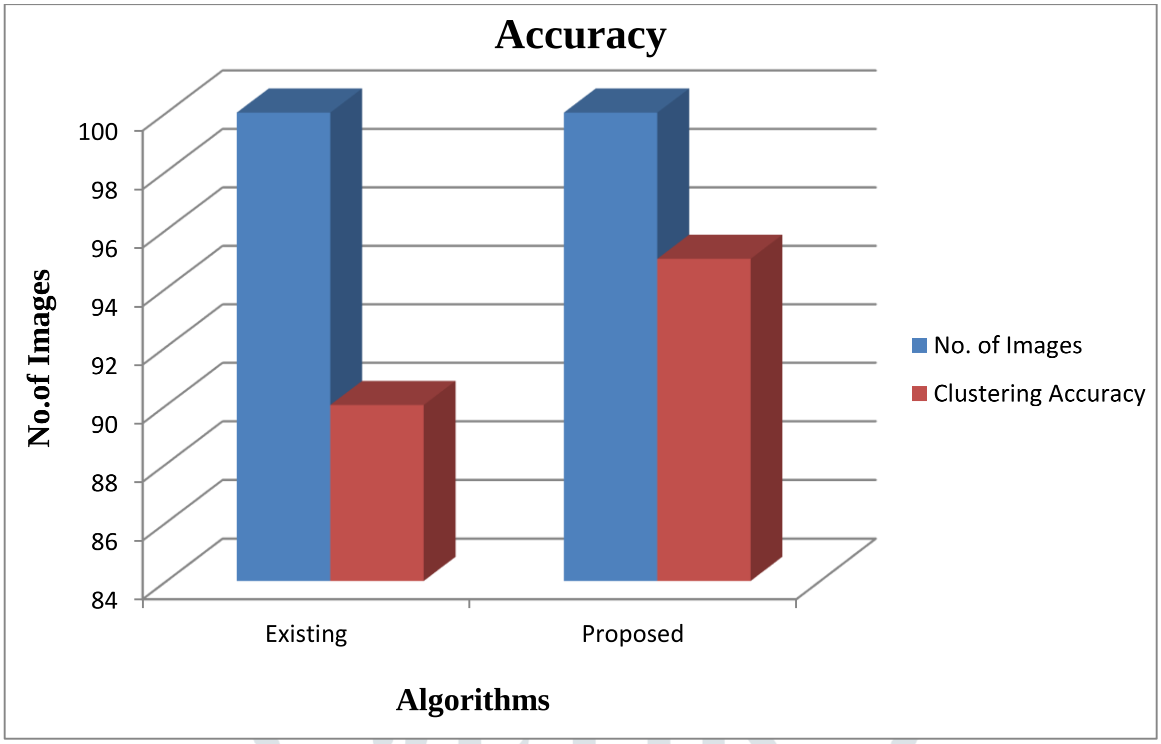

Figure 7. Brain Image Clustering Accuracy Graph

CONCLUSION AND FUTURE SCOPE

1. Conclusion

Author studied 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 and initialize/refine a lesion probability map. In the supervised component, we combined different-order statistical features extracted from both the tissue/lesion probability maps obtained from the un- supervised component and the original MRI intensity and applied three SVM classifiers for final voxel-based lesion classification.

2. Future scopes

In future more method can be combined to increase the efficiency of the system.

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