ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

Brain Tumor Diagnosis Using Deep Neural Network (DNN)

Suraj S. Gawande, Vrushali Mendre

Department of Electronics & Telecommunication Engineering, Smt. Kashibai Navale College of Engineering, Vadgaon Bk. Pune, India

ABSTRACT- A brain tumor detection and classification has been design & developed. The computer based method is used to detect the tumor. Deep Neural Network (DNN) using stack autoencoders has been implemented for classification of tumor. The MRI images of different patients with three kinds of brain tumor: Meningioma, Glioma and Pituitary are used for classification. The Image processing techniques such as image segmentation, feature extraction have been developed for detection of tumor in MRI images. The watershed transform technique is used for segmentation. The texture based features and intensity based features are extracted with help of Gray Level Co-occurrence Matrix (GLCM) & Discrete Wavelet Transform (DWT). Finally a DNN using stack autoencoders has been developed to identify type of brain tumor. Our network has stack autoencoders which consist of two autoencoders for feature learning and one softmax layer for classification. We have obtained a good result with 92.3% accuracy. Finally a Graphical User Interface (GUI) has been created to show the classifier output.

KEYWORDS- Deep Neural Network (DNN), Gray Level Concurrence Matrix (GLCM), Discrete Wavelet Transform (DWT).

I. INTRODUCTION

During the previous couple of years deep learning has gained an immense attention by demonstrating promising results in the different field, for example, speech recognition, handwritten character recognition, image classification, image detection and segmentation [1]. There is future desire that deep learning enhance or make biomedical applications, for example, image enrollment, multimodal image examination, high speed imaging and computer based diagnosis. There are a various deep learning application in medicinal field, for example, organ cancer detection and cell tracking. Tumor is comprised of irregular (Not normal) cells. There can be two conceivable outcomes of cerebrum tumor: Malignant (Cancerous) or Benign (Non- cancerous). The consistent development of tumor cells inside the skull will harm the cerebrum for all time or it might bring about the demise of the patient [3]. Along these lines an early recognition of tumor and the correct treatment arranging is exceptionally basic to make the patient cure inside a period. Magnetic Resonance Image (MRI) has turned out to be so mainstream in restorative petitioned for discovery of cerebrum tumor. MRI examine utilizes an effective magnetic field and radio frequency pulses to create detail image of delicate tissues inside the mind. The tissues are clearer in MR images. Radiologist is the specialists who are specialize reading these images. Radiologist dependably propose MRI image of brain for determination (diagnosis).

The quantity of research in automatic cerebrum tumor detection has developed radically in decades ago. The work done in most recent couple of years on human brain classification has accomplished promising outcomes by means of machine learning and classification methods, for example, SVM, Artificial Neural Network (ANN) and so on. The cerebrum tumor identification and classification framework utilizing the neuro-fuzzy logic utilize the basic classification strategy [2]. A pair of DWT and energy criteria for signal decomposition & reconstruction for data dimensionality reduction and classification using Bayesian ANNs had accomplished exceptionally promising outcomes [5]. The tumor classification technique built from the blend of DWT, GLCM for feature extraction and Probabilistic Neural Network (PNN) as a classifier achieved maximum recognition rate [8].

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering
(An ISO 3297: 2007 Certified Organization)
Website: www.ijircce.com
Vol. 5, Issue 5, May 2017

In this work, the objective was to develop high speed classifier using DNN to classify the abnormality of brain. We propose architecture for automatic brain tumor detection and classification. Our network is based on Mina Rezaei at al. [1] with certain improvements and with specific enhancements. The input is brain MRI image. At first the image pre-preparing is applied on an input image. The watershed transform system is use for location of irregular tissues inside the tumor. In the segmentation output, the size and shape of the tumor is shown. The textural and intensity base features are drawn by utilizing GLCM and DWT. The DNN using stack autoencoders is used as a classifier. We stack the autoencoders and the softmax layer to construct the deep network with 10 hidden layers (for deeper learning). The features learning and selection has been done consecutively at two distinct phases of stack autoencoder i.e autoencoder 1 and autoencoder 2. Feature learning and selection keeps away from the overfitting issues. Consequently by using autoencoder deep neural network we have achieved better outcome for brain tumor classification.

II. DATA DESCRIPTION

In this research we have used three different brain dataset to estimate our proposed method.

a) Pituitary Brain Tumor Images

The pituitary gland is connected directly to part of the brain called the hypothalamus. The 100 MRI images of pituitary brain tumor have collected. The MR image acquisition protocol for each subject includes: T1-weighted contrast-enhanced images.

