AUTOMATED DETECTION OF MULTIPLE SCLEROSIS LESIONS – A COMPARISON BETWEEN SVM AND NESTED SVM

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Abstract- **Multiple sclerosis (MS) is an autoimmune disorder and potentially debilitating disease which is accompanied with degradation of myelin sheath. It is mainly characterized by white matter lesions. The main objective is to assess the changes in brain Fluid Attenuated Inversion Recovery (FLAIR) Magnetic Resonance (MR) images with clinical judgment to provide accurate assessment of MS disease progress and to segment the lesions and assist neurologists in order to provide the most effective therapeutic regime, with least human intervention. Three main steps are performed in the process of detection of MS lesions which include preprocessing, in order to make the image suitable for further processing and extract the feature set to train the Support Vector Machine (SVM) and Nested Support Vector Machine and finally segment the lesions using the trained samples. SVM achieves robust pattern recognition performance. Nested SVMs compared to non nested SVMs exhibit more stable rankings and decreased sensitivity to parameter settings.**

Keywords- **Multiple Sclerosis (MS), Fluid Attenuated Inversion Recovery (FLAIR) Magnetic Resonance (MR) images, Support Vector Machine (SVM), Nested Support Vector Machine.**

I. INTRODUCTION

Multiple sclerosis (MS) is a demyelinating autoimmune disease. A healthy, functioning immune system seeks to protect the body by attacking foreign bodies and substances; autoimmune diseases occur when the body's immune system attacks itself. It represents a common cause of neurological disability in young adults resulting from the interruption of myelinated tracts in the central nervous system. With MS, the immune system attacks the body's tissues (brain and spinal cord myelin is damaged or destroyed). The name "Multiple Sclerosis" means that a patient has more than one sclerosis, which is a plaque, or lesion that can appear both in the white matter and in the gray matter of the brain, or in the spinal cord. Lesions can lead to a breakdown of the myelin sheath, the protective layer surrounding the axons. This breakdown is known as demyelination. The disorder is most commonly diagnosed between ages 20 and 40, but can be seen at any age. MS is caused by damage to the myelin sheath, the protective covering that surrounds nerve cells. When this nerve covering is damaged, nerve signals slow down or stop. The symptoms, severity, and course of MS vary widely depending partly on the sites of the plaques and the extent of the demyelination. This is the reason why MS is an extremely unpredictable disease: lesions can occur anywhere in the central nervous system and the stages and rates of demyelination vary depending on the lesion.

The type of symptoms depends on the location of the damage. Symptoms commonly include bladder problems, such as urinary incontinence, bowel problems, such as constipation, cognitive problems (e.g., memory loss), difficulty in walking, dizziness and sensations of spinning, extreme tiredness, headache, hearing loss, itching, mental health problems (e.g., depression), muscle stiffness or spasms, numbness and tingling, pain, seizures and sexual problems such as reduced sensation.

Tests to diagnose multiple sclerosis include: Lumbar puncture (spinal tap) for cerebrospinal fluid tests, including CSF oligoclonal banding, MRI scan of the brain and MRI scan of the spine are important to help diagnose and follow MS, Nerve function study (evoked potential test). All these tests are taken in conjunction with a neurological examination to verify the different symptoms experienced by the patient. Early diagnosis is important, because MS can cause permanent neurological damage and getting on medication as soon as possible can help mitigate the symptoms.

Patients are recommended to seek care from a neurologist experienced in treating multiple sclerosis. MS symptoms are managed through a combination of treatment approaches that include medications, self-care, and physical and occupational therapy. Investigators are studying the benefits of stem cell transplantation procedures. Stem cells are produced in the bone marrow and are the early forms for all blood cells in the body (including red, white, and immune cells). Early studies indicate that stem cell transplantation may slow MS progression. Larger randomized controlled trials are currently under way.

II. REVIEW OF PREVIOUS METHODS

Using Fuzzy connectedness J.K. Udupa et al (1997) proposed a methodology used for estimation of MS lesion volume using dual echo fast spin echo MR imagery. T2 and PD images were used to detect lesions. Delineation of lesions is done by fuzzy connectedness. Lesion quantification is performed by concepts related to fuzzy connectedness and algorithms for extracting a fuzzy object in a given image. Performance in recognizing lesions was not perfect and therefore we need operator assistance. Through manual segmentation intra and inter operator correlation coefficient and overall coefficient of variation is found. False positives are eliminated by the operator and user assistance is needed in accepting or rejecting computer detected lesions which is time consuming and tedious.

