Journal of Science and Technology Vol. 13, No. 2
ISSN 1605 – 427X
Engineering and Computer Sciences (ECS)
www.sustech.edu

December/2012

Brain Tumor Detection Using Artificial Neural Networks

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Abstract- In this study a functional models of Artificial Neural Networks (ANNs) is proposed to aid existing diagnosis methods. ANNs are currently a "hot" research area in medicine, particularly in the fields of radiology, cardiology, and oncology. In this paper an attempt was made to make use of ANNs in the medical field. Hence a Computer Aided Diagnosis (CAD) system using ANNs to classify brain tumors was developed in order to detect and classify the presence of brain tumors according to Magnetic Resonance (MR) Image, and then determined which type of ANNs and activation function for ANNs is the best for image recognition. Also the study aimed to introduce a practical application study for brain tumor diagnosis. Neural network must be able to determine the state of the brain according to MR image. In all procedures, image processing and ANNs design, MATLAB was incleded. From each MR Image a Harlick texture features was extracted to prepare training data which was introduced to neural network as input and target vectors. ANNs was designed using MATLAB tool "nntool". Results obtained explain Elman Network, with log sigmoid activation function, surpassing other ANNs with a performance ratio of 88.24%.

Keywords: *Magnetic Resonance Imaging,* Brain Tumor Haralick Texture Features, Feed Forward Back Propagation, Recurrent Network, Elman Network, nntool.

المستخلص:

قدمت هذه الدراسة نماذج وظيفية لشبكات عصبية اصطناعية لتساعد الطرق الحالية المستخدمة في مجال التشخيص الطبي . أضحت الشبكات العصبية الاصطناعية من المجالات البحثية الحيوية في مجال الطب لاسيما في مجال الأشعة وأمراض القلب والأورام. هذه الورقة بذلت محاولة لاستخدام الشبكات العصبية في المجال الطبي. وعليه طور نظام تشخيص بواسطة الحاسب (CAD) لسرطان الدماغ باستخدام الشبكات العصبية الاصطناعية بغرض الكشف عن سرطان الدماغ من صورة الرنين المغناطيسي. ايضاً اهتم البحث بتحديد نوع الشبكة الصبية ونوع دالة التفعيل الافضل لتطبيق التعرف على الصور. قدمت الورقة نموذج عملي لاستخدام الشبكات العصبية للتعرف على الصور الطبية. التطبيق العملي هو نظام تشخيص سرطان الدماغ حيث يفترض بالشبكة العصبية أن تستطيع تحديد حالة الدماغ طبيعي/غير طبيعي من صورة الرنين المغناطيسي. استخدمت الورقة برنامج MATLAB في كل الاجراءات المتبعة ويشمل ذلك معالجة الصورة وتصميم الشبكات العصبية الاصطناعية. لكل صورة رنين مغناطيسي تم استخلاص معالم Harlick للنسيج وذلك لتحضير بيانات التدريب التي تقدم للشبكة العصبية في شكل متجهات دخل وهدف. الشبكات العصبية تم تصميمها باستخدام حزمة nntool في برنامج MATLAB. النتائج المتحصل عليها اظهرت تفوق شبكة Elman ذات دالة التفعيل Log sigmoid على بقية الشبكات الاخرى بمعدل اداء 88.24%.

Introduction

One of the important goals of Artificial Neural Networks is the processing of information similar to humor interaction actually neural network is used when there is a need for brain capabilities and machine idealistic. The advantages of neural network information processing arise from its ability to recognize and model nonlinear relationships between data. In biological systems, clustering of data and nonlinear relationships are more common than strict linear relationships (1).

Conventional statistical methods can be used to model nonlinear relationships, but they require complex and extensive mathematical modeling. Neural networks provide a comparatively easier way to do the same type of analysis. Well design and training of Neural Network make it qualified for decision making operations when it faced with new data outside training data; this will provide ANNs with high reliability exactly like an expert person.

There are two problems that face ANNs designers in any application comprising of i) network structure, and ii) network generalization. In designing ANNs, a suitable architecture for the specific application must be well chosen; this involves:

a. Choosing a suitable network type for application,
b. Number of layers,
c. Number of nodes in hidden layers, and
d. Activation functions between layers.

