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Development of a Computerized Diagnostic System for Brain MRI Tumor Scanning Using a Robust Information Clustering Technique

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Abstract

This paper presents the development of a computerized diagnostic system for brain MRI tumor scanning using a robust information clustering technique. The method used for this study is data collection, data processing, feature extraction, artificial neural network, activation function, training algorithm, and classification. The method was modelled using a structural approach that developed the Artificial Neural Network (ANN) algorithm, using tansig activation function and back-propagation training algorithm. The brain tumor detection algorithm developed was implemented with MATLAB Simulink application, and tested with Mean Square Error (MSE) and Regression (R) analysis. The result showed that the MSE is 0.002488 and the Regression result is 0.9933. The algorithm was also comparatively compared with an existing system and the result showed that the new system achieved better regression performance than the others. Then it was deployed as a clinical decision system for the diagnosis of brain tumors and tested, the result showed that it was able to detect patients with brain MRI data.

Keywords

Back-Propagation, Magnetic Resonance Imaging (MRI), Neural Network, Simulink, Tansig.

INTRODUCTION

Brain tumors consist of abnormal growing tissues in the brain, resulting from the uncontrolled multiplication of cells [1]. This tumor not only increases the pressure and size in the brain but also causes abnormal neurological challenges. According to the National Brain Tumor Foundation (NBTF), over 300% of all people suffering from brain tumors died in developed countries. If such a mortality rate was recorded for the advanced part of the world, with the best medical facilities so far today, one will then question the devastating effect this epidemic cell has caused in developing and underdeveloped countries [2].

According to [3], Brain tumors are classified into two categories which are metastatic and primary brain tumors. In primary tumors, the cells are originally brain cells, but in metastatic tumors, the cells have already grown and spread into the brain from another infected area of the body. Examples of metastatic brain tumors are glioblastoma, gliomas, pituitary adenoma, acoustic neuroma, and haemangioblastoma among others [4].

Recently gliomas have gained lots of research attention with the main focus due to their increase in cases over the past decade [5]. Consequently, various approaches such as biopsy, spinal tap, MRI scan, neurologic exams, and angiogram have been applied to help solve this problem and diagnose the tumor, however, the main challenge is early detection of this tumor before they get to a certain stage [6].

When this tumor is detected early and treated, the probability of one surviving is so high compared to the reverse. The method of detection involves data collection approaches such as Magnetic Resonance Imaging (MRI), and computer thermograph imaging among others [7].

Among these techniques, the MRI is among the standard techniques used for data collection via radiology machines. This MRI is a non-invasive Vivo imaging approach that employs radio frequency signals to excite target tissues to produce an internal image view under the influence advanced magnetic field [8]. During this scan, information about the various modalities in the brain cell is revealed which are employed for the segmentation of tumors by the radiologist. However, many a time, when the tumor is young, they are not detected by the radiologist due to human error and this has remained a very big problem. This is due to their ability to detect is fully dependent on what the human eye can see at the time of the scan result. However, when the tumor is young, they are almost invisible to the human eyes from scan result as the attributes of an MRI result for a brain tumor vary based on size, and shape, among other characteristics [9].

The use of artificial intelligence techniques and image processing has been proposed by [1] [10] [11] [8] for the development of an automated brain tumor diagnostic system and achieved better results when compared to human experts many a time. From the techniques, the use of machine learning has achieved better results, with an algorithm such as K-Nearest Neighbor (K-NN), Support Vector Machine (SVM), and Artificial Neural Network (ANN) among others [12]. But so far, the artificial neural network achieved better recognition accuracy when

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compared to the rest algorithms.

ANN is a biologically inspired neuron that can learn and make accurate decisions when trained with data. This algorithm will be adopted in this research to develop a clinical decision system for the system [13]. This, when achieved, will help provide an easy-to-use, reliable, and cost-effective system that can be deployed at health centers can facilitate early detection of brain tumors in both rural and urban communities. In many rural localities today in Africa, the average person cannot afford the cost of medical care due to economic reasons (poverty) and the high cost of modern hospital treatments. Health centers are provided in most of these regions as an alternative to hospitals for easy access, but these medical centers lack facilities to diagnose brain tumors due to the high cost of the diagnosis machine, others that have the diagnostic system lack integrity as they are not developed with data collected from Nigerian hospitals. These problems have resulted in the late detection of brain tumors in African communities and the figures keep rising according to the World Health Organization (WHO) every year (2018). Other problems are the issues of human error from radiologists during the analysis of brain tumor data. All these issues have remained a major problem that needs urgent attention and will be addressed in this research using artificial intelligence techniques.

