Analysing thalamus and its sub nuclei in MRI brain image to distinguish schizophrenia subjects using back propagation neural network

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Abstract: In this paper, we presented precise and proficient techniques for measuring the human thalamus, medial dorsal and the pulvinar nucleus with magnetic resonance imaging (MRI). In spite of the fact that thalamic nuclei are not straightforwardly visible on traditional MRI image. We applied a novel and competent image pre-processing techniques to enhance the visual quality of MRI image. In addition to this we have used various segmentation algorithms to accurately extract entire thalamus from brain MRI images. Diffusion MRI is used to extract various nucleus of thalamus. Several optimal features such as textures, morphological are derived from thalamus and medial dorsal regions which are then used to train the artificial neural network model (ANN). Our artificial neural network model accurately classifies between schizophrenic and healthy subjects based on thalamic anatomy for larger sample sizes.

Keywords: thalamus; artificial neural networks; magnetic resonance imaging; MRI; schizophrenia; GLCM; sobel; level set; fast marching.

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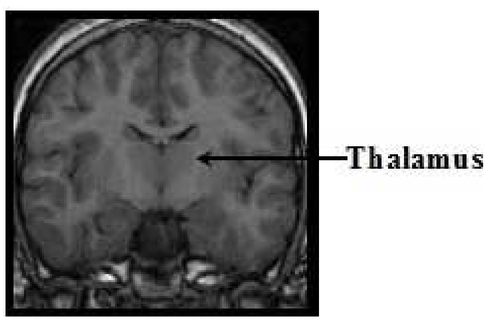
1 Introduction

The thalami are the parts of the forebrain superior to the midbrain, close to the focal point of the mind with nerve filaments anticipating out to the cerebral cortex. Both parts of this structure of the mind in the human are each about the size of a walnut. These are around three centimetres long, at the most stretched out section 2.5 centimetres crosswise over and around 2 centimetres in stature. The two thalami are noticeable bulb shaped masses, around 5.7 cm long.

The thalamus is frequently depicted as a transfer station in light of the fact that a lot of the data that returns to the cerebral cortex initially stops in the thalamus before being sent on to its goal. The thalamus is subdivided into various nucleus that have useful specialisations for managing specific sorts of data. At the foremost of the thalamus is a core called the front nucleus. It is widely associated with the hippocampus and is thought to be required in memory. The dorsomedial nucleus is thought to be required in emotional behaviour and memory. The ventral front nucleus and ventrolateral nucleus are thought to be required in motor functions. The pulvinar nucleus is a substantial nucleus that is involved in processing visual stimuli. A few neuro-pathological thinks about have announced variations from the norm in thalamus could prompt subjective brokenness that portrays schizophrenia.

Figure 1 Thalamus coronal view



Schizophrenia is turmoil of the brain influencing how one act thinks and sees his general surroundings. People with schizophrenia have a changed view of reality and may see you or hear things that are not genuine talk in bizarre ways or feel that they are being kept an eye on feel that others are attempting to hurt them makes it troublesome for them to work in some cases with typical exercises of everyday life.

Schizophrenia can be classified into three gatherings, for example, positive, negative and disrupted in view of relative manifestations. Constructive side effects incorporate hallucinations and delusions the individual has a troublesome time deciphering what is genuine. Negative manifestations incorporate loss of inspiration and trouble discovering delight and fun exercises. They may display decreased passionate expression and discourse. A complicated manifestation depicts surprising intuition and discourse or odd conduct and additionally improper reactions to social circumstances.

Figure 2 Schizophrenia subjects thalamus view

Assortment of neuro imaging strategies, for example magnetic resonance imaging (MRI), positron emission tomography (PET), computed tomography (CT) and magneto-encephalography are utilised to examine the structure of thalamus. We have used MRI imaging technique to analyse the anatomy of thalamus.

2 Related work

In Behrens et al. (2003) identified the thalamic nuclei in diffusion tensor imaging. They have applied probabilistic tractographic algorithm to find the connections between thalamus and cortex area. Their outcomes give the main quantitative show of consistent implication of anatomical availability between human gray matter structures utilising dispersion information and the principal network based division of gray matter.

