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Classification of Tissues for Detecting An Inflammatory Disease in Brain MRI

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Abstract:
Detection of an inflammatory disease on magnetic resonance image (MRI) is most important as a disease activity and surgical purpose in medical field. We propose an approach to provide tissue segmentation while appearing an inflammatory disease. The two stage of classification process uses in this method 1)a Bayesian classifier that performs a brain tissue classification at each voxel of reference and follow-up scans using intensities and intensity differences, and 2) a random forest based lesion-level classifier provides a identification of an inflammatory diseases. The method is evaluated on sequential brain MRI of 160 subjects from a separate multi-center clinical trial. The proposed method is compared to the manual identification and gives better performance, sensitivity with fault detecting rate than manual identification. For new lesions greater than 0.15 cc in size, the classifier has near perfect performance (99% sensitivity, 2% false detection rate), as compared to ground truth. The proposed method was also shown to exceed the performance of any one of the nine expert manual identifications.

Key words: *Bayesian classifier, Lesion level Random forest classifier, an inflammatory disease*

1. Introduction

In medical image processing the detection of new Multiple Sclerosis (MS) lesions or an inflammatory disease that is an inflammatory disease on Magnetic Resonance Imaging (MRI) is important as a disease activity and surgical purpose. Brain Magnetic Resonance Imaging (MRI) is widely used in surgical and diagnosis purpose in that the image processing is used to give the result. Brain tissues classified as three ways that is, White
Matter (WM), Gray Matter (GM), Cerebrospinal Fluid (CSF).Multiple sclerosis (MS) is a chronic autoimmune disorder affecting movement, sensation, and bodily functions. It is caused by destruction of the myelin insulation covering nerve fibres (neurons) in the central nervous system (brain and spinal cord). MS is a nerve disorder caused by destruction of the insulating layer surrounding neurons in the brain and spinal cord. This insulation, called myelin, helps electrical signals pass quickly and smoothly between the brain and the rest of the body. When the myelin is destroyed, nerve messages are sent more slowly and less efficiently. Patches of scar tissue, called plaques, form over the affected areas, further disrupting nerve communication. The symptoms of MS occur when the brain and spinal cord nerves no longer communicate properly with other parts of the body. MS causes a wide variety of symptoms and can affect vision, balance, strength, sensation, coordination, and bodily functions.

Multiple sclerosis affects more than a quarter of a million people in the United States. Most people have their first symptoms between the ages of 20 and 40; symptoms rarely begin before 15 or after 60. Women are almost twice as likely to get MS as men, especially in their early years. People of northern European heritage are more likely to be affected than people of other racial backgrounds, and MS rates are higher in the United States, Canada, and Northern Europe than in other parts of the world. MS is very rare among Asians, North and South American Indians, and Eskimos.Multiple Sclerosis (MS) is considered a disease of the white matter because normally lesions appear in this area but,it is also possible to find some of them in the gray matter.[It is a progressive disease characterized by disseminated demyelination of nerve fibers of the brain and spinal cord. It begins slowly, usually in young adulthood, and continues throughout life with periods of exacerbation and remission. The first signs are often paresthesias, or abnormal sensations in the extremities or on one side of the face. Other early signs are muscle weakness, vertigo, and visual disturbances, such as nystagmus, diplopia (double vision), and partial blindness. Later in the course of the disease there may be extreme emotional lability, ataxia, abnormal reflexes, and difficulty in urinating.

2. Related Work

Sclerosis lesions in brain MRI by using I)Shochastic model.(ii)Markov model to increase the load correlation but, less accuracy [1].Petronella Anbek, H.c.Bisschops and Jeroen Vander Grand suggested that the probabilistic segmentation of white matter lesions in MR imaging by using K-Nearest Neighbor method to increase the accuracy but, the computational time is increased[2].Baseem A.Abdullah, Mel-Ling Shyu, Terri A.Scanduna, Nigel John gives brief details about the segmentation of Multiple Sclerosis Lesions in brain MRI is used to provide accurate edges but, the design is complex[3].Anjum Hayet, Gandal, Ahmad Khan gives brief information about a review of automated techniques for brain tumor detection from MR images for an Identification of brain tissues and detect the diseases.It used to provide high sensitivity[4].M.Eifadal, J.Zhang, H.Denn suggested that the abnormality detection of brain MR image segmentation by using Iterative Conditional Mode Algorithm but,it gives less accuracy[5].Muhamad Abdel.Mottaleb, Baseem A.Scandura contributed that a topology-preserving approach to the segmentation of brain images with multiple sclerosis lesions by using T2-Weighted techniques but, it have computational complexity[6].V.B.Padole, D.S.Chaudhari, K.K.Mektha gives brief description about brain MAI Segmentation by using T1 and T2 weighted spatially constrained Fuzzy C-means clustering to provide Effective performance and robust to noise[7].

