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Evaluation of Iron Content in SWI brain Images based on GLCM features

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ABSTRACT

Susceptibility Weighted Imaging (SWI) provides information about susceptibility differences of any tissue from its surrounding structures. The detection of iron accumulation in brain is required for diagnosis and treatment of iron overload in various neurodegenerative diseases. Gaussian and Rician noise have much influence on the quality of the SWI images. In the preprocessing step, Gaussian filter is used for removing noise or distortion in images while retaining the original quality of the image. Segmentation of an image means partitioning it into different regions which vary in some characteristics. Accurate segmentation of brain images is a tedious task. Fuzzy C-Means segmentation algorithm is used for detection of iron content in SWI brain images. After segmentation, textural features based on GLCM are extracted and provided as input to a multilayered Feed forward Neural Network for classification.

Keywords: susceptibility; Gaussian; rician; GLCM

1. INTRODUCTION

Medical images play an essential role in clinical applications to help in proper diagnosis and treatment of diseases. A Study on Susceptibility Weighted Images (SWI) focus mainly on the analysis of the images and its visual interpretation by experts in the field of radiology. However, it is time consuming and basically depends on the expertise of the radiologist. In order to overcome these limitations, the computer-aided methods are becoming significant. Digital image processing methods when implemented with soft computing techniques are of great deal in visual interpretation of SWI images [1]. Tissue magnetic susceptibility differences are determined by using SWI based techniques, to produce a unique contrast. The unique contrast generated is distinct when compared to that of spin density values, T1, T2, and T2* [2].

An enhanced contrast magnitude image which is sensitive to iron deposition is produced by combining the magnitude and phase data. Normally brain iron content shows a rapid rise as age increases. The basal ganglia show more iron content in brain. In various brain related diseases, the amount of iron in the central part of nervous system indicates an abnormal level [3][4]. Susceptibility-weighted imaging of iron deposition is helpful for describing Alzheimer disease [3] and certain pediatric disorders.

The oxygen transportation from lung to tissues is performed by hemoglobin and iron plays an important role in it. Iron is an important component that must be properly regulated. Iron in most cases leads to oxidative stress and the consequences are free radicals production. The excess load of ferrous iron may result in reaction with hydrogen peroxide and leads to the production of vigorous hydroxyl radicals by Fenton reaction and the subsequent death of neurons by apoptosis [5]. Regions of brain like globus pallidus have high iron concentrations.

To enhance the contrast of susceptibility influenced image, the data regarding the magnitude part is combined with information of the phase part in the SWI Image. We found many filtering techniques for

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removing Gaussian and Rician noise, but Gaussian filter shows a better performance [6]. Fuzzy C-Means segmentation algorithm is used for detection of iron content in SWI brain images because of its faster clustering rate [7]. In this research work, the textural features based on GLCM are extracted from the segmented SWI brain image and applied to a multilayered neural network which uses Feed forward operation for classifying the inputs.

2. METHODOLOGY

The input data set consists of Susceptibility Weighted images of brain. Both normal and abnormal images were considered. The steps involved in the evaluation of iron content in brain are shown in figure1.

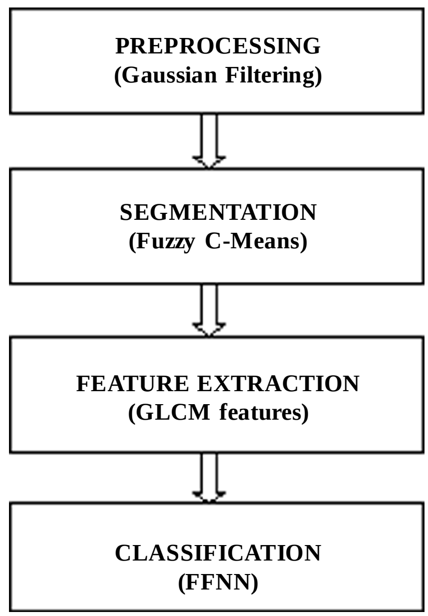

Figure 1: Steps involved in the evaluation of iron content in brain.

3. PREPROCESSING

The Gaussian and Rician noise affects the quality of the SWI. The most commonly used filter for performing smoothing operation is the Gaussian filter. Marr et al. [8] showed that Gaussian filter is comparable to the feature enhancement algorithm namely Difference of Gaussian (DOG) filter in certain aspects.