Jonasson et al. (2007) exhibit an extremely delicate similitude measure that recognises exceptionally inconspicuous contrasts between areas inside thalamus. They have introduced a technique for dividing white matter and the gray matter structures from diffusion tensor magnetic resonance images. They have utilised an arrangement of coupled level set functions driven by the region based constrain including each of the tensors having a place with a specific region. Their proposed strategy has a higher adaptability in regards to the state of the nucleus and that it lessens the impact of noise because of the self-regularisation of the surfaces. In expansion to that their technique produces great outcomes for division of the thalamus.

Spinks et al. (2002) gives a reliable, computerised technique for outlining the entire thalamus. They have utilised the colourised tricolour image to help the manual analysis better recognise the fringes of the structure. To define thalamus and medial dorsal automatically they adopted ANN model. The efficiency of their artificial neural network model was measured using intra-class correlations and percentage of overlay assessment.

Heckenburg et al. (2006) suggested a self-loader thalamus division technique that depends on another kind of deformable model Lagrangian surface flow. Both the limit and area data are consolidated in the model development handle so that the model is extremely vigorous to image noise and little gaps. Since the thalamus has low contrast, utilising limit data alone is most certainly not extremely dependable. It is more desirable over consolidate the limit data alongside the region data. They assessed inside likelihood esteem utilising the dissemination by a nonparametric strategy, for example, the Parzen technique since it is differentiable, more nonexclusive.

Rittner et al. (2010) work exhibits a strategy to segment human thalamus by applying the various levelled watershed change to the tensorial morphological gradient delineate from the dispersion tensor field. Their analysis affirmed that the proposed calculation can outline the primary nucleus of the thalamus. Rather than other DTI-based division calculations, their proposed technique requires no manual seed initialisation.

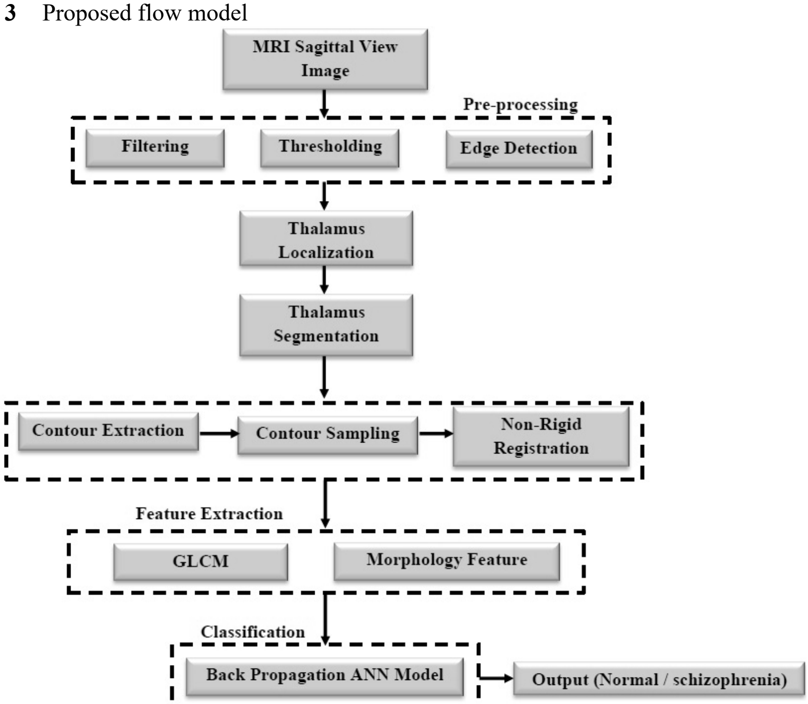
3 Materials and methods

Morphological and texture analysis features was applied to magnetic resonance images of 115 subjects with schizophrenia and 76 normal subjects with average aging. The T1 weighted magnetic resonance images with sagittal planes were acquired. The morphological parameters were centred on Fourier descriptor and texture parameters were based on grey level co-occurrence matrix. For each subjects ten texture parameters and six morphological parameters were extracted and fed as input to the neural network model.

4 Proposed model

The proposed system mainly alienated into two stages, conformist image acquisition and pre-processing techniques are used in first stage. In second stage a neural network framework was developed to classify disorder subjects from normal.