Network Generalization means how much the neural network is able to work with different data. Designers of ANN are always faced by the extend of network generalization, i.e. despite a well designing and training of ANN that decreases the performance error to the least value; ANN fails when fed with a new input data and gives worst performance. Many studies were carried out using artificial neural networks for brain tumor detection and recognition.

Kumar and Raju (2), present a computer-aided diagnosis system for early prediction of brain cancer using texture features and neuro classification logic. The Tumor mass detection and Cluster micro classification was used for cancer prediction. Nine distinct invariant features and the calculated minimum distance for the prediction of cancer were used to predict tumor in a given MRI image. Also Kadam et. al. (3) suggested a Neural Network based brain tumor detection system involved both hardware and software requirements.

Image was resized to a convenient size to make the processing and analyzing to be carried out more effectively, and adaptive filter was applied to remove the spurious signals present in the image. Then the region of interest (ROI) was segmented. A gray tone spatial dependence matrix approach, introduced by Haralick, was used to extract a set of eight texture features from the tumor and the normal regions. Back propagation neural network was designed and trained for the detection of the tumor present in human brain (2).

Brain Tumor

The term “tumor,” which literally means swelling, can be applied to any pathological process that produces a lump or mass in the body. Tumors are a major manifestation of a vast and varied group of diseases called neoplasms or more commonly cancers. However, many other diseases such as infections can produce tumors, and they are a source of confusion in imaging diagnosis (4).

Neoplasms arise from normal body cells that through a series of transformations lose the capacity to respond to the usual physiological mechanisms that control growth. Uncontrolled growth leads to the formation of a tumor. Slowly growing tumors that lack the capacity to spread to distant sites are called benign, and rapidly growing tumors that can infiltrate

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surrounding tissues and spread to distant sites (metastasize) are called malignant [5].

Brain has sensitive tissues; so small tumor will cause big problems.

Brain tumors can divided according to the place of creation to primary and secondary tumors.

a. Primary tumors are tumors begin their creation inside the brain.
b. Secondary tumors are tumors which begin in other parts of human body and then move to the brain like lung cancer and breast cancer.

Primary brain tumors have special property that they cannot moved be outside the brain. Also brain tumors can be classified based on the type of the cells that are affected and their appearance under the microscope. Types of tumors commonly found are Oligodendroglioma, Meningioma and Glioblastoma [6].

People with tumors or potential tumors are imaged for detection, classification, staging, and comparison. Detection can be subdivided into diagnosis, case finding, and screening, depending on the level of suspicion. People referred diagnosis, because they have signs and symptoms of cancer are noted [1].

MR imaging is used to detect tumor place, but usually it is difficult to determine the type of tumor with visual observation only. Utilizing ANN, help in diagnoses because of its capability to determine all correlations and variances between pixels in the image.

Material and Methods

In this paper a typical image recognition system is proposed. The system process and flow is shown in Figure 1. MR images for three tumor types which are Oligodendroglioma, Meningioma and Glioblastoma were collected, and the image segmentation algorithm was designed and then applied to determine image edges and isolate image from the background. Each image was cut to frames, and each frame was filtered using an enhancement filter to get a clear frame. All the processes were done in the pre processed stage [6].

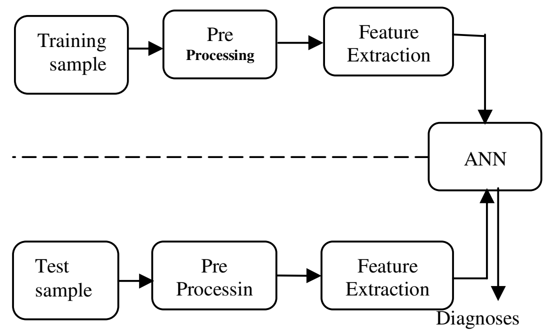

Figure 1: Image recognition system

Next stage is features extraction. For medical images; Haralick [7] determines 13 features that well describe the texture of image. Table 1 describes the Haralick texture features.

Neural Network Design:

For image recognition application; Feed Forward Back Propagation neural network is good choice [8]**.** The number of layers, nodes and activation functions are determined according to the application needed and there is no specific rule for choice. This study suggests a new approach using trial and error but with specific strategy.