It has been established that brain tumor presents a very complex problem irrespective of the method used to perform the analysis. Many techniques such as deep learning using convolutional neural networks, image processing with segmentation, and fuzzy logic techniques among others have been used to solve this problem over time. However, despite the success, a solution has not been obtained using data collected from Nigerian hospitals for the intelligent diagnosis of brain tumors.

This research is focused on developing a metastatic-based brain tumor detection system using artificial intelligence techniques with the following set out objectives:

- To study the characteristics of brain tumors via data collection.
- To develop a brain tumor detection algorithm using an artificial neural network.
- To implement the algorithm developed with Simulink/Mathlab.
- To evaluate the performance, validate the results**,** and comparatively analyze the algorithm with the existing system.

MATERIALS

- 0.3T MRI system
- Laptop
- Inverter system
- Rs232 Serial Converter cord
- DICOM Software, etc

The DICOM software which enabled access to patient MRI imagery was installed on the laptop and then connected to the MRI machine using the serial converter cord. The inverter system was used to power the setup for a reliable power supply, and then the MRI data scanned from the test patients were collected.

Method

The method used for the system development is data collection, data processing, feature extraction, artificial neural network, activation function, training algorithm, and classification.

The data used for the study was collected from Memfy's Hospital Enugu as the primary source of data collection. The sample size of data provided by the hospital is the MRI data of 25 patients under the age of 45 with brain tumor cases where each patient provided 15 samples. The secondary source of data collection was the kaggle repository which provided 4,240 sample MRI data with the total sample size of data collected and used as the training dataset being 4615 MRI data with a brain tumor. The samples of the data collected are shown in Figure 1, while the attributes are in Table 1.

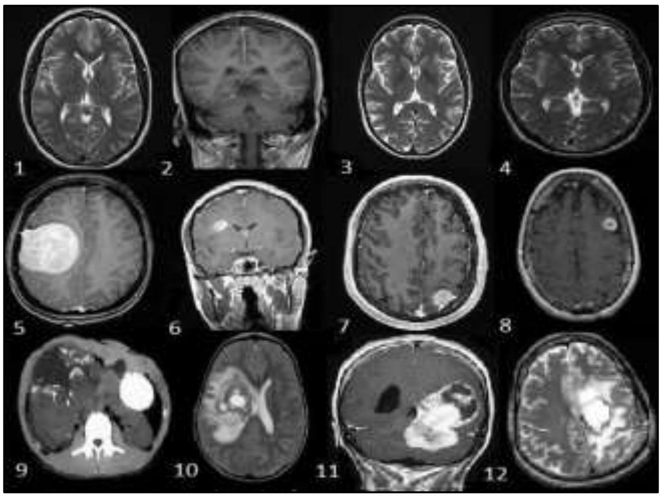

Figure 1. Data sample of brain MRI scan

Figure 1 presented the MRI sample data of the brain scan with the attributes of the brain tumor presented in Table 1.

Table 1. Attributes of Brain Scan [14]

S/N	**Attributes**
1	Medulloblastoma
2	Memimgioma
3	Pituitary
4	Low-grade Astrocytoma
5	Malignant astrocytoma
6	Malignant glioma
7	Ependymoma
8	Mixed glioma
9	Ganglioglioma
10	Choroid plexus tumor

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S/N	Attributes
11	Suprasellar
12	Craniopharyngioma
13	Germ cell tumor
14	Hypothalamic

Data processing

This process involves the removal of noise from the data collection for reliability. The data processing was done using the Gaussian filter model which removed the excess frequency which has the potential to dent the feature of the MRI scan before processing.

Data Extraction

This process was used to drill the MRI data from the scanned result into a statistically compact feature vector. The extraction process was done using a static and dynamic approach as given in [15]. This process was used to drill the data and extract the feature for training using the artificial neural network model developed in the next section.

Brain Tumor Detection Algorithm

To develop the brain tumor algorithm, the model of the feed-forward neural network in [16] was adopted and sued to develop the algorithm. The artificial neural network model was developed using a single neuron and activation function and then interconnect to form the neural network model based on the attributes of the brain tumor data characteristics as given in Table 1. The model of the neural network was presented in Figure 2.