Figure 3 Proposed flow model



For noise removal we applied median filter which decreases noise by substituting each pixel with the median of the adjacent pixel values. The operation of median filter on the input image $h^1(i^1, j^1)$ is defined as,

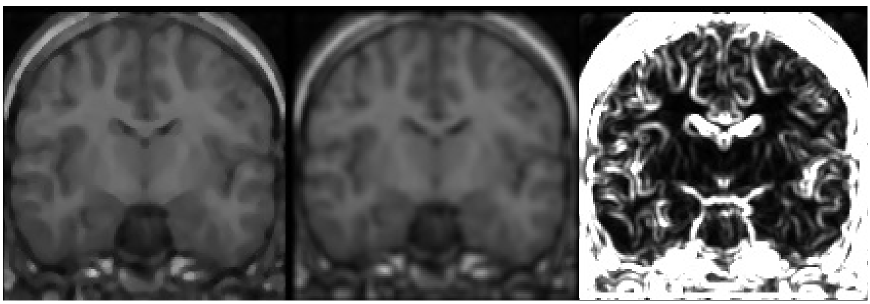
$$f^1(i^1, j^1) = Median_{(i,j)\in N}\{h(i, j)\}$$

whereas,

the locality of the pixel (i^1, j^1) is N.

$f^1(i^1, j^1)$ = smoothing of an input image.

Figure 4 Image filters output, (a) median filter (b) mean filter (c) variance filter

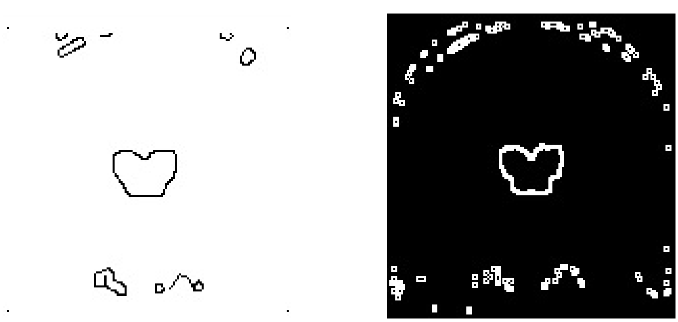


(a) (b) (c)

Figure 5 Kernels for gradient computation in x and y directions

A	B	C
D	x(i, j)	F
G	H	I

Figure 6 Edge detection, (a) canny edge detector (b) sobel edge detector



(a) (b)

The sharp variations in intensity of the input image are detected using sobel edge detector with 3 * 3 kernels. The sobel edge detector calculates the gradient values in an explicit path. To calculate the gradient values in both directions (x, y) we have applied 3 * 3 weighted kernels for convolution as shown in Figure 5.

For each pixel the absolute gradient value is calculated based on the 3 * 3 kernel neighbourhood.

5 Thalamus segmentation

Thalamus division has turned out to be increasingly basic for an extensive variety of medical applications. Thalamus changes regarding volume are included in a substantial amount of diseases. In a perfect domain a segmentation strategy finds the gathering of pixels that compare to anatomical structures or areas of interest for the image, for the most part this is finished by recognise items or districts of interest from everything else. Once the districts of intrigue are segregated from the rest of the image, certain portraying estimations can be made and these can be used to order the regions. The most essential ascribes used to recognise the region of interest on given image are grey intensity level, however in some cases different properties, for example, texture can be utilised.

Figure 7 Segmentation of thalamus, (a) level set method (b) fast marching method

(a) (b)

We have applied partial differential equations based segmentation algorithms such as level sets and fast marching to segment the whole thalamus. In PDE based algorithm the boundaries are found by progressive evaluation of the differences among neighbouring pixels. Generally, the algorithm will congregate at the edge of the object where the variances are the maximum. The basic steps followed in proposed contour based segmentation algorithm are as follows:

a Select the principal seed points from the mid-sagittal plane of thalamus.

b Initiate minor spheres around the seed point inside the mask.

c Compute the mean and standard deviation for inner and outer surfaces.

d Compute the average gradient to the surface at step N, for every point p, on the hyperspace.

e Calculate the vicinity points Np for p, until merging which are lying in the same straight line with respect to p.

f For every pixel the Bayesian decision was taken at point T, based on the parameter,

$$-1 \text{ if } \pi o \; po \; I(T) \geq \pi bg \; pbg \; I(T)$$
$$+1 \text{ if otherwise}$$

where π = area erstwhile probability, p = pdf for object and background.

g Curvature is progressed until the thalamus is segmented.

