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Multiple sclerosis detection from brain MRI images using least square-SVM

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Abstract

Multiple sclerosis (MSC) is a disease that impairs brain-to-body communication by causing the immune system to attack the protective sheath that surrounds nerve fibers. Early detection of the disease is very important so that proper medication helps an individual to recover. In this work, a framework based on LS-SVM has been proposed to detect multiple sclerosis from brain Magnetic Resonance Images (MRI). The proposed framework is categorized into four stages: named as pre-processing, extraction of the region of interest, segmentation of multiple sclerosis using LS-SVM, and, evaluation of results. During MRI image procurement the image is contaminated by the noise from scanners which is successfully eliminated in pre-processing stage by contrast enhancement and histogram equalization. The region of interest (ROI) is extracted from its skull by morphological operations followed by Gaussian filtering and adaptive histogram equalization. Multiple sclerosis is detected from ROI images by using LS-SVM-based segmentation. Finally, results are evaluated on various evaluation metrics such as accuracy, sensitivity, specificity, Dice

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and Jaccard. An overall accuracy of 96.39% has been achieved in multiple sclerosis extraction from brain MRI images.

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1. Introduction

Multiple sclerosis is an autoimmune condition that damages healthy parts of the brain and spinal cord [1] which comprise of central nervous system. The neurological system in MS is typically destroyed, including the myelin coating, nerve fibres, and the cells which make the myelin. If the injuries are serious, they may permanently alter the brain and spinal cord [2]. Multiple sclerosis is a neurological disease and thus the proposed framework is based on MRI Images. Researchers have suggested a number of different techniques in this domain of multiple sclerosis detection and can be categorized as supervised [3-9], unsupervised.

Supervised algorithms can segment MS lesions with high accuracy by the training from previously labelled data. For instance, a thorough analysis of traditional segmentation methods such as thresholding, region expanding, and Bayesian methods is provided by [3]. Brain MRI image segmentation using automated segmentation algorithms [4] showed the effectiveness of atlas-based segmentation. On various imaging modalities, the likelihood that a voxel represents a component of a lesion was predicted using logistic regression [5]. For MS lesion segmentation, a boosting classifier-based segmentation makes use of contextual information and prior knowledge [6]. Automatic segmentation using a voxel-by-voxel categorization utilising a knowledge-based method [7]. Semi-supervised clustering was utilised to automatically segment MRI images [8].

In the current study, an attempt has been made to design an optimal fit MSC lesion segmentation model with low computational cost and high accuracy. The significant contribution of the proposed framework for MSC detection are as follows:

(1) To extract MSC from brain MRI images with higher precision.
(2) To design LS-SVM based framework for the extraction of MSC from brain MRI images which require fewer samples for training as compared to DL based model which in turn reduces hardware cost.

The remaining paper is organized as follows; dataset and methodology of the proposed framework are described in Section 2. The experimental results are described and discussed in Section 3. Finally, the work is concluded in Section 4.

2. Dataset and Methodology

In this section the dataset has been used to extract MSC from brain MRI images is described.

2.1 *Dataset Description*

The images used for the extraction of MSC from MRI images is obtained from dataset of Brain Magnetic Resonance Imaging Dataset of Multiple Sclerosis with Consensus Manual Lesion Segmentation and Patient Meta Information [9]. The MSC lesion exist in each modality is visible but most clearly visible in FLAIR as mentioned in Figure 1.

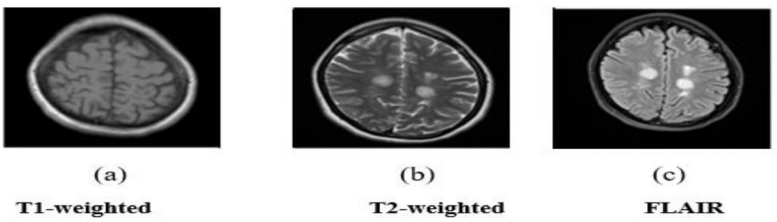


Figure 1

Sliced brain MRI of same patient (a) T1 weighted (b) T2 Weighted (c) FLAIR

2.2 *Proposed Methodology*

In this work, a multistage framework based upon mathematical morphology, pixel-based classification using LS-SVM has been proposed. The steps in the proposed framework are: Pre-processing, pixel-based classification and performance evaluation. Pre-processing includes mathematical morphological operations for image enhancement and skull removal. Pixel-based classification using LS-SVM methodology and performance evaluation using five different performance metrics. Figure 2 describes the different phases of the multistage framework's implementation.