Koen Van Leemput et al (2001) [3] proposed a method for the segmentation of MS lesions using model outlier detection, in multispectral MR images. Intensity based tissue classification is performed using a stochastic model for normal brain images and detect MS lesions as voxels. MS lesions are detected as outliers. Disagreement in the degree of spatial correspondence between segmentation by experts and automatic methods is seen.

By Robust parameter estimation algorithm, Faguo Yang et al proposed an automatic algorithm for segmentation of white matter lesions in brain MRI. Assuming the intensity values to be Gaussian distributed, mean vector and Covariance matrix is estimated using a tissue distribution model. A measure defined the content of voxel belonging to lesions. Prior knowledge about brain tissue distribution is essential to estimate model parameters, which helps improve the robustness of the algorithm.

R. Khayatia et al.(2008) [4] presenting an approach for fully automatic segmentation of MS lesions in Fluid Attenuated Inversion Recovery (FLAIR) Magnetic Resonance (MR) images using Bayesian Classifier in Adaptive Mixtures Method (AMM) and Markov Random Field (MRF). MRF model is used to obtain and upgrade the class conditional probability density function (CCPDF) and the a priori probability of each class. Priori probabilities of the classes as well as parameters of the classes (i.e., means and variances) are attained and updated, utilizing MRF model and AMM. Training samples were not needed.

Multivariate pattern classification was used by Zhiqiang Lao et al (2006) [7] for Automated Segmentation of White Matter Lesions in 3D Brain MR Images. It is based on local features determined by combining multiple MR acquisition protocols, including T1-weighted, T2-weighted and Proton Density (PD)-weighted and Fluid Attenuation Inversion Recovery (FLAIR) scans. The segmentation result of the rater was used for evaluating inter-rater agreement and for comparing it against computer-rater agreement. The amount of intensity overlap between WMLs and normal tissue varies greatly across different modalities. SVM is used here as a classifier for WML segmentation. It is essential to select typical non-lesion samples to train SVM, instead of using the whole set of non-lesion samples. Misregistration usually results in a significant number of false positive segmentations around the cortex. The extracted features are not as sensitive to misregistration. The proposed automatic lesion segmentation algorithm is reasonably highly correlated to the manual raters, while being consistent and reliable relative to the inter-rater agreement.

Sushmita Datta and Ponnada A. Narayana (2012) [5] proposed a segmentation method for multichannel three-dimensional MR brain images in multiple sclerosis which uses a comprehensive and automated segmentation technique that combines nonparametric and parametric statistical techniques to classify tissues\lesions on the high resolution 3D images. The skull-stripped images were corrected for intensity non uniformity using the module in SPM2 followed by the application of anisotropic diffusion filter to reduce noise while preserving the edges. The numbers of training points were selected for GM, WM, CSF and lesions. It also includes novel features to improve the overall classification while automating the technique. Novel features such as integrating anatomical knowledge using the brain template for minimizing false classifications and improving the parcellation of gray matter structures. Here the focus is only on the classification of THWLs along with GM, WM, and CSF. There is a very small fraction of false classifications that could result from misalignment of FLAIR with T2 images following the rigid body registration.

Elizabeth M. Sweeney et al.(2013) [2] has proposed an automated statistical method for segmenting MS lesions in MRI studies which includes logistic regression models incorporating multiple MRI modalities to estimate voxel-level probabilities of lesion presence. The OASIS (Automated Statistical Inference for Segmentation) method involves two iterations of model fitting: the first is to perform initial lesion segmentation and the second is to use this initial lesion segmentation to remove lesions, which can distort the smoothed volumes. After the final model is fit, the regression coefficients are applied to produce three dimensional maps of voxel level probabilities of lesion presence. OASIS method is trained on a subset of dataset. The total number of lesions and the total lesion volume is computed either by manual or semi automated segmentations. A recalibration of the population-level segmentation threshold is necessary for each new data. The threshold is adjusted manually.