Table 1 Segmentation method run time

Segmentation methods	*Execution time*
Level set	270 ms
Fast marching	382 ms

6 Image registration

Registration is the procedure where by at least one image are lined up with a reference image. This is essential with the goal that a gathering of images can be viably looked at. Image registration enlistment in the medicinal area is especially troublesome when complex changes are required to relate the images. Image enlistment was embraced to guarantee that all cerebrum MRI checks in a given gathering complied with a solitary arrangement of facilitate axes.

Figure 8 Localisation of thalamus and its sub-nuclei

Mostly the image registration process maps the target image to a fixed image based on certain similarity methods. We have applied mean square error similarity method to measure the variance over all pixels. The MSE method is suitable for images with similar modality.

7 Feature extraction

Registration feature extraction is a dimensionality lessening strategy broadly utilised as a part of image processing techniques. Different approaches such as structural, statistical and transform based methods are adopted for extracting texture behaviour from an image.

For our work we have applied statistical based method which extracts texture features such as GLCMs from MR image in addition to morphologic features like circularity, perimeter, area, compactness, etc. The above said texture features were extracted from segmented mediodorsal, pulvinar sub nuclei and whole thalamus of schizophrenia subjects.

Grey level co-occurrence matrices are square matrices of size N, where N represent total grey level in the given image. Given the distance (d = 1 to 4 pixel, or 5 pixels) and direction ($\theta = 0^o, 45^o, 90^o$, or 135^o) for an element (i, j) of matrices, The GLCM provide number of times grey level i co-occur with grey level j. We have extracted ten parameters such as contrast (x_1), correlation (x_2), sum of squares (x_3), inverse difference moment (x_4), sum average (x_5), sum variance (x_6), sum entropy (x_7), entropy (x_8), difference variance (x_9) and difference entropy (x_{10}) for all subjects. Using these GLCM parameters we have analysed any difference exists among schizophrenia and control subjects.

Table 2 Sample GLCM feature set

GLCM parameters	*Mediodorsal region* (*left*)
Contrast	2.56
Correlation	0.98
Sum of squares	78.01
Inverse difference moment	0.60
Sum average	86.39
Sum variance	309.48
Sum entropy	1.56
Entropy	1.78
Difference variance	1.47
Difference entropy	0.54

Table 3 Sample morphological feature set

Features	*Mid-dorsal* (*left*)	*Mid-dorsal* (*right*)	*Pulvinar* (*left*)	*Pulvinar* (*right*)
Area	354	276	390	443
Perimeter	80.4	79.8	102.2	273
Circularity	0.7	0.5	0.4	0.3
Roundness	0.6	0.5	0.4	0.5
Solidity	0.9	0.8	0.7	0.9

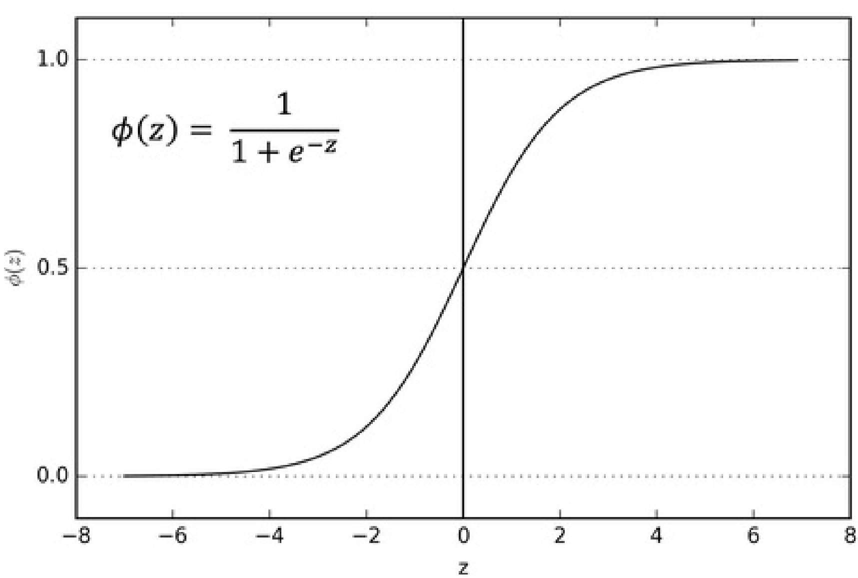
8 Classification

Decision making in classification problems is one of the utmost jobs of human action. Based on different features (attributes) extracted from an object, one can categories that object to a specific group or class. Basically the classification problems divided into two groups namely binary and multi class. In binary classification the given object belongs to one of the two classes, whereas in multiclass the object categorised to numerous classes. Different classification methods such as neural networks, support vector machines; Bayes, decision trees, etc. are developed. We have adopted artificial neural network classifier model for our proposed work.