Michel J.Berg,Sken Ebholm,Edward A.Ashton suggested that the accuracy and reproducability of manual and semiautomated quantification of Ms lesions by MRI Geometrically Constrained Region Growth Method. It required large time for computation[8].Mareel Bose,Fabrico Hertz,Jem-Paul gives brief idea about automated change detection in muiltimodal serial MRI:application to MS lesions evolution by using joint histogram equalization method. It used to reduce the fault but, sensitivity is less[9].Reza Forghanl,Alan C.Evans gives brief information about the automation “Pipeline” Analysis of 3-D MRI Data for clinical Trials:Application to MS is used enhance to detect small treatment effects[10]. A.Criminist,J.Sholton,A.Blake Los Angeles suggested that the discriminative,Semantic Segmentation of brain tissue in MR images by using random decision forest classifier. It gives an accurate classification but, CSF is most difficult to label accurate [11]. Guido Gorig, Daniel Wolti, Alan Colchester gives brief information about exploring the discrimination power of the time domain for segmentation and characterization of lesions in MRI data by using spatial analysis.It provides high sensitivity to detect fluctuation structures [12]. Stevan L. Hartmann, Mitchell H.Parks,Benoit.M.Dswart gives idea about the automatic 3-D segmentation of internal structures in brain MR Images is difficult to find the regions[13].Fernand.S.Cohen, Zhengweiyang, Jonathan Nissanov suggested that the automatic Matching of homologous histological Sections for identification and curve matching, robust to non- uniform sampling noise[14].

3. Proposed System

The histogram equalization is an approach to enhance a given image. The approach is to design a transformation *T(.)* such that the gray values in the output is uniformly distributed in [0, 1].Histogram equalization yields an image whose pixels are (in theory) uniformly distributed among all gray levels. Sometimes, this may not be desirable. Instead, we may want a transformation that yields an output image with a pre-specified histogram. This technique is called histogram specification.

The Sobel operator is used in image processing, particularly within edge detection

Algorithms. Technically, it is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. At each point in the image, the result of the Sobel operator is either the corresponding gradient vector or the norm of this vector. The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations. On the other hand, the gradient approximation which it produces is relatively crude, in particular for high frequency variations in the image. It uses many situations in medical image processing for Brain MRI new lesion detection that is surgical purpose, diagnosis, tumor detection. of a histogram provides useful information for contrast enhancement. The histogram equalization is an approach to enhance a given image.In terms of histograms, the output image will have all gray values in “equal proportion” .This technique is called histogram equalization. This technique is called histogram equalization.

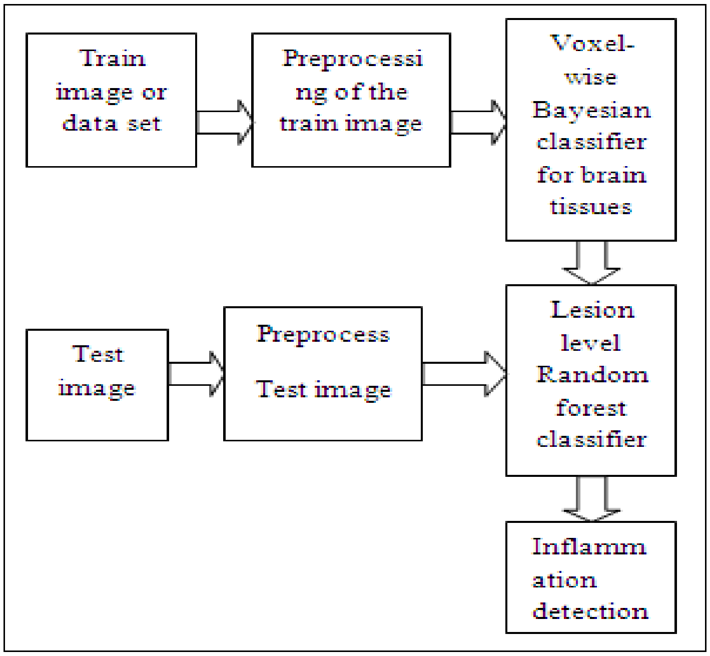

Figure 1: Block Diagram

Any one of the training image get from one particular data base. In that image is gray level which has few levels compare to RGB image. It uses many situations in medical image processing for Brain MRI new lesion detection that is surgical purpose, diagnosis, tumor detection.