Firstly, the initial number of layers, nodes and activation function determined; and the value of performance error recorded. Then, for the same architecture; activation function type changed and the performance error recorded. This procedure repeated, and the activation function that provides the least performance error selected.

Secondly, the number of hidden nodes should be increased and then decreased. The performance error was recorded. This was mainly done to study whether the application needs to optimize the number of nodes. If the performance error value is still high, a new layer must be added. Finally the ANN that gives the least performance error will be selected. To handle the problem of the ANN generalization and make it more general, there are two ways [9]:

Table1: Haralick Texture Features

Feature	Mathematical description
Angular second Moment	$f_1 = \sum_i \sum_j \{p(i,j)\}^2.$
Contrast	$f_2 = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{\substack{i=1 \\ \lvert i-j \rvert = n}}^{N_g} \sum_{j=1}^{N_g} p(i,j) \right\}$
Correlation	$f_3 = \frac{\sum_i \sum_j (ij)p(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y}$
Sum of square variance	$f_4 = \sum_i \sum_j (i-\mu)^2 p(i,j)$
Inverse Difference Moment	$f_5 = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j)$
Sum Average	$f_6 = \sum_{i=2}^{2N_g} i p_{x+y}(i)$
Sum Variance	$f_7 = \sum_{i=2}^{2N_g} (i-f_8)^2 p_{x+y}(i)$
Sum Entropy	$f_8 = -\sum_{i=2}^{2N_g} p_{x+y}(i) \log \{p_{x+y}(i)\}$
Entropy	$f_9 = -\sum_i \sum_j p(i,j) \log (p(i,j)).$
Difference Variance	$f_{10} = \text{variance of } p_{x-y}$
Difference Entropy	$f_{11} = -\sum_{i=0}^{N_g-1} p_{x-y}(i) \log \{p_{x-y}(i)\}$
Information measure of correlation 1	$f_{12} = \frac{HXY - HXY1}{\max\{HX, HY\}}$
Information measure of correlation 2	$f_{13} = (1 - \exp[-2.0(HXY2 - HXY)])^{1/2}$

*Note: All the equations in Table (1) were programmed using Matlab.

MATLAB program using nntool was written for image processing and Haralick feature extraction, and it is used in designing ANN.

a. Regularization, where ANN is trained until its performance becomes un-changeable then the sum of squared error and weights for network are fixed to its least value.
b. Early stopping, where the training data is divided into three groups, first group for training, the second for validation test, and the third for testing.

Then the error in performance for the second group is observed, if ANN loses its validation to deal with new data; the performance error should be increase and the training to be stopped, and weights to be fixed at the last values before network looses their generalization. Then best values of weights would be employed in the test of the third group. In this paper we used the second method. Three ANNs were designed and trained, which Feed Forward Back Propagation (BP NN), Recurrent and Elman network.

Feed Forward Back Propagation (BP NN) design

BP NN was designed and trained using nntool in Matlab. First, one hidden layer between input and output layers with 250 nodes was chosen. The type of activation function chosen in the first was Log sigmoid.

Then for the same network, activation function was replaced first by Tan sigmoid function, and then by pure linear functions. Using the network with Log sigmoid function, a number of nodes in hidden layer were first increased to 270 and then decreased to 230 to find out if this application needs more or less nodes.

Recurrent Network (RNN) Design

As in the case of BP NN, the initial hidden nodes number was set to 250 nodes, and the performance error was recorded. The number of nodes was decreased to 200 and performance error was recorded. Finally, the number of nodes was increased to 300, and this was found to give the ideal performance for RNN.

Elman Network Design:

The initial hidden nodes number was set to 250 nodes, and the performance error was

Journal of Science and Technology Vol. 13, No. 2
ISSN 1605 – 427X
Engineering and Computer Sciences (ECS)
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recorded. The number of nodes was decreased to 240, and the performance error was recorded.

After that number of nodes was increased to 280. Since decreasing nodes made the performance better, nodes were decreased many times to get the best performance. The best performance was achieved when nodes became 200 nodes.

Results

For the BP NN with 250 nodes and Log sigmoid activation function, the obtained results and the performance error are plotted in Figure 2.