Babaud et al. [9] showed that when images are smoothed using Gaussian filter, second derivative scale space representation implies that transition from a small to large scale results in vanishing of existing zero-crossings but new zero-crossings are never produced. This is a unique property of Gaussian function when compared with a wide category of signals.

This special property of Gaussian function helps to determine zero-crossings on a very large extent of scales. It also provides the means to regain the complete signal at range of scales which are comparatively very small.

Yuille et al. [10] illustrated that, for two dimensional signals, as the scale increases, zero crossings are not produced only by the special filter that uses Gaussian function. Yuille et al. also explained that, in the case nonlinear directional derivatives adjacent to the gradient, zero-crossings are created when the values of scale increases.

The Gaussian filter is rotationally symmetric. During the process of smoothing operation by convolutions, separability is very essential for computational accuracy in the spatial domain [11].

The impulse response of the Gaussian filter is the function namely Gaussian function. In case of Gaussian filters, the impulse response is designed in such a way that during the decrease of rise and fall period, the input values given to the step function is not increased. Thus minimum possible group delay takes place since the Gaussian filter gives no overshoot to a step function. Mathematically, convolution of input signal with Gaussian function is done by Gaussian filter and this alters the input signal.

The performance analysis done on various filters clearly shows that the image corrupted by Gaussian and Rician noise can be denoised more efficiently by Gaussian filter [6].

4. SEGMENTATION

The main objective of segmentation operation is partitioning an input image into different regions or edges based on similar properties. Various methods have been implemented to perform segmentation on the images. Most of methods are based on the two basic properties namely discontinuity based and similarity based. The success of iron detection in SWI images depends on efficient image segmentation methods, so an accurate segmentation of medical images is primary in clinical diagnosis and treatment planning.

The Fuzzy C-Means (FCM) image segmentation is considered to be a clustering technique which uses unsupervised learning and is subjective to various issues. The issues includes analysis of features, clustering, medical diagnosis and image segmentation [12][13]. FCM algorithm was developed by J. C. Bezdek et al. which shows that the membership grade plays an important role. The membership grade specifies the extent to which each data element can be included to a cluster in the image.

Consider the data set, $x = [x_1, x_2, ..., x_d]^T$, the performance index or the objective function for segmentation of data is minimized by FCM algorithm as explained by [14].

$$J_m(u,v) = \sum_{i=1}^{c} \sum_{k=1}^{d} u_{i,k}^m \left\| x_k - v_i \right\|^2 \tag{1}$$

In the above equation, d represents the total number of data samples in the input vector X, c is the total number of clusters, u_{ik} represents element of the partition matrix U. The size of the matrix U is $(c \times d)$ which contains the membership function. v_i is the center of the i^{th} class. The fuzzy membership function is controlled by a weighting factor represented by m. The Fuzzy C-Means method partitions the vector represented by X into c fuzzy subsets. Here u_{ik} represents the memberships of x_k in class denoted by i.

The FCM method is illustrated as explained in the steps given below [11]:

1: To start the process, the initialization phase includes the following:

- The image is scanned across each line to generate vector X that contains the picture element values represented by the gray levels of the given image.
- Randomly initialize centers of clusters represented by vector $V^{(0)}$.

Repeat iteration t = 1 till the algorithm has converged:

2: Calculate the membership matrix $U^{(t)}$ of element u_{ik} using:

$$u_{ik} = \left(\sum_{j=1}^{c} \left(\frac{\left\| x_k - v_i \right\|}{\left\| x_k - v_j \right\|} \right)^{\frac{2}{m-1}} \right)^{-1} \tag{2}$$

3: Vector $V^{(t)} = [v_1, v_2, \ldots\ldots, v_c]$ is calculated as:

$$v_i = \frac{\sum_{k-1}^{d} u_{ik}^m}{\sum_{k-1}^{d} u_{ik}^m} \tag{3}$$

4: Test for convergence: if $||V^{(t)} - V^{(t-1)}|| > \varepsilon$, then the iteration t is incremented by value one and then go to the Step 2, else algorithm has converged. ε is a positive value that denotes the threshold chosen.

5. FEATURE EXTRACTION

The statistical analysis of texture includes determining the remarkable features from the statistical distribution of the combinations of intensity levels at specific locations. These specific points are relative to each other in the image.