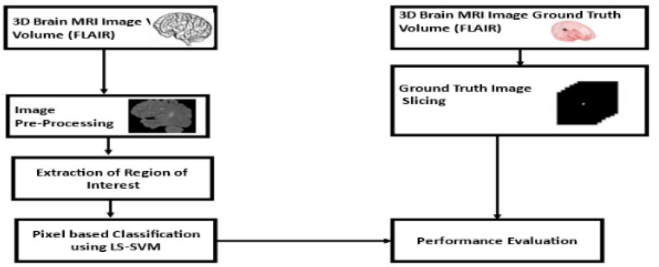


Figure 2

Proposed Framework

2.2.1 Pre-processing

Brain volume images requires pre-processing to remove noise and to extract only brain region for getting the accurate details in the diagnosis process.

a. **Slicing**

Image Slicing has been performed on MRI images (FLAIR) present in the dataset.

b. **Contrast elongation**

Let I be the RGB image obtained after slicing of 3-D brain MRI image. Contrast elongation has been performed on I to get I_{ac} at the lower threshold of 0.15 and greater than 0.2.

c. **Histogram Equalization**

In this step, histogram equalized image I_{he} has been constructed from the input image I to improve intensity level contrast of the image.

d. **Thresholding**

In this step, thresholding is performed on the image obtained by the product of I_{ac} and I_{he} to obtain I_{th} image so as to eliminate the low intensity regions.

e. **Mathematical Morphological Operation**

Opening operation has been performed on I_{th} image with a sphere radius of 6 voxels to isolate the brain skull getting I_{brain} image [10]. Opening operation is erosion followed by dilation as mentioned in Eq. (1).

$$I_{brain} = Dilation(Erosion(I_{otsu})) \tag{1}$$

f. **Gaussian Filtering**

Gaussian Filtering has been applied for image smoothing on I_{bo} image obtained after product of input image I and I_{brain}. Let y be the intensity value of I_{bo} image obtained in the above step then Image after gaussian filtering (using standard deviation as 0.8) has been obtained as mentioned in the Eq. 2

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} * e^{\frac{-y^2}{2\sigma^2}} \tag{2}$$

2.2.2 Pixel-based Classification using LS-SVM

In this step to identify the MSC lesion from non- MSC region a supervised technique called as least square support vector analyses data and finds patterns which are used for the classification task. It is a variant of SVM because of reformulation of the objective function. This classification task has been performed by placing equality constraints instead of inequalities in traditional SVM. For linear LS-SVM, classifier formulation is as explained in Eq 3. In this μ and $\hat{u}$ are hyperparameter to tune the regularization w is the weight vector, e is error, b is linear coefficient estimated from training data.

$$J(w,b,e) = \mu E_w + \supset E_D \tag{3}$$

$$E_w = \frac{1}{2} w^T w \tag{4}$$

$$E_D = \frac{1}{2}\sum_{i=1}^{N} e_i^{\,2} = \frac{1}{2}\sum_{i=1}^{N} (y_i - (w^T \varphi(x_i) + b))^2 \tag{5}$$

Radial basis function (RBF) kernel is employed, μ for regularization constant and σ for the width of the kernel. The explanation for the LS-SVM results can be found in Eq 6.

$$M(x) = \begin{cases} 1, & \text{if pixel belongs to multiple sclerosis} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

2.2.3 Evaluation Metrics

To estimate the segmentation performance different performance parameters are identified as mentioned in Eq. 7-11. These parameters are:

True Positive (T_P) = True Positive are MSC pixels present in both ground truth image and MSC extracted by proposed framework.

True Negative (T_N) = True Negative are non- MSC pixels not present in both ground truth image and image extracted by proposed framework.

False Negative (F_N) = False negative are the pixels that are MSC in ground truth image but present as non-MSC in the image extracted by the proposed framework.

False Positive (F_P) = False positive are the pixels that are non-MSC in ground truth image but present as MSC in the image extracted by the proposed framework.

$$\text{Sensitivity} = \frac{T_P}{T_P + F_N} \tag{7}$$

$$\text{Specificity} = \frac{T_N}{T_N + F_P} \tag{8}$$

$$\text{Accuracy} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{9}$$

$$\text{Dice Score} = \frac{2 * T_P}{2 * T_P + F_P + F_N} \tag{10}$$

$$\text{Jaccard} = \frac{T_P}{T_P + F_N + F_P} \tag{11}$$

3. Experimental Results and Discussion

3.1 *Experimental Settings*

The experiments have been performed in MATLAB R2022a. environment on system having 2.5 GHz i5 CPU, RAM of 16GB and graphic card of NVIDIA RTX. Figure 3, 4, 5 and 6 provides the segmentation results.

3.2 *Experimental Results and Analysis*

CLAHE enhancement has been performed after image pre-processing as CLAHE works on low contrast medical images.