3.1. Preprocessing of the Train Image

- **Histogram Equalization:** Histogram provides a global description of the appearance of the image. If we consider the gray values in the image as realizations of a random variable R, with some probability density, histogram provides an approximation to this probability density. The shape

3.2. Voxelwise Bayesian Classifier

The Bayesian Classification represents a supervised learning method as well as a statistical method for classification. Assumes an underlying probabilistic model and it allows us to capture uncertainty about the model in a principled way by determining probabilities of the outcomes.

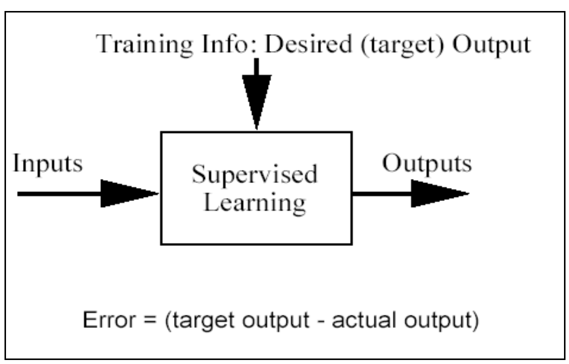

Figure 2: Schematic Diagram of Bayesian Classifier

Bayes classifier employs single words and word pairs as features. It allocates user utterances into nice, nasty and neutral classes, labelled +1, -1 and 0 respectively.This numerical output drives a simple first-order dynamical system, whose state represents the simulated emotional state of the experiment's personification,

3.3. Preprocessing or the Test Image

- **Median filtering:** The median filter is a nonlinear digital filtering technique, often used to remove noise. Median filtering is very widely used in digital image processing because it preserves edges while removing noise. The median filter is a sliding-window spatial filter. It replaces the value of the center pixel with the median of the intensity values in the neighborhood of that pixel. Median filtering is a nonlinear operation often used in image processing to reduce "salt and pepper" noise. A median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges. Median filters are particularly effective in the presence of impulse noise, also called 'salt – and – pepper' noise because of its appearance as white and black dots superimposed on an image.

- **Edge detection using SOBEL:** The Sobel operator performs a 2-D spatial gradient measurement on an image. Typically it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. The Sobel edge detector uses a pair of 3x3 convolution masks, one estimating the gradient in the x-direction (columns) and the other estimating the gradient in the y-direction (rows). A convolution mask is usually much smaller than the actual image. As a result, the mask is slid over the image, manipulating a square of pixels at a time or the norm of this vector. The Sobel operator is based on convolving the image with a small, separable, and integer valued filter n horizontal and vertical direction and is therefore relatively inexpensive in terms of computations. On the other hand, the gradient approximation which it produces is relatively crude, in particular for high frequency variations in the image.

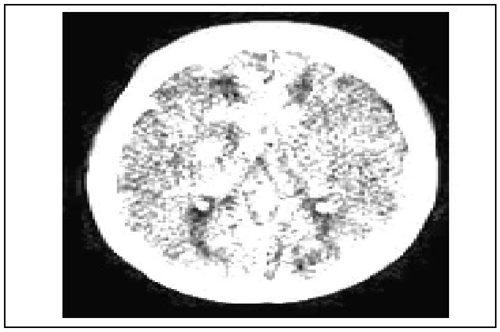

Figure 3: Edge Detection

The Sobel operator represents a rather inaccurate approximation of the image gradient, but is still of sufficient quality to be of practical use in many applications. More precisely, it uses intensity values only in a 3×3 region around each image point to approximate the corresponding image gradient, and it uses only integer values for the coefficients which weight the image intensities to produce the gradient approximation.

3.4. Train Image/Test Image Matching

The test image going to rotate by using geometrical rotated signals for match the position of both train and test image.Test and train image is compare to detect differences b/w that images. The convolution of two functions is an important concept in a number of areas of pure and applied mathematics such as Fourier analysis, Differential Equations, Approximation Theory, and Image Processing. Nevertheless convolutions often seem unintuitive and difficult to grasp for beginners. This project explores the origins of the convolution concept as well as some computer graphic and physical interpretations of convolution which illustrate various ways the technique of smoothing can be used to solve some real world problems

3.5. Lesion Level Random Forest Classification

This section gives a brief overview of random forests and some comments about the features of the method.We assume that the user knows about the construction of single classification trees. Random Forests grows many classification trees. To classify a new object from an input vector, put the input vector down each of the trees in the forest. Each tree is grown as follows:

- If the number of cases in the training set is N, sample N cases at random - but with replacement, from the original data. This sample will be the training set for growing computed for each pair of cases. If two cases occupy the same terminal node, their proximity is increased by one the tree.
- If there are M input variables, a number m<<M is specified such that at each node, m variables are selected at random out of the M and the best split on these m is used to split the node. The value of m is held constant during the forest growing.
- Each tree is grown to the largest extent possible. There is no pruning.