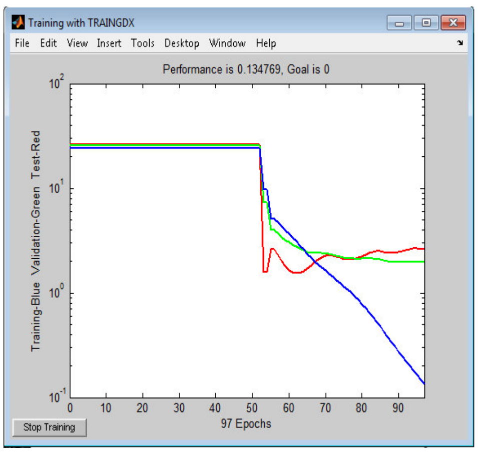

Figure 2: Training result for BP NN with 250 nodes and Log sigmoid activation function.

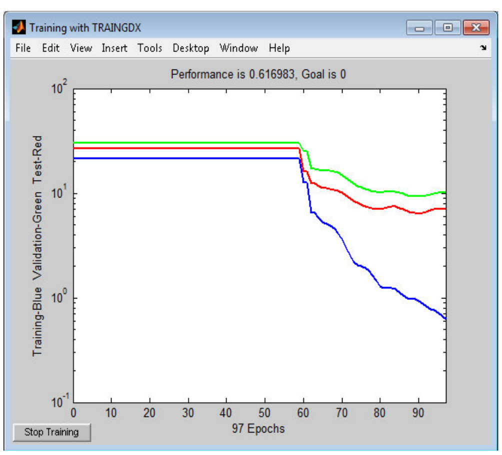

Figure 3: Training result for BP NN with 250 nodes and Tan sigmoid activation function.

For the same network, when The Log sigmoid activation function replaced by Tan sigmoid and then by pure linear function, the results achieved is shown in Figures 3 and 4.

From the results in Figures 2, 3 and 4, Log sigmoid gave the least value for the performance error. So the Log sigmoid function is the best activation function for the medical image recognition applications.

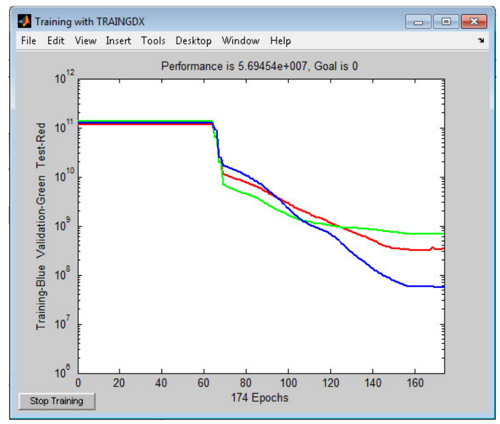

Figure 4: Training result for BP NN with 250 nodes and pure linear activation function.

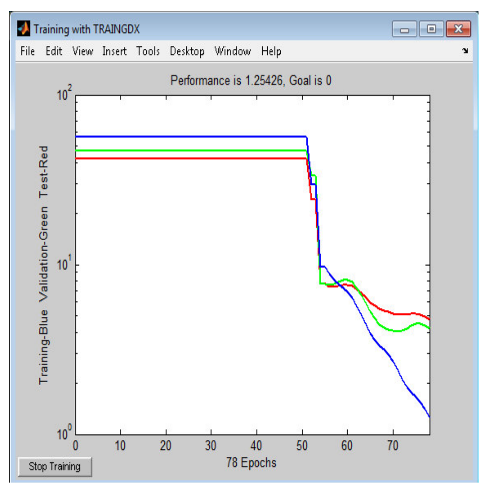

Figure 5: Training result for BP NN with 230 nodes

Now for the network with Log sigmoid, the number of nodes was decreased to 230 and then increased to 270. The results achieved are shown in Figure 5 and 6.

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ISSN 1605 – 427X
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When the Results in Figures 5 and 6 compared with the result in Figure 2; it is clear that increasing the number of nodes contribute to the enhancement of the BP NN performance. The best performance was achieved when nodes were 300. The ideal BP-NN for the application and its performance are shown in Figure 7 and 8.