Test Case-1 In this test case, MRI images are selected from Group-1 having MSC in glowing condition. After pre-processing contrast limited adaptive histogram equalization has been performed with a clip limit of 0.005 and uniform distribution to make finer details visible in brain MRI.

The experimental results are evaluated on different metrics as shown in Table 1.

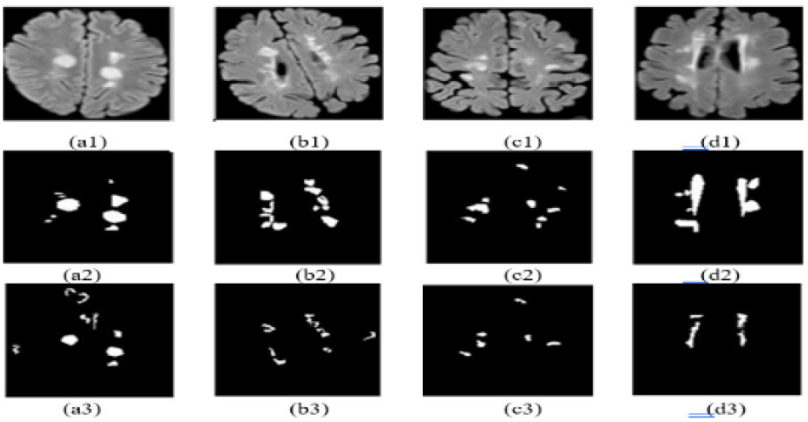


Figure 3

G-1 Segmentation Results (a1-d1) Pre-processed Image (a2-d2) Ground Truth Image (a3-d3) Least-Square Support vector Machine Segmented brain Image.

Table 1

Segmentation Performance of Group-1 brain MRI Images

Figure	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice (%)	Jaccard (%)
Fig. 3(a1)	97.24	46.04	99.11	54.01	36.99
Fig. 3(b1)	96.84	26.29	99.60	38.52	23.85
Fig. 3(c1)	98.53	38.86	99.81	52.54	35.63
Fig. 3(d1)	95.61	20.94	99.85	33.91	20.42

Test Case-2 In this test case, MRI images were chosen in which MSC is not in glowing condition but it is visible in MRI image. After pre-processing contrast limited adaptive histogram equalization has been performed with a clip limit of 0.02 and Rayleigh distribution to improve interpretation of MSC pixel. The experimental results are evaluated on different metrics as shown in Table 2.

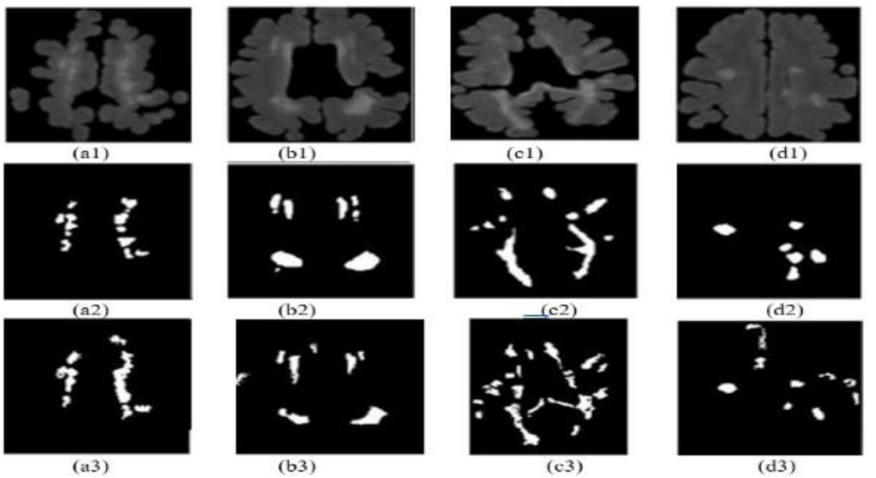


Figure 4

G2-Segmentation Results (a1-d1) Pre-processed Image (a2-d2) Ground Truth Image (a3-d3) Least-Square Support vector Machine Segmented brain Image.

Table 2

Segmentation Performance of Group-2 brain MRI Images

Figure	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice (%)	Jaccard (%)
Fig. 4(a1)	97.57	83.02	98.05	68.75	52.38
Fig. 4(b1)	97.06	59.08	99.21	68.25	51.80
Fig. 4(c1)	93.55	61.00	95.93	56.27	39.15
Fig. 4(d1)	96.95	42.86	98.53	44.42	28.55

Test Case-3 In this test case, MRI images were chosen in which MSC is not in glowing condition as well as only thin details of MSC is visible as MSC is at many different locations of brain MRI image. After pre-processing contrast limited adaptive histogram equalization has been adopted with a clip limit of 0.0005 and Rayleigh distribution. The experimental results are evaluated on different metrics as shown in Table 3.