The convolution of two functions is an important concept in a number of areas of pure and applied mathematics such as Fourier analysis, Differential Equations, Approximation Theory, and Image Processing. Nevertheless convolutions often seem unintuitive and difficult to grasp for beginners. This project explores the origins of the convolution concept as well as some computer graphic and physical interpretations of convolution which illustrate various ways the technique of smoothing can be used to solve some real world problems Most of the options depend on two data objects generated by random forests. *W*hen the training set for the current tree is drawn by sampling with replacement, about one-third of the cases are left out of the sample. This data is used to get a running unbiased estimate of the classification error as trees are added to the forest. It is also used to get estimates of variable importance. An inflammations are determined by considering contiguous (defined by 18-connectedness in threedimensions) sets of voxels labelled as new lesion. The subset of new lesion candidates that meet a minimum size requirement of three voxels (as is the clinical norm) form the input to a second, lesion-level classification stage using a random forest classifier. A random forest is a discriminative classifier that consists of a ensemble of decision tree classifiers, where the final classification is determined by summing the votes cast by each individual trees.

Using random subsets of training data and features for each individual tree helps prevent over fitting, to which traditional decision tree classifiers are prone. Random forests have shown to be powerful classifiers for a number of different classification tasks, including MS lesion segmentation. By considering lesions as a whole, we can extract higher level features for a lesion-based (as opposed to voxel-based) classification. The Random Forest classifier provides as output a confidence measure between 0 and 1 for each new lesion candidate, corresponding to the percentage of individual decision trees that classified the candidate as new lesion. Our final solution, consisting of a set of new lesions, is then the set of new lesion candidates that meet a user-defined threshold.