III.METHODOLOGY

The proposed work is a series of steps involved in segmentation of MS Lesions: Data acquisition, Preprocessing, Feature Extraction, Training using SVM and Nested SVM and Segmentation of MS Lesions. Fig 1 shows the block diagram of the proposed work:

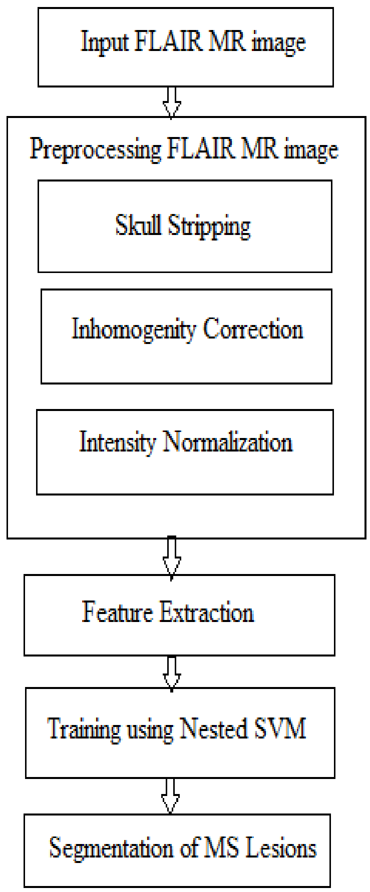


Fig 1: Block diagram of the proposed work

i. Preprocessing:

The initial step performed in preprocessing of the MR image is skull stripping and this is done to remove the non brain portion of the image. Inhomogeneity correction is performed to remove the noise due to poor coil performance and eddy currents. Intensity normalization is performed using image enhancement techniques. Preprocessing using the above steps makes the image suitable for further processing.

ii. Feature Extraction:

The best choice for applications involving very high dimensional data is feature selection. From the available data we select a subset of relevant features before using it for training. This avoids overfitting and improves the generalization ability of the final classifier. When the features are selected we get a better understanding and ability to visualize the data. Feature extraction is done using histogram based features like mean variance entropy and co occurrence matrix based features like skewness and smoothness index. These values are extracted in order to train the SVM or Nested SVM.

Mean: $\mu=\sum_{i=0}^{G-1} ip(i)$

Variance: $\sigma^2=\sum_{i=0}^{G-1}(i-\mu)^2\, p(i)$

Entropy: $-\sum_{i=0}^{G-1}\ \sum_{j=1}^{Nf} co(i,j)log_2(co(i,j))$

Skewness: $\mu_4=1/\sigma^4\sum_{i=0}^{G-1}(i-\mu)^4 p(i)-3$

iii. Training and Segmentation:

Support Vector Machine:

Like any classifier, the aim of an SVM is to find a decision function that tends to separate the samples with minimal error. Once the Support Vector Machine is trained the lesions in the input samples are segmented with the help of the extracted features. In Machine learning, Support Vector Machine (SVM) is a supervised classifier with associated learning algorithm that analyzes data for classification and outlier's detection. SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. In simple, SVM locates the hyper-plane that separates the decision functions into two classes for the dataset. SVM model is a representation of the points in feature space.

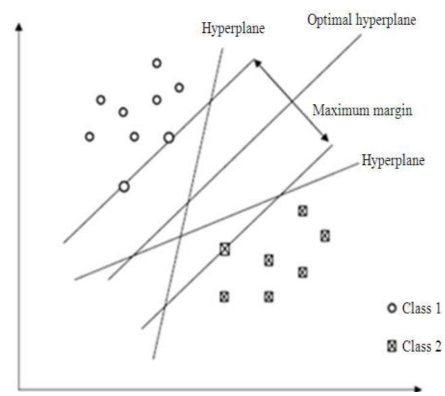


Fig. 2: SVM classification

SVM minimizes the bound on the errors made by the learning machine over the test dataset which were not used during training. It does not minimize the objective function of the training datasets. Hence, SVM performs perfectly over the images that do not belong to the training dataset and learning of difficult datasets during its training process. Such difficult to classify datasets in training are called Support Vectors. In fig. 2, the classes are separated by a margin denoted by points which is marked as 'X's and 'O's after the location of hyper-plane using SVM classification. In this Support Vectors are present near the boundary of a hyper-plane of the two classes. SVM has been proved as one of the most accurate classifier with high efficiency and also with accuracy in classifying results. SVMs are still effective in cases where number of dimensions is greater than the number of samples.

Nested Support Vector Machine:

The One-Class Support Vector Machine (OC-SVM) and Cost-Sensitive Support Vector Machine (CS-SVM) are state-of-the-art machine learning methods for estimating density level sets and solving weighted classification problems, respectively. As in the case of nested SVM the hyperplane is used to minimize the generalization error of the classifier. An SVM ensemble model is constructed by training an individual SVM on each nested feature set. The ensemble methodology is adapted for combining a large number of feature set. Feature sets extracted may have different dimensionalities. Ensemble is employed in order to improve the classification accuracy. In a random sample we denote R_d as a d-dimensional feature vector and y_i as is its class; in one-class classification, all the y_i's are the same; the SVM finds a hyperplane that separates data in high dimensional space H based on maximum margin principle. A reproducing kernel Hilbert space H is generated by a positive semidefinite kernel k and this kernel function k corresponds to an inner product in H.