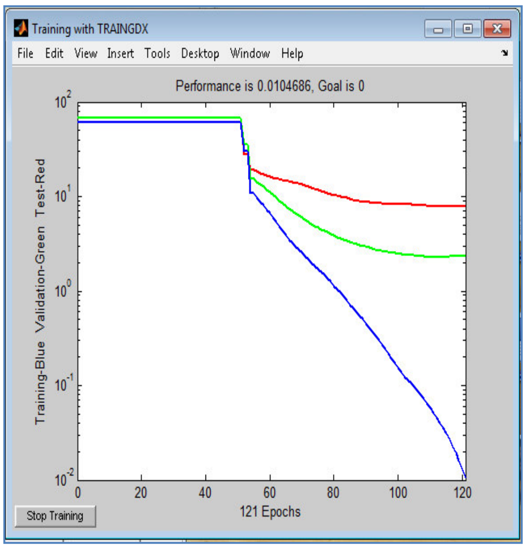

Figure 6: Training result for BP NN with 270 nodes

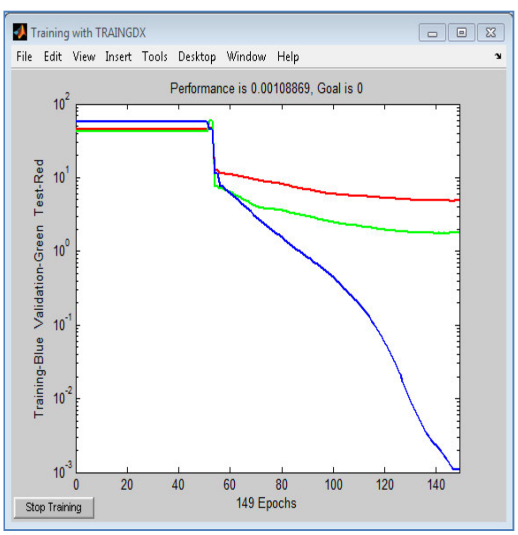

Figure 7: Training result for the ideal BP NN with 300 hidden nodes and Log sigmoid activation function

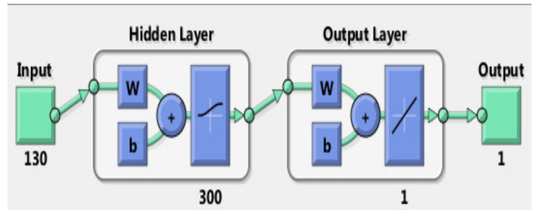

Figure 8: The ideal BP NN architecture.

The result of RNN with Log sigmoid activation function and 250 nodes in hidden layer are shown in Figure 9. In Figure 10 the number of nodes was decreased to 200.