4. Implementation

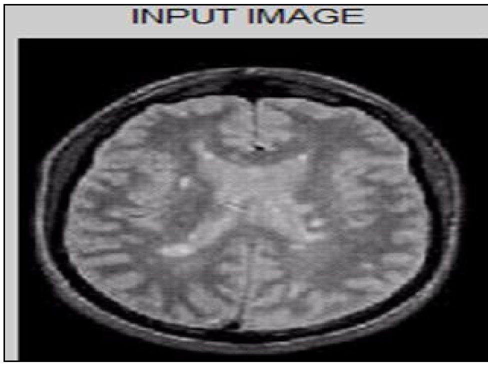

Figure 4: Train Image

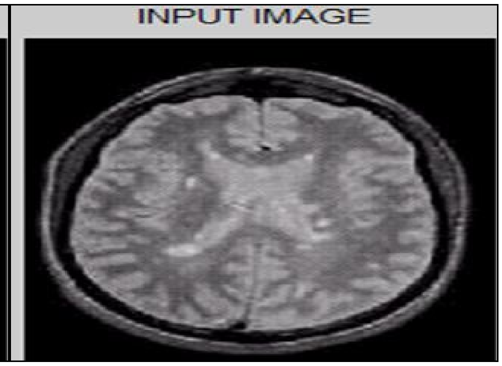

Figure 5: Test Image

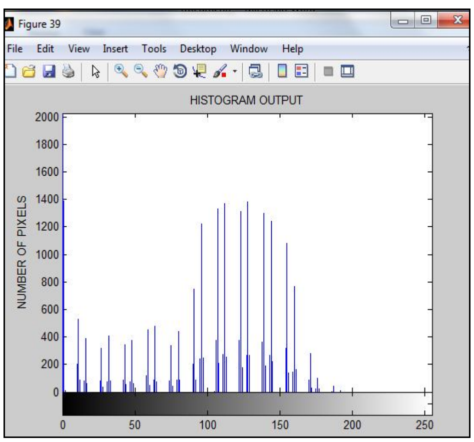

Figure 6

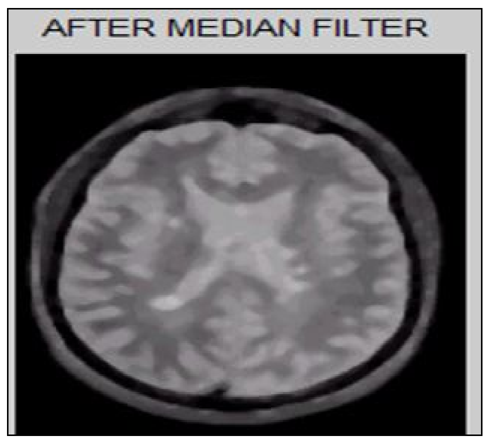

Figure 7

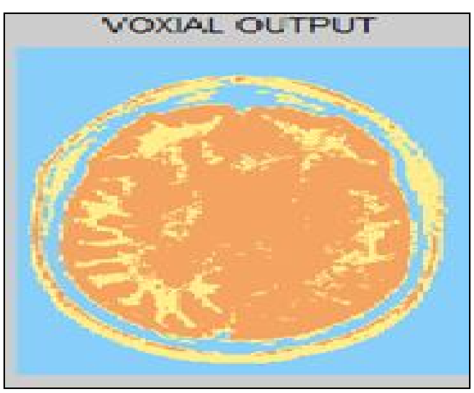

Figure 8

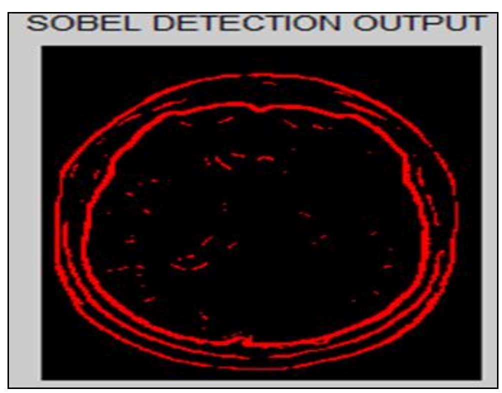

Figure 9

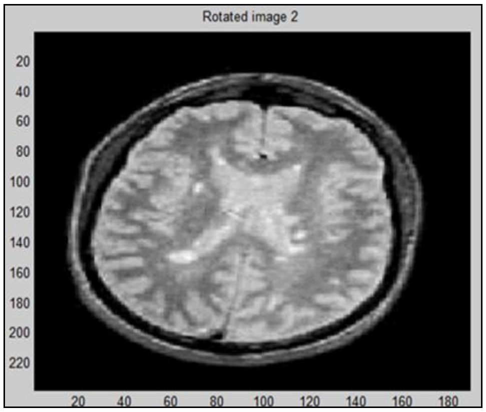

Figure 10: Less Level Random Field

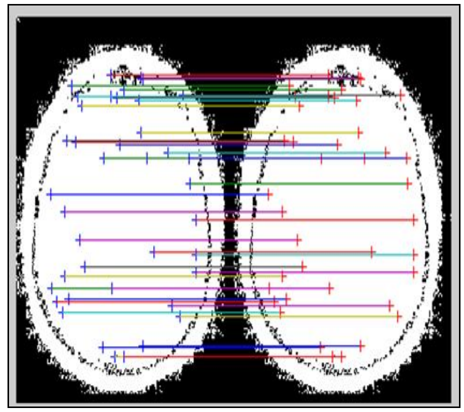

Figure 11: An Inflammation Detection

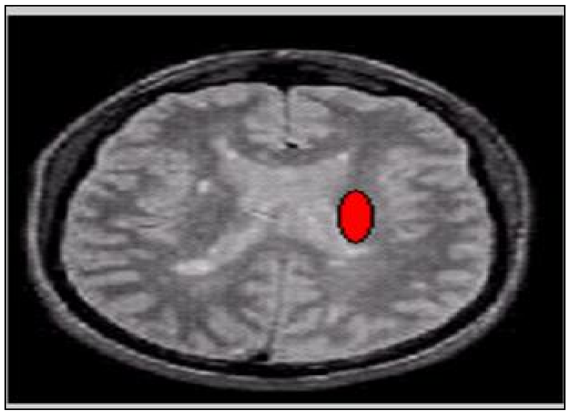

Figure 12

5. Conclusion and Discussion

We have presented a framework for automated detection of new MS lesions using a two-stage classifier that first performed a joint Bayesian classification of tissue classes at each voxel of reference and follow-up scans using intensities and intensity differences, and then performed a lesion-level classification using a random forest classifier. The new lesion classifier allows for trade-off of sensitivity and specificity through the use of a user-specified confidence threshold (or target sensitivity). Sample points of operation showed that our classifier is able to detect new lesions as small as three voxels with a sensitivity and false detection rate and a sensitivity with false detection rate as compared to a reference standard. Comparisons to manual identification of new lesions using only sequential FLAIR scans showed better performance than any individual expert rater and comparable performance to consensus segmentation combining manual identification of new lesion from nine independent raters

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