One- Class SVM:

One class SVM is used to estimate a level set of an underlying probability density given a data sample from the density. OC-SVM solves optimization problems via its dual nature, which depends only on a set of Lagrange multipliers. These Lagrange multipliers define a decision function that determines whether a point is an outlier or not. Generally, only a fraction of the Lagrange multipliers take non-zero values; and are called support vectors.

Cost Sensitive SVM:

Original SVM solves errors in both classes equally and there are many cases where the numbers of data samples from each class seem unbalanced or false negatives and false positives incur different costs. This issue can be handled using CS-SVM.

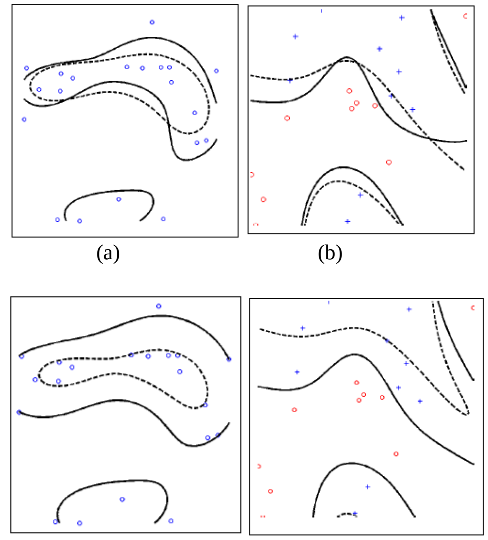
Nested One-Class SVM:

Nested SVM uses an alternative formulation of the OC-SVM involving a different parameter λ, which traces out the same class of decision functions, and asymptotically has a one-to-one correspondence to the original parameter.

For a Nested SVM a finite number of density levels are selected and a finite family of nested level set estimates is generated. Decomposition algorithm is used to find the estimate set obtained through feature extraction performed on the MS lesion.

Nested Cost-Sensitive SVM:

Nested CS-SVMs are capable of producing nested positive decision sets depending upon the training feature. This can also be performed similar to the OC-SVM.



(a) (b)

(c) (d)

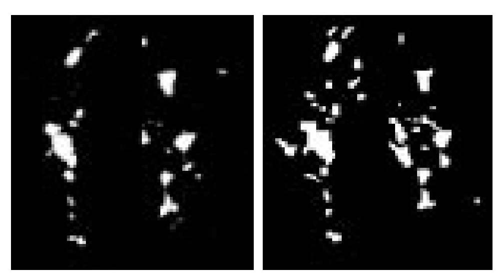
Fig 3. (a) One Class SVM (b) Cost Sensitive SVM (c) Nested OC-SVM (d) Nested CS-SVM

Like the solution paths for conventional SVMs, nested SVM solution paths are also piecewise linear in the control parameters, but require far fewer breakpoints.

IV.RESULTS AND DISCUSSION

Initially pre-processing is done to remove the non-brain tissues and also to improve the contrast of FLAIR MR Brain images. Feature extraction methods are used to get textural features which acts as an input to our classifier.

Two classifiers are used namely Support Vector Machine and Nested Support Vector Machine. Support Vector Machine is a binary classifier which is used to orientate hyperplane in such a way as to separate from the closest members of both classes. As shown in the above descriptive figures, Nested Support Vector Machine linearly interpolates the coefficients of finite nested collections. The entire algorithm was developed based on MATLAB code.



(a) (b)

Fig 4. (a) Segmentation using SVM (b) Segmentation using Nested SVM

V. CONCLUSION

In one class problems, all the instances are assumed from the same class. We develop the nested cost-sensitive SVM (NCS-SVM), which aims to produce nested positive decision sets.

In this paper, we have introduced a fully automatic detection of Multiple Sclerosis lesions in brain MR images. Our approach is to compare the performance of Support Vector Machine. SVM demonstrates great potential and usefulness in segmentation and nested SVMs exhibit greater stability. Automatic processing for one patient can be done in a less time in an ordinary computer while the manual segmentation could take hours. Results obtained in this paper have shown that the segmentation results using nested SVM outwit those of non-nested SVM and these prove to be better than the other supervised learning algorithm. To conclude, the proposed scheme is a novel and user friendly segmentation from practical view point.

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