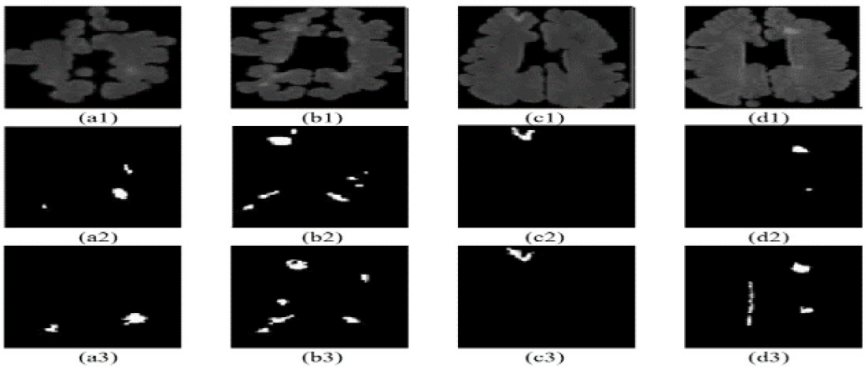


Figure 5

G3-Segmentation Results (a1-d1) Pre-processed Image (a2-d2) Ground Truth Image (a3-d3) Least-Square Support vector Machine Segmented brain Image.

Table 3

Segmentation Performance of Group (G3) brain MRI Images

Figure	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice (%)	Jaccard (%)
Fig. 5(a1)	99.17	60.00	99.55	57.99	40.84
Fig. 5(b1)	98.81	66.07	99.36	64.53	47.64
Fig. 5(c1)	99.69	70.83	99.85	71.13	55.19
Fig. 5(d1)	99.15	96.43	99.17	51.43	34.62

Test Case-4 In this test case, MRI images were chosen in which MSC is not visible. Contrast limited adaptive histogram equalization has been performed with a clip limit of 0.01 and exponential distribution to prevent over saturation. The experimental results are evaluated on different metrics as shown in Table 4 and 5.

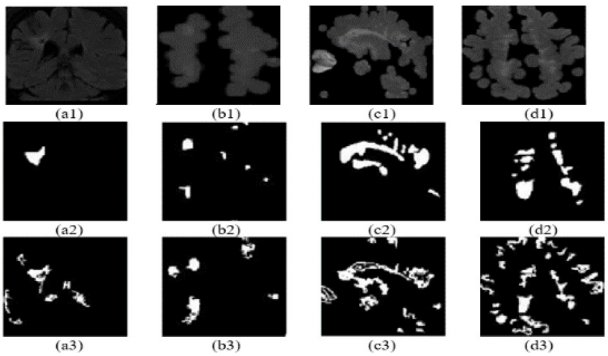


Figure 6

G4-Segmentation Results (a1-d1) Pre-processed Image (a2-d2) Ground Truth Image (a3-d3) Least-Square Support vector Machine Segmented brain Image.

Table 4

Segmentation Performance of Group-4 brain MRI Images

Figure	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice (%)	Jaccard (%)
Fig. 6(a1)	97.23	75.98	97.52	42.41	26.91
Fig. 6(b1)	96.27	74.09	96.68	42.06	26.63
Fig. 6(c1)	92.24	59.56	94.68	51.56	34.73
Fig. 6(d1)	89.01	57.91	90.98	38.62	23.93

Table 5

Overall Segmentation Results for 60 patients

Group	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dice (%)	Jaccard (%)
Group-1	96.93	22.48	99.75	31.95	20.05
Group-2	93.58	65.88	94.71	42.28	28.95
Group-3	89.35	46.32	90.28	32.17	21.83
Group-4	77.45	64.93	77.92	12.11	7.32

4. Conclusion

This paper has presented a multistage framework to segment MSC lesion from two-dimensional slice of a three-dimensional brain magnetic

resonance nifty image. In the proposed approach, pre-processing has been applied and four groups have been identified based on the lesions present in the image. Afterword MSC and non-MSC pixels are classified using LS-SVM segmentation technique. Segmentation performance has been analyzed and an accuracy of 96.39% has been achieved in the MSC extraction from sliced brain MRI image. An overall maximum sensitivity of 65.88% (shows the correct identification of MSC pixels) and maximum specificity of 99.75% (shows the correct identification of non-MSC pixels) has been achieved. In the future, we like to experiment with various feature extraction techniques in order to uncover more important features that are accountable for segmentation accuracy.

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