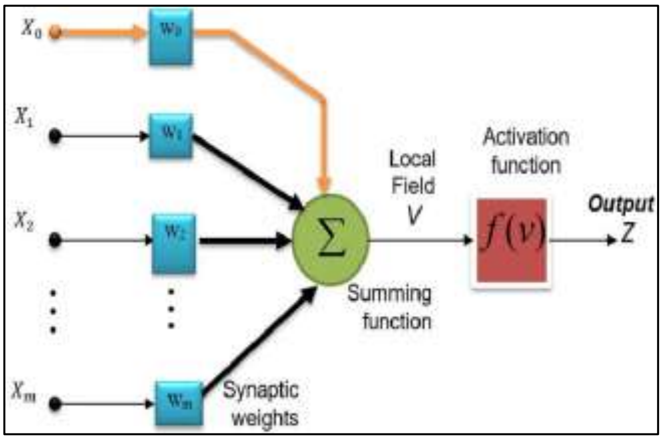

Figure 2. Model of a Single Neural Network

Figure 2 presented the model of a single neural network developed with neurons (X) which have weight (w), and summed and activated with the f(v) activation function to produce the output Z. The choice of activation function used is the tansig activation function as it does not explode during training unlike the sigmoid function and also does not have issues of convergence during training. The neural network model was reconfigured with the training parameters in Table 2 to form the neural network model used for training the brain tumor data collected.

Table 2. Neural Network parameters

Parameters	Values
Epoch	100
Epoch between display	10
Maximum time to train in sec	Infinity
Maximum validation failure	5
Number of hidden layers	3
Momentum factor	0.75
Learning rate	0.01
Minimum performance gradient	1e-6
Number of input neurons	14
Weight of neurons	14

Table 2 was used to develop the neural network model as shown in Figure 3 with the input layers, hidden layers, and output layer. The hidden layers are the section of the neural network where the computation process was done using the training algorithm. The activated neurons from the input are processed in the hidden layer using the training algorithm to learn the neurons of the brain tumor attributes until the least mean square error is achieved and the algorithm develops.

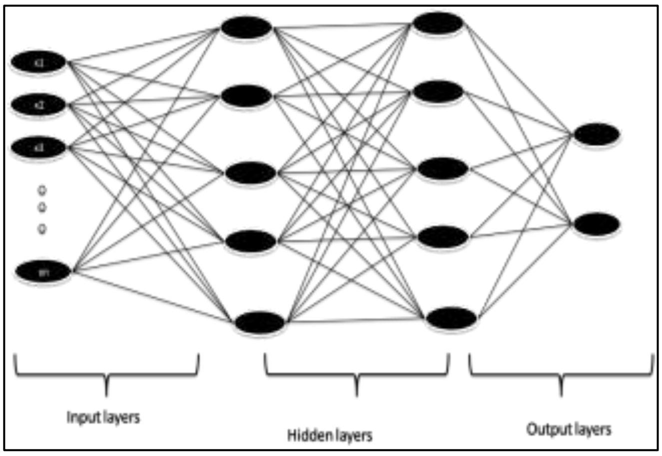

Figure 3. Model of the neural network architecture

Figure 3 presented the model of the neural network used to train the data collected from the sampled patients. The block diagram of the training process was presented in Figure 4.

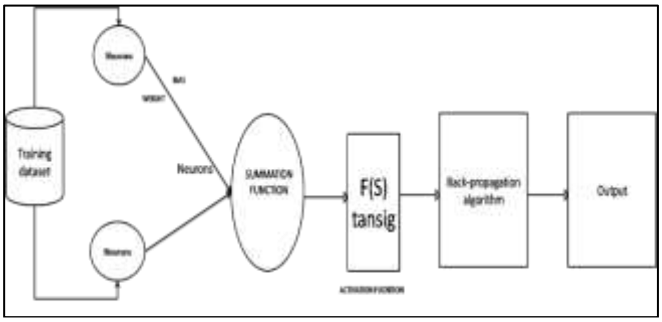

Figure 4. Model of the Neural Network Training

The neural network model block shown in Figure 4 was used to train the data collected to generate the brain tumor algorithm as the output. The training algorithm used is the back-propagation algorithm adopted from [1] and used to train the data and the generated brain tumor time series classification algorithm is presented in the pseudocode below:

1. *Start*
2. *Load brain tumor data*
3. *Initialize activation function*
4. *Initialize training algorithm*
5. *Initialize epoch values and intervals*
6. *Configure the neural network model as in Figure 3.3*
7. *Train neural network with Figure 3.4*
8. *Check for the Least Mean Square Error (MSE)*
9. *If*
10. $MSE \approx 0$ *Then*
11. *Generate the reference brain tumor algorithm*
12. *Else*
13. *Back-propagate and adjust the weight*
14. *Return to step (8)*
15. *Apply step (11)*
16. *End*

The system flow chart:

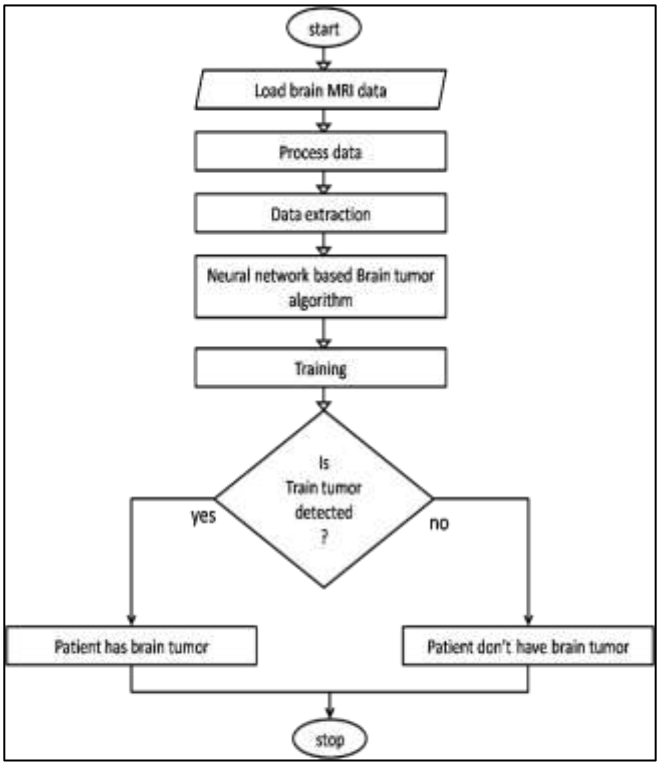

Figure 5. Brain Tumor Detection System flow chart

Figure 5 presents the brain tumor detection logical flow chart showing how the algorithm was used to develop the brain tumor detection system. The figure showed how data input from the MRI scan was loaded into it for processing with the Gaussian filter adopted and feature extraction method adopted too. The algorithm developed was then used to classify the check for a brain tumor and make intelligent decisions. The system developed was implemented in the next section.

SYSTEM IMPLEMENTATION

The system developed was implemented with a database toolbox, neural network toolbox, statistic and machine learning toolbox, and data processing toolbox in Simulink. The neural network toolbox was configured with the algorithm developed. The feature extraction toolbox was used to configure the statistics and machine learning toolbox, the Gaussian filter was used to configure the data processing toolbox. Then all the toolboxes were integrated into Simulink to develop the new system.

Figure 6 presented the neural network toolbox used to develop the new system. The tool showed the four items labeled a,b,c, and d. Before the training begins, the neural network divides the data into training, test, and validation sets in the ratio of 70:15:15; (a) presented the input neural network model configured when the brain tumor data was loaded for training. The (b) presented the back-propagation process which took place during the training process to adjust the neurons until the best version of the brain tumor classification algorithm was generated. The (c) was used to show how the training set was tested with the test set to make classification before the result was achieved. (d) Shows the training tool which was also used to evaluate the performance of the algorithm with regression and MSE.