The classifier centred on Artificial neural network have been investigated widely for non-parametric characterisation utilising a set of training vectors giving connections between input features or, on the other hand estimations to yield output classes. Such grouping techniques that do not require any earlier probabilistic model of class dispersions of input vectors. Through proper training they acquire this relationship. Although there are many classifiers, we have selected back propagation neural network model for our work. It has been widely used in many applications such as signal processing, in manufacturing industries for automatically detecting the defects and many classification applications.

In artificial neural network, a neuron element (or) processing element is the basic unit which process the input data, yield the sum of threshold weight of all input as an output. In multi-layer neural network the weighted sum of input passed as argument to a nonlinear activation function. The nonlinear activation functions are commonly used because it can adjust with assortment of information and to separate between the outputs. Based on the range the activation function are alienated into sigmoid, hyperbolic tangent, rectified linear unit. The sigmoid activation function is applied if we want to foresee the probability as output, which occurs between values 0 and 1. In our work we need to predict the probability of given subject is normal (value 0) or disorder (value 1). The input and output value in a sigmoid function is differentiable. So we have chosen sigmoid function.

Figure 9 Sigmoid transfer function

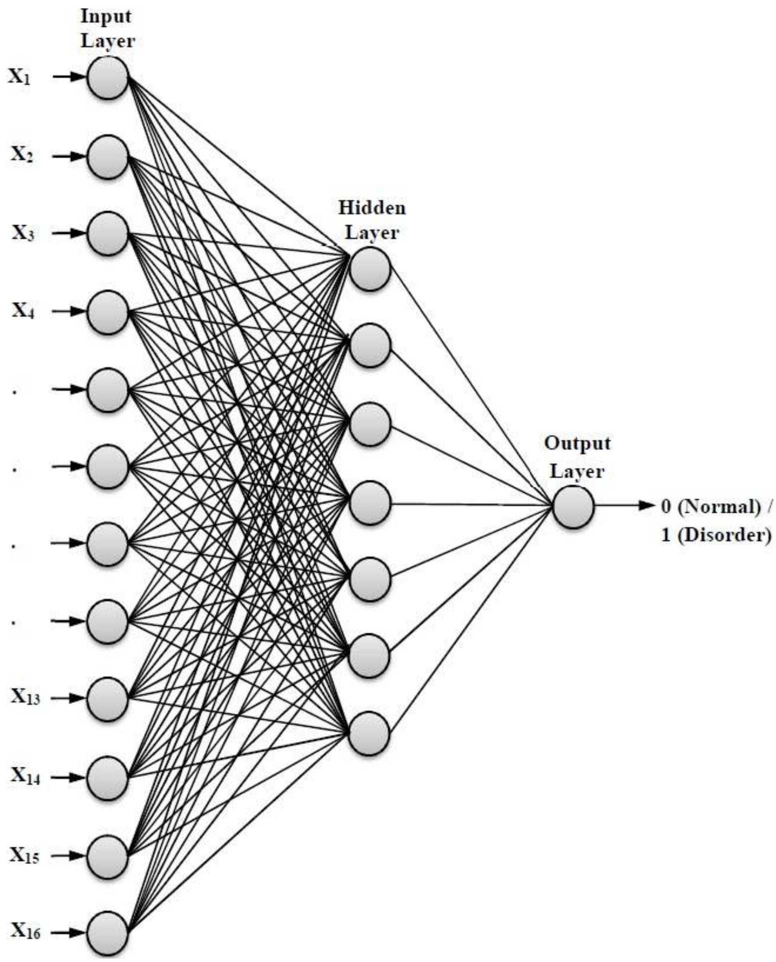


In our proposed multilayer feed forward neural network model, the input layer contains 16 nodes; single hidden layer has seven nodes and an output layer.