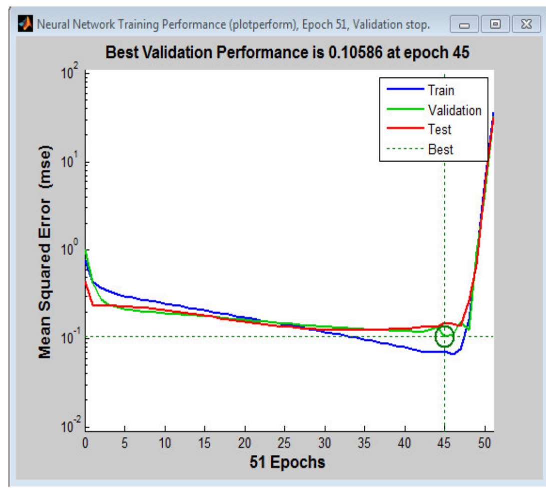

Figure 9: Training result for RNN with 250 nodes

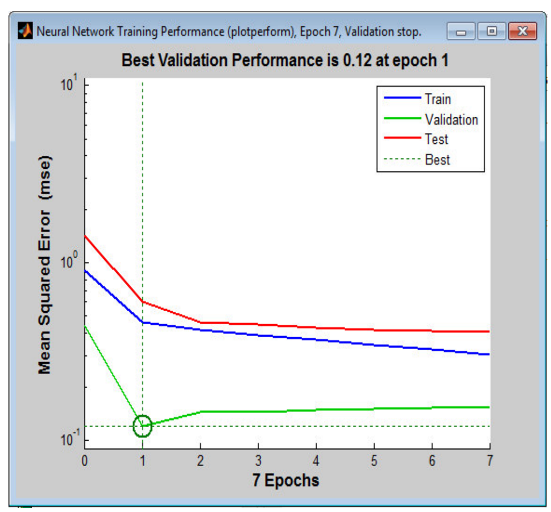

Figure 10: Training result for RNN with 200 nodes

Journal of Science and Technology Vol. 13, No. 2
ISSN 1605 – 427X
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Note that from Figure 10, the performance error increase when the numbers of nodes decrease. The results and the ideal RNN architecture are shown in Figures 11 and 12.

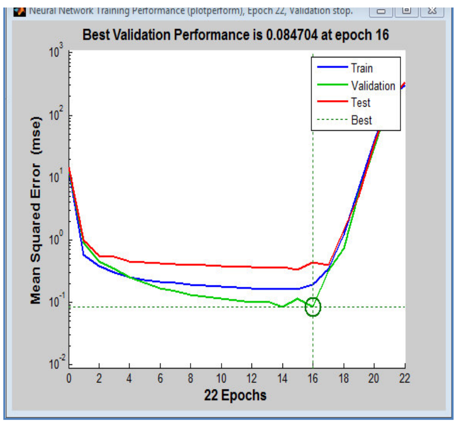

Figure 11: Training result for the ideal RNN with 300 hidden nodes and Log sigmoid transfer function

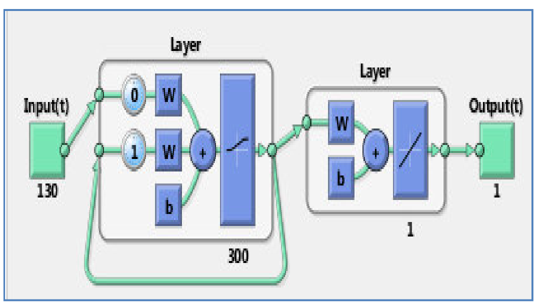

Figure 12: The ideal RNN architecture

Figures 13, 14 and 15 show the results of Elman network, where the number of nodes was set to 250, 240 and 280, respectively.

It is clear that decreasing the number of nodes enhanced Elman network performance. The best performance was achieved when nodes number was adjusted to 200. The ideal Elman network for application and its performance are shown in Figure 16 and 17.

After training stage was finished; the three networks were tested using new samples. The samples involved MR images for normal brains, MR images for the three brain tumor types (Meningioma, Glioblastoma and Oligodendroglioma), and MR images for other types of brain tumor.

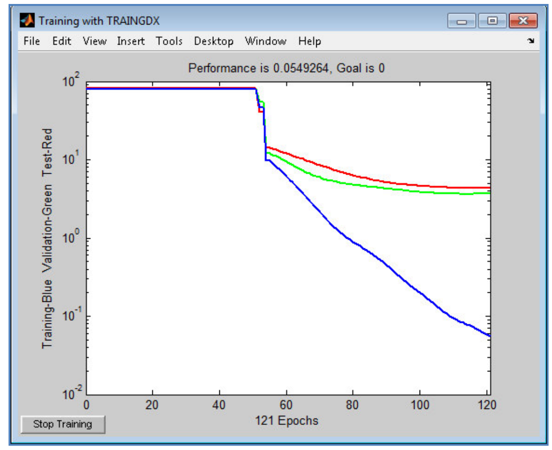

Figure 13: Training result for Elman network with 250 nodes the number of nodes decreased to 230 and 280.

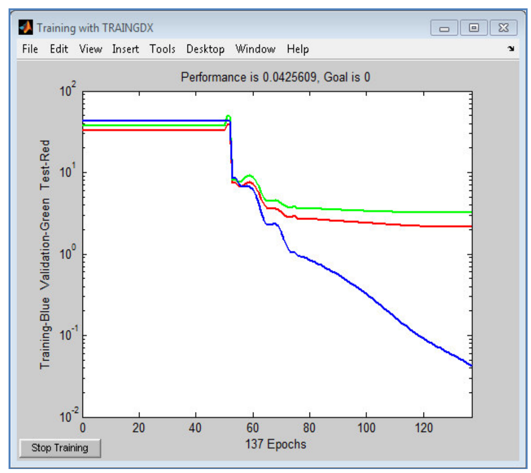

Figure 14: Training result for Elman network with 240 nodes.