N–Order statistics is obtained based on the total number of picture elements (pixels) which represents intensity values in the image. The gray level co-occurrence matrix (GLCM) determination is based on texture feature extraction method which extracts textural features that comes under second order statistics.

The size of the GLCM matrix is defined by the number of rows and columns in the matrix. The size of the matrix must be matched with the levels of gray (G), in the given image. The distance between the pixels are represented by (Δx, Δy). The relative frequency for this distance is calculated by the elements of matrix described by $P(i, j \mid \Delta x, \Delta y)$.

The values for second-order probabilities are calculated for variations in levels (i & j) of gray scale image at distance d for a specific angle θ. The GLCM provides unique characteristic features. G represents the number of gray levels used and m denotes the mean value of P, σ_x, σ_y, μ_x and μ_y represents the standard deviation (SD) values and mean values of P_x and P_y. $P_x(i)$ denotes the i_{th} value determined from the sum of the rows of $P(i, j)$:

$$P_x(i) = \sum_{j=0}^{G-1} P(i, j) \text{ and } P_y(j) = \sum_{i=0}^{G-1} P(i, j) \tag{4}$$

$$\mu_x = \sum_{i=0}^{G-1} iP_x(i) \text{ and } \mu_y = \sum_{j=0}^{G-1} jP_y(j) \tag{5}$$

$$\sigma_x^2 = \sum_{i=0}^{G-1} \left(P_x(i) - \mu_x(i)\right)^2 \tag{6}$$

$$\sigma_y^2 = \sum_{j=0}^{G-1} \left(P_y(j) - \mu_y(j)\right)^2 \tag{7}$$

Various textural features are calculated by using following equations. The unique valued textural features thus obtained are used for training the classifier.

a) Homogeneity or Angular Second Moment:

$$ASM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left\{P(i, j)\right\}^2 \tag{8}$$

b) Contrast

$$\text{Contrast} = \sum_{n=0}^{G-1} n^2 \left\{\sum_{i=1}^{G} \sum_{j=1}^{G} P(i, j)\right\}$$

$$\text{where } |i - j| = n \tag{9}$$

c) Correlation based feature:

$$\text{Correlation} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{\{i \times j\} \times P(i, j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y} \tag{10}$$

d) Energy

$$\text{Energy} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left(P\left(i, j\right)\right)^2 \tag{11}$$

The following table lists some of the features that were extracted from the input dataset are given in.

Table 1
GLCM features extracted from the input dataset

Case/Features	*Contrast*	*Correlation*	*Energy*	*Homogeneity*
Abnormal1	0.0200	0.9549	0.5285	0.9900
Abnormal2	0.0260	0.9260	0.4999	0.9870
Abnormal3	0.0183	0.9519	0.6003	0.9908
Normal1	0.0435	0.9125	0.4527	0.9783
Normal2	0.0500	0.8999	0.4437	0.9750

6. CLASSIFICATION

There are various categories of artificial neural network (ANN). A neural network which implements feed forward classification is a type of ANN in which a cycle is not formed by the connections between units. In a feed forward neural network, several layers of computational units form the network. Usually it is interconnected in a feed forward manner. The neurons present in various layers are interconnected with subsequent layer neurons using direct connections [15]. The most widely used activation function for many applications is the sigmoid activation function which is applied to the units of the networks. Multilayered feed forward neural network (FFNN) is a classification method in which the neurons are ordered into many layers to form the network (Fig. 2). The first and last layers are called input and output layers respectively. The intermediate layers are called hidden layers. Images are classified using the two layer FFNN.