Table 4 Sample input to neural network model

Sub	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}
S1	2.5	0.98	78.0	0.6	86.3	309.4	1.5	1.7	1.4	0.5	0.4	0.4	1.3	1.3	5.2	5.8
S2	2.2	0.93	18.1	0.7	95.1	70.12	1.2	1.4	1.7	0.4	0.5	0.5	1.3	1.4	5.3	6.1
S3	2.5	0.95	16.7	0.6	84.5	80.3	1.3	1.6	1.9	0.2	0.51	0.57	1.42	1.48	5.20	5.87
S4	2.3	0.92	26.3	0.5	92.1	104.6	1.6	1.4	1.4	0.3	0.54	0.59	1.41	1.46	5.67	5.81
S5	2.1	0.96	68.4	0.8	88.3	85.7	1.4	1.7	1.3	0.4	0.56	0.60	1.52	1.61	5.43	5.73

Figure 10 Back propagation neural model



The hidden layer output (h_{out}) is computed by multiplying input values (x_i) from each neuron from input layer with weight matrix (W_i) is added with a bias value (b_i) matrix of every single neuron in hidden layer. The output layer output (y_{out}) is computed by multiplying weight matrix (W_h) of hidden layer output to values of hidden layer output for each neuron plus a bias for output layer.

$$h_{out} = \text{tansig}\left(W_i x_i + b_i\right)$$

$$\text{tansig}(n) = \frac{2}{\left(1 + e^{-2n}\right)} - 1$$

We have applied back-propagation method for training each network. In this method the weight and bias are updated every time after the input of each subject is passed into the neural network.

Figure 11 Backpropagation RMS error calculation

```
> backprop (eta=0.15, bpIterLimit=150000)
iter   rms |-sample------|
/1e3 error | # error dy1 |
   0 0.244   4 0.545 0.5
  50 0.001   4 0.031 0.0
 100 0.000   6 0.010 0.0
 150 0.000   5 0.008 0.0
> ANN weight numerical optimization
  (optyIterLimit = 50; WeightCount = 12)
  IterCount  rms error
          0  1.09E-002
          2  1.69E-022
```

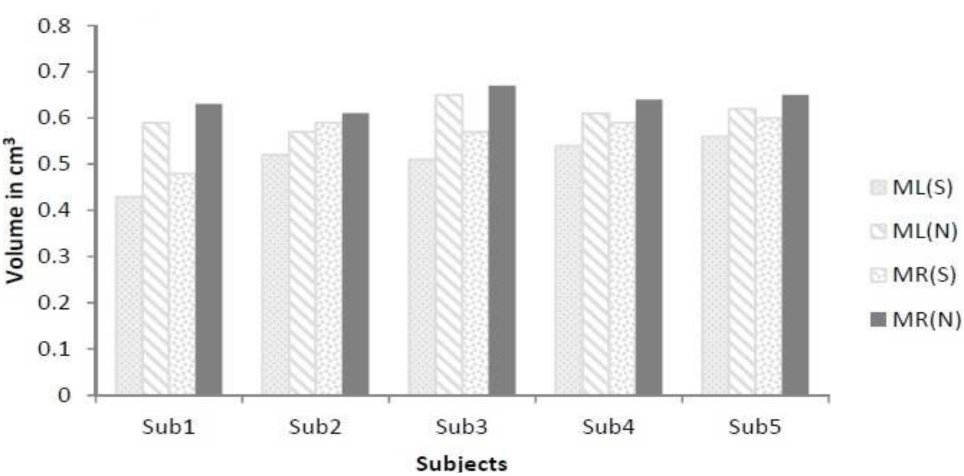
Figure 12 Hidden layer weights

```
> Neural network weights
hidden layer -----------
  1.14629E+003 -4.17652E+004 -8.05337E-001 -8.19385E-001 -8.52531E-001 -8.00350E-001 -8.32543E-001
```