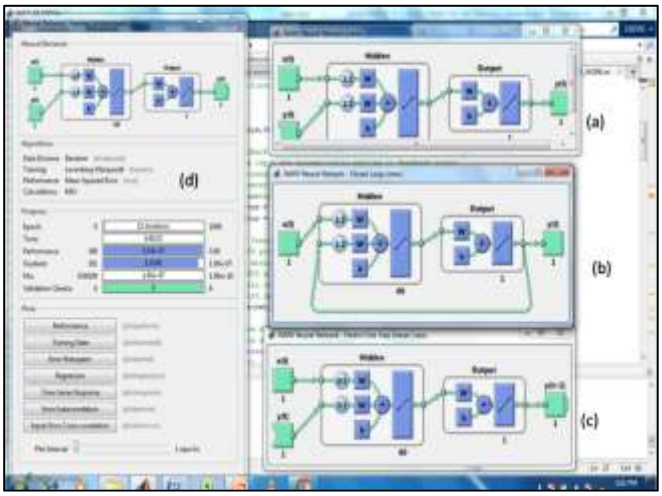

Figure 6. The Neural Network Toolbox

RESULTS OF NEURAL NETWORK TRAINING

This section presents the performance of the neural network algorithm developed. The result used MSE and regression to measure the performance of the algorithm to check the error recorded during the process and also the relationship between the true and false positive rate using a regression analyzer. The MSE result of the neural network was presented in Figure 7.

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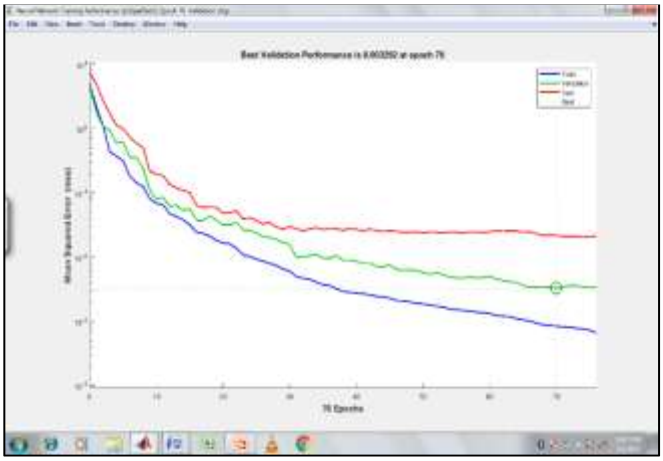

Figure 7. The MSE Performance.

Figure 7 presented the MSE performance of the brain tumor detection algorithm developed. From the result, it was observed that the MSE result is 0.003292Mu at epoch 70.

This implication of the result showed that the error achieved in the training of the algorithm is approximately zero and hence acceptable with an indication that the least error was recorded during the training process. The Regression performance was also presented in Figure 8.

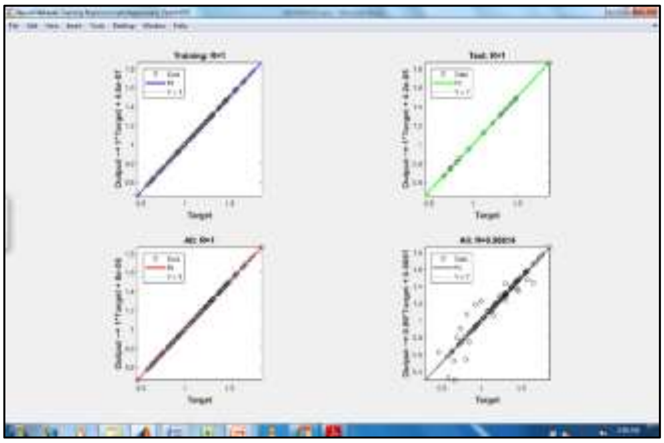

Figure 8. The Regression Performance.

From Figure 8 the regression result presented the performance of the algorithm in detecting brain tumors. The result first showed that during the training process that fitting was not achieved, thanks to the activation function used. The regression was measured using the average of the training, test, and validation sets to record the regression of the algorithm as R=0.96614. This result implied that the performance of the algorithm to detect brain tumors is very good as it is approximately equal to the ideal regression value of 1.

Validation of the Algorithm Result

The algorithm validation was done using a tenfold cross-validation technique which measured the performance of the brain tumor detection algorithm tenfold and then compute the average using MSE and Regression as presented in Table 4.

Table 4. Validation result of the filter with GDA

S/N	MSE (Mu)	Regression
1	0.003292	0.9954
2	0.003254	0.9976
3	0.003155	0.9951
4	0.003358	0.9968
5	0.002373	0.9939
6	0.002415	0.9953
7	0.001752	0.9920
8	0.002173	0.9942
9	0.003214	0.9972
10	0.003451	0.9988
Average	0.002488	0.9933

Table 4 presented the system validation performance using MSE and Regression, the average result showed that the MSE is 0.002488 and the Regression result is 0.9933.