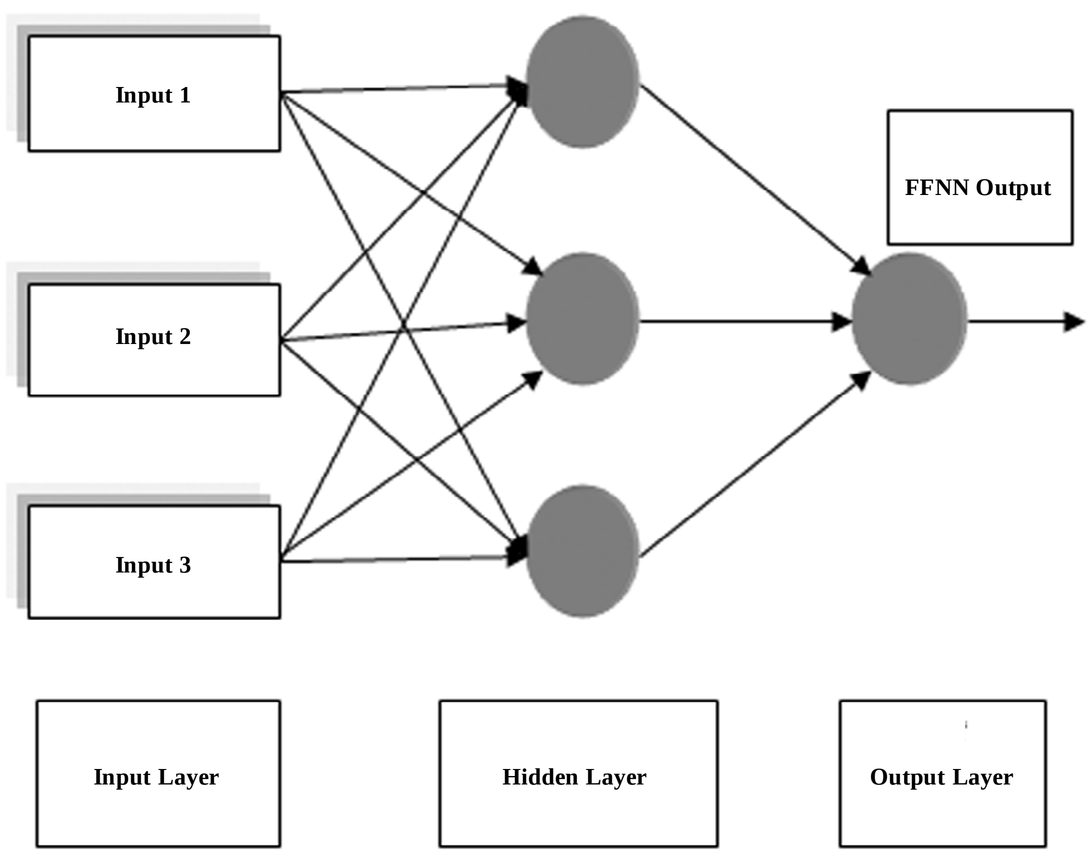

Figure 2: Basic Feed Forward Neural Network

For classification purpose, number of input neurons selected is 4 and that of hidden neurons is assumed as 3 and then increased based on training. Number of output neurons is 2. Activation function used for generating the two layer FFNN is the sigmoid function [16].

7. EXPERIMENTAL RESULTS

The Original Image is a SWI image of brain. It is clear that the SWI image corrupted by Gaussian and Rician noise can be denoised more efficiently by Gaussian filter. Since the Gaussian filter is more efficient for Rician and Gaussian noise removal, it is used to filter the noise in the input SWI image