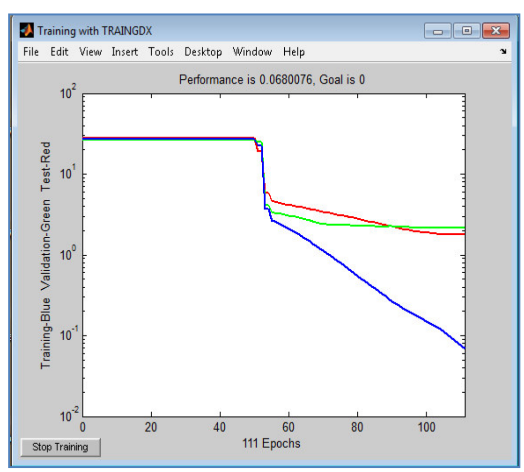

Figure 15: Training result for Elman network with 280 nodes

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ISSN 1605 – 427X
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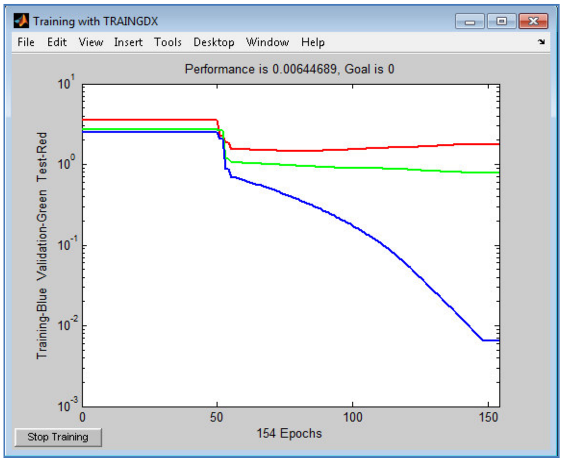

Figure 16: Training result for the ideal Elman network with 200 hidden nodes and Log sigmoid transfer function

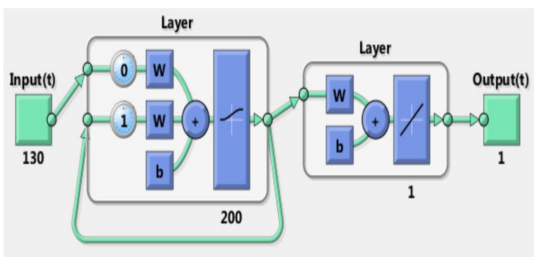

Figure 17: The ideal Elman architecture

Performance ratio for each ANN was calculated using the formula:

$$Performance\ ratio\ \% = \frac{Correct\ Samples}{Total\ Samples} x100\ \% \qquad (1)$$

The results showed that for BP NN and RNN, the performance ratio was 76.47%, while for Elman it was 88.24%.

Discussion:

Many studies in the field of brain tumor detection using ANN, used BP NN for image recognition [2,3,8,10]. This paper shows that Elman network gives better results compared to BP NN and RNN networks.

Moreover, the studies in this field focused on the preprocessing stage of MR images before it fed to the neuro recognizer. Studies in [4] and [5] perform segmentation for abnormal regions in MR image and then presented the segmented region for ANN. So, failures occurred in preprocessing stage lead to whole system failure.

The procedure followed in this work was focused on ANN as a sole method for the brain tumor recognition.

Finally, while the MR images dataset which is used in this work and explained in Ref [11], contains different modalities of MR images which increase the recognition difficulty for ANN. However, in spite of this limitation, the proposed ANN gave good results.

Conclusions

This paper presents an automated recognition system for MR imaging using ANNs. It was observed that when Elman network was used during the recognition process, the duration time and the accuracy level were high, compared with other ANNs systems.

This work used dataset contains all modalities T1, T2 of MR Images, which is gave it high power, accuracy and yield in detecting any type of abnormalities.

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