System Integration as a Brain Tumor Detection System

After the development of the proposed system, tested, and validated the algorithm; it was integrated as a clinical decision system using MATLAB software as shown in Figure 9.

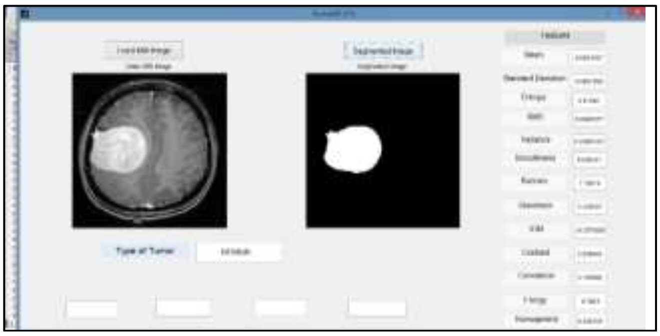

Figure 9. The system results

Figure 9 presented the brain tumor detection system with the MRI upload which was processed with the Gaussian filter to segment the segment of the cell and identify and reveal key parts of the MRI for a better feature extraction process in Figure 10.

Figure 10. Brain MRI diagnosis for tumour

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Figure 10 presented the result of the feature extraction process which was used to drill the important features of the brain tumor attributes and then classified with the algorithm developed to detect brain tumors as shown in Figure 11.

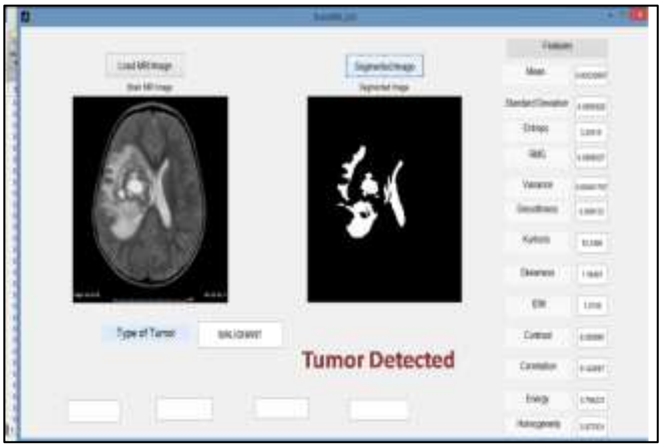

Figure 11. Brain MRI diagnosis Result

Figure 11 showed how the algorithm was used to classify the features of the input MRI data to detect tumor problems in the patient. The next result also showed the system performance when used to test for a patient without a brain tumor and the result was presented in Figure 12.

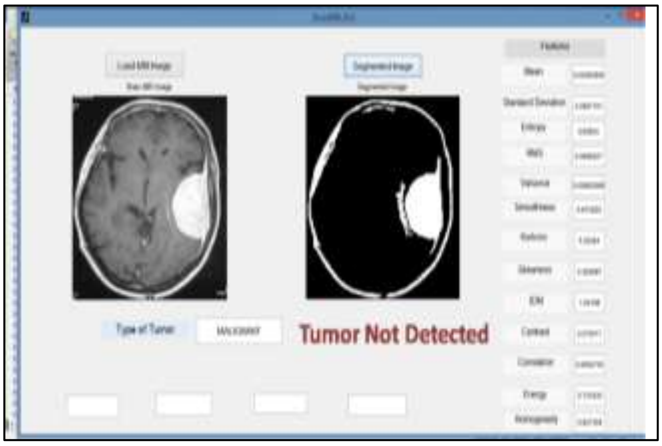

Figure 12. Bain MRI diagnosis for malignant tumour

CONCLUSION

The study has successfully developed an expert system for the diagnosis of brain tumors using an artificial neural network. This was achieved via data collection of MRI patients below 45 years and then used to develop a brain tumor detection algorithm. The algorithm was integrated as a clinical decision system and then tested with regression and MSE. The result showed that the MSE is 0.002488 and the Regression result is 0.9933. The performance was compared with the existing state-of-the-art algorithms and then the result showed that the new system performed better. The performance was also compared with the existing algorithm developed recently and the result showed that the new algorithm achieved better regression performance when compared to the rest.

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