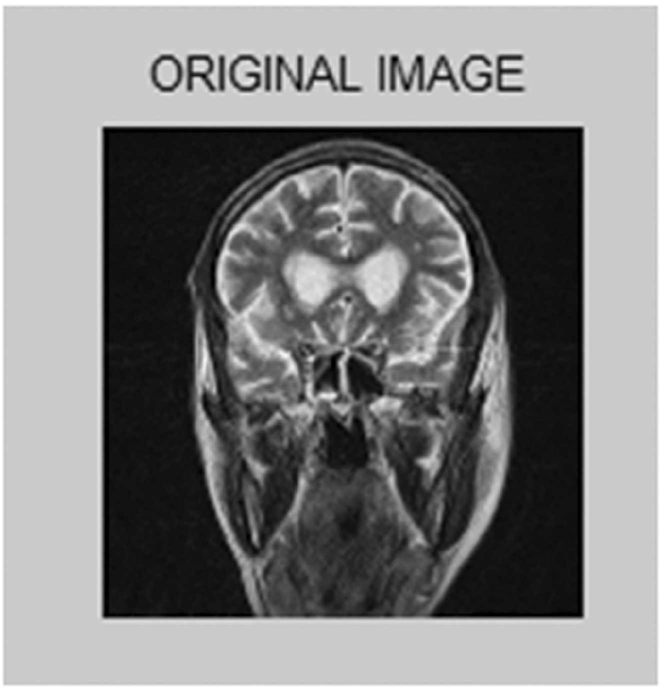

Figure 3: Original Image

Figure 4: Gaussian Filtered Image

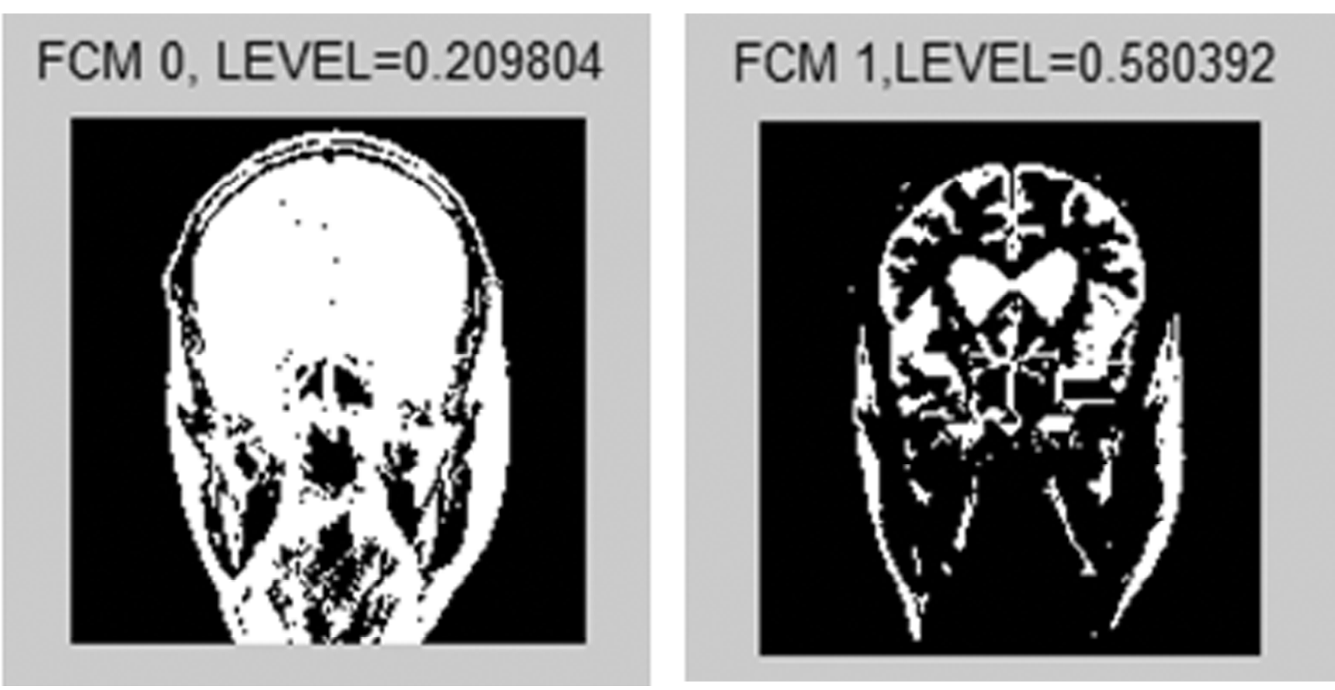

Figure 5: Fuzzy C-Means segmented image at two levels

during the preprocessing stage. The extraction of iron region in brain is done Fuzzy C-means clustering method.

The Fuzzy c-Means image is then dilated to expand the shapes contained in the segmented image as shown in Fig. 6.

Figure 6: Dilated Image

Four GLCM textural features namely contrast, correlation, energy and homogeneity are extracted from the textural image. The input dataset consists of 20 SWI brain images with 7 abnormal (iron content) and 13 normal (without iron content) images. All the four textural features are calculated for the SWI brain input dataset and used for training the two layer FFNN. The output of the FFNN is assumed to be 1 for iron content SWI brain input image and -1 for non-iron content SWI brain input image. The system was implemented using Matlab 7.9.0 (R2009b). The performance criterion used is MSE (Mean Square Error) and the goal was 10^{-8} which is proved to be very acceptable goal. The performance goal is reached after 4000 training iteration.

The training state of feed forward neural network at 300 epochs is shown in figure 7.