9 Experimental results

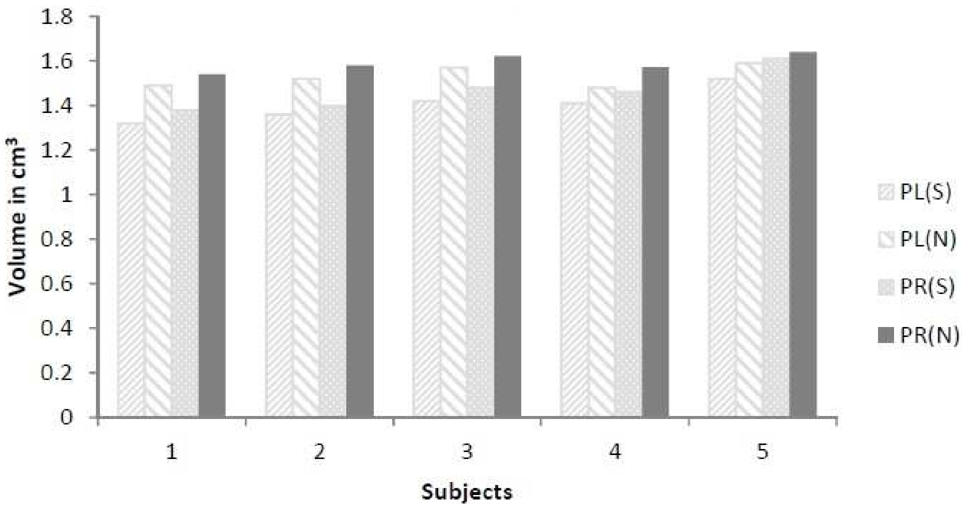
The performance of the proposed system is measured by taking 20 MRI images of schizophrenia and normal subjects. From each subject whole thalamus, mediodorsal and pulvinar regions are extracted. Figure 13 depicts the volume of each sub-nucleus for the given subjects.

Figure 13 Mediodorsal sub nuclei size



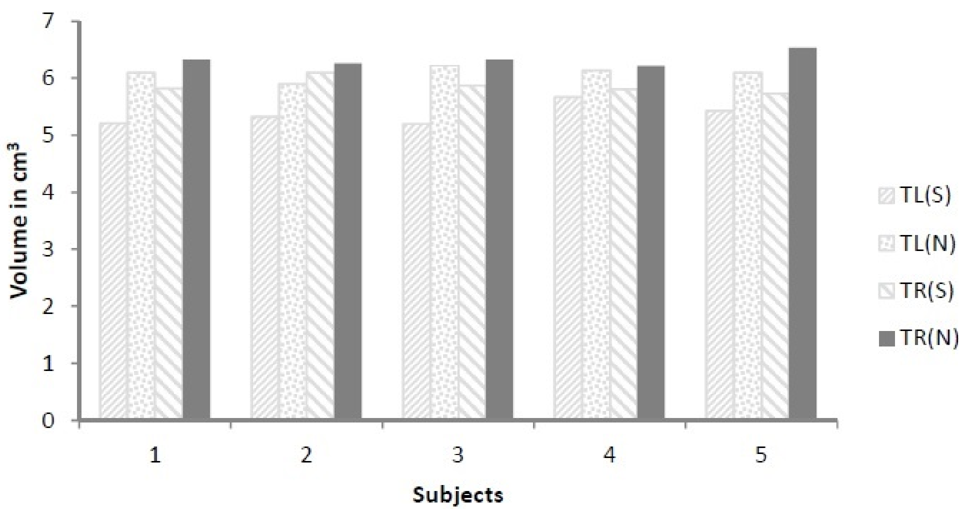
Notes: ML(S) – mediodorsal left thalamus (schizophrenia); ML(N) – mediodorsal left thalamus (normal); MR(S) – mediodorsal right thalamus (schizophrenia); MR(N) – mediodorsal right thalamus (normal).

Figure 14 Pulvinar sub nuclei size



Notes: PL(S) – pulvinar left thalamus (schizophrenia); PR(S) – pulvinar right thalamus (schizophrenia); PL(N) – pulvinar left thalamus (normal); PR(N) – pulvinar right thalamus (normal).