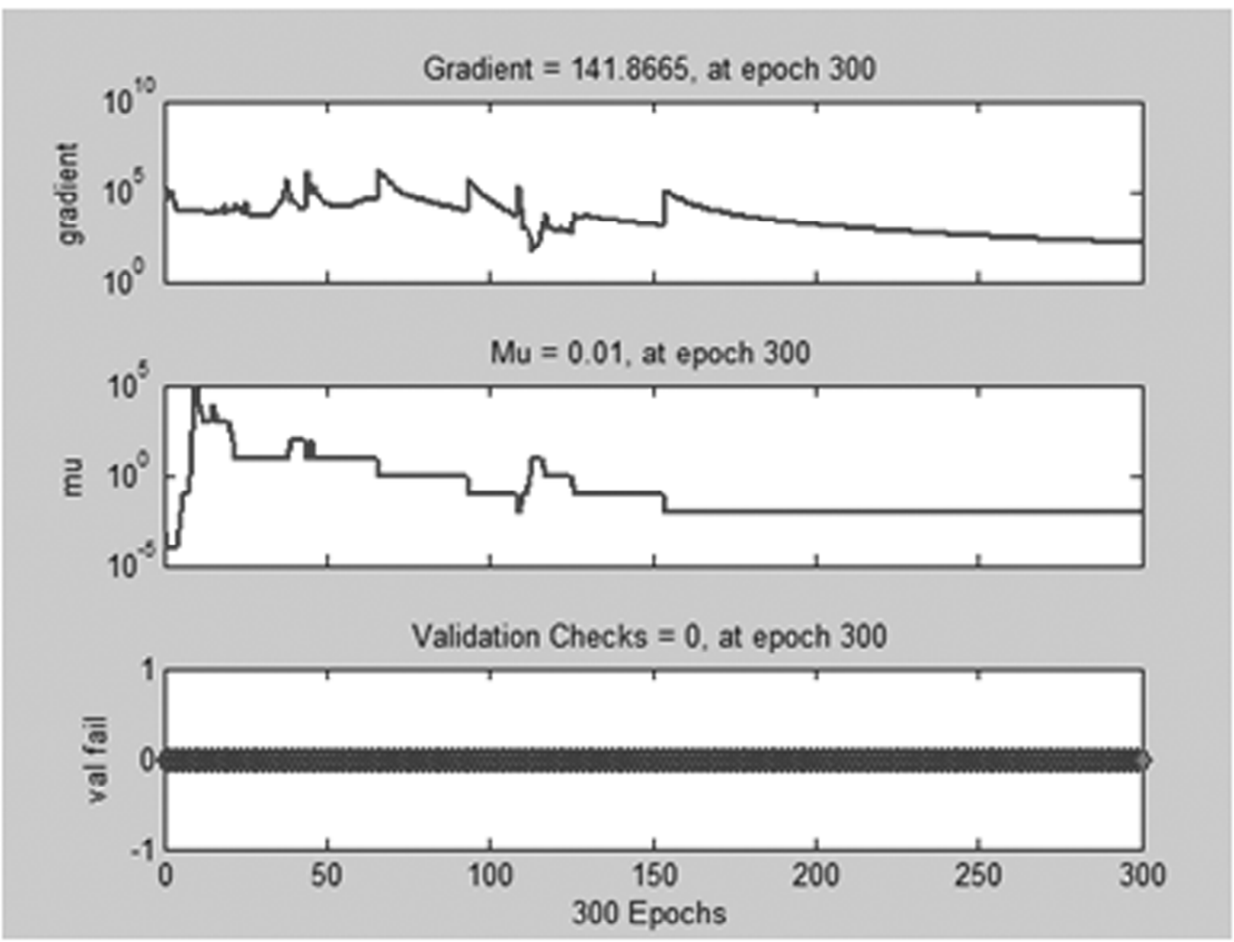

Figure 7: Training state of feed forward neural network at 300 epochs

4. CONCLUSION

In this paper, Fuzzy C-Means segmentation algorithm followed by GLCM based feed forward neural network for detecting iron region in brain was successfully done using Matlab. This helps in the clinical diagnosis of brain iron in SWI images.

The accurate results of FCM algorithm effectively extract the iron content from brain SWI images. The FCM method is implemented because of its simplicity and its clustering rate is faster than the other method. The feed forward neural network uses GLCM features for better classification of iron content brain SWI images.

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