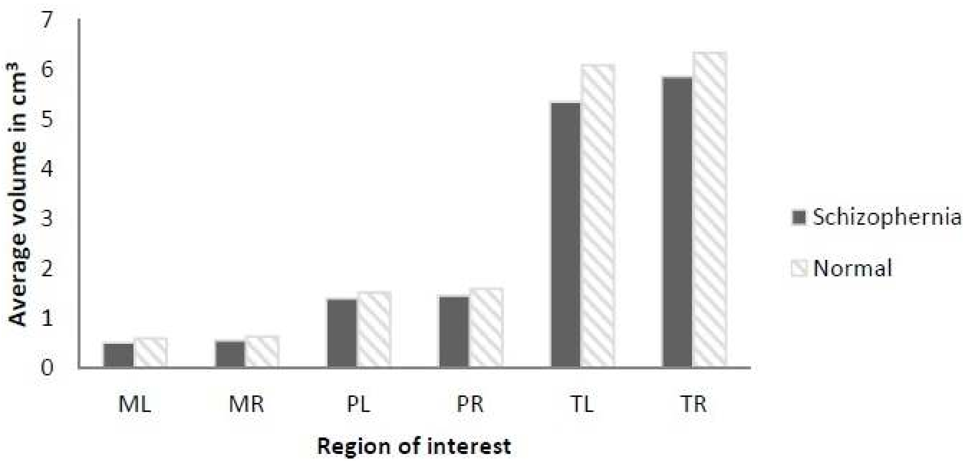
Figure 15 Thalamus size



Notes: TL(S) – thalamus left (schizophrenia); TR(S) – thalamus right (schizophrenia); TL(N) – thalamus left (normal); TR(N) – thalamus right (normal).

The accuracy of classification algorithm are measured using the metrics True positive (TP), false positive. The overall result shows that neural network model provides highest accuracy rate in schizophrenia and normal subjects compared to Bayes method.

Figure 16 Average size of thalamus and its sub nuclei



Notes: ML – mediodorsal left; MR – mediodorsal right; PR – pulvinar right; TL – thalamus left; TR – thalamus right.

Figure 17 Segmentation algorithms performance

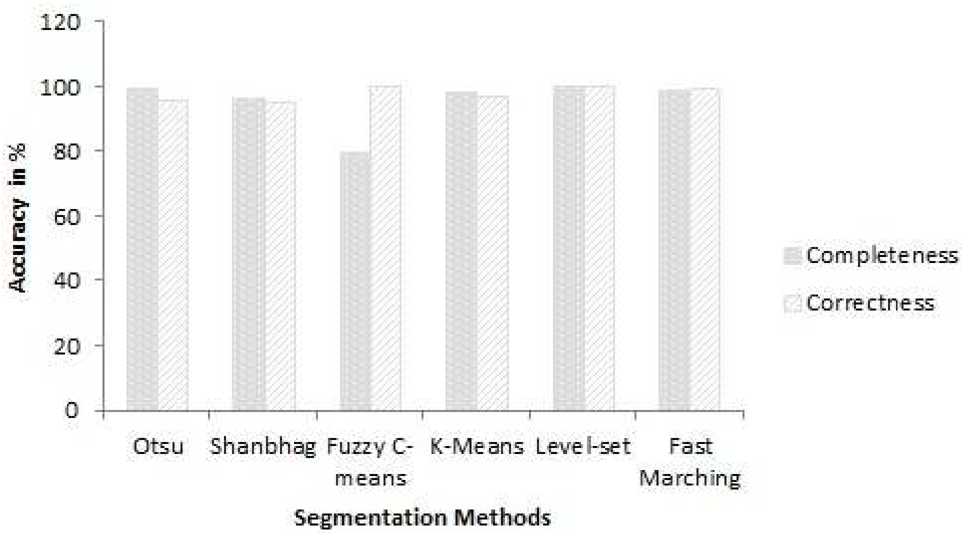


Table 5 Classifier performance

Training attempt	*No. of input neurons*	*No. of hidden neurons*	*No. of output neurons*	*Learning rate*	*Total MSE*	*No. of correct guesses*	
						Control	*SZ*
1	12	9	2	0.2	0.0126	12/15	13/15
2	22	16	2	0.2	0.2265	12/15	11/15
3	16	7	2	0.2	0.0083	15/15	14/15

10 Conclusions

The proposed system is used to segment the thalamus and its sub nuclei's (mediodorsal and pulvinar). Various statistical and morphological features are extracted from the thalamus mid sagittal brain MRI images. To classify the schizophrenia and normal subjects we have proposed statistical based method. This paper associates different classification methods with our neural network model. To detect the most appropriate method for the segmentation of thalamus, it associates three grey-level segmentation techniques. From the experimental results obtained it is concluded that for pre-processing a median filter with sobel edge detector is best. The level-set and fast marching methods are suitable for segmentation of thalamus and its sub nuclei's. The feed forward neural network model with back propagation is suitable for the classification of schizophrenia with normal subjects. Through these approaches better likelihood accuracy in diagnosing schizophrenia has been attained.

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