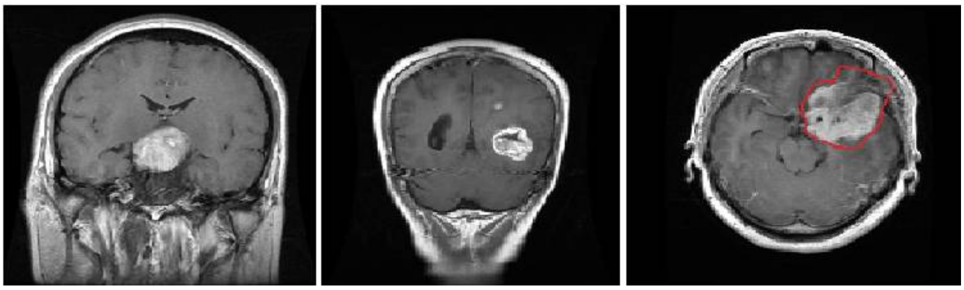
b) Glioma Brain Tumor Images

The glioma tumor are the most common primary brain tumor. They occur in all age groups, with 75 to 84 year olds. The 100 T1-weighted contrast-enhanced MRI images of glioma brain glan has been collecetd.

c) Meningioma Brain Tumor Images

Meningiomas develop in meninges which is a membraine like structures surrounding spinal cord and brain. The T1-weighetd contrast-enhanced MRI images of 100 patients has collected.

All the 300 MRI images of pituitary, glioma & meningioma brain tumor has been collecetd from SKN Hospital in Pune.



(a) (b) (c)

Figure 1. We trained our architecture by three different categories of brain MRI (a): Shows pituitary brain tumor. (b): Shows glioma type of tumor. (c): presents meningioma gland.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering
(An ISO 3297: 2007 Certified Organization)
Website: www.ijircce.com
Vol. 5, Issue 5, May 2017

III. METHOD

The whole design & development carried out in three stages: 1) Image Processing involves tumor segmentation 2) Feature Extraction 3) Implementation of classifier. The processing is done on cancer affected MRI images of brain. Image enhancement, tumor separation and then feature extraction using GLCM & DWT. Extracted features are provided to the classifier as an input for classification. A suitable Autoencoder DNN is developed to recognize the type of tumor in the classifier output. The Graphical User Interface (GUI) is created to make the system user friendly. The block diagram for the proposed system is shown in fig. 2 below.

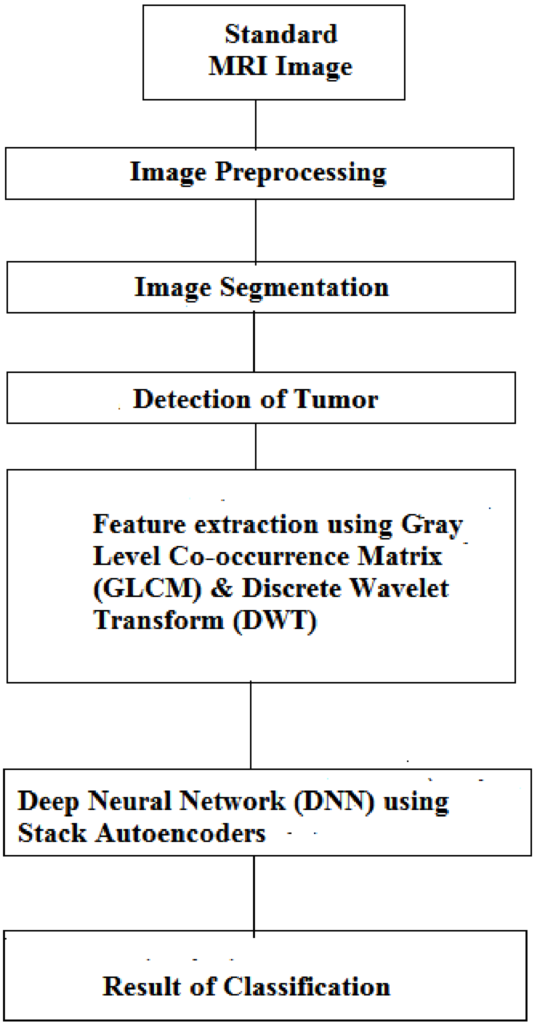


Figure 2. Block Diagram of the System

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering
(An ISO 3297: 2007 Certified Organization)
Website: www.ijircce.com
Vol. 5, Issue 5, May 2017

IV. IMAGE CLASSIFICATION STAGES

a) Stage One: Tumor Segmentation

The very first step in the proposed system is to separate the tumor region from the rest of the image i.e. separation of abnormal tissues and normal tissues. Many segmentation techniques has been studied and implemented in past few years for brain tumor detection. In our research, we have used watershed transform method for segmentation of tumor. The advantages of this method are, the resulting boundaries form closed and connected regions. This method is very easy to implement and simple to understand. The watershed segmentation is well known edge based segmentation algorithm [6]. Watershed means a basin-like landform defined by highpoints & ridgelines that move down into lower elevations and small valleys. In geographically, the line separating two catchment basins, as shown in fig. 3 is called as watershed line. The water or rain falls on both side of watershed line will flow in to the same lake or dam. The concept has used in image processing for solving segmentation problems. The watershed is useful for the value of higher intensity. The technique for segmenting the digital images that use a type of region growing method based on an image gradient. Gradient descent describes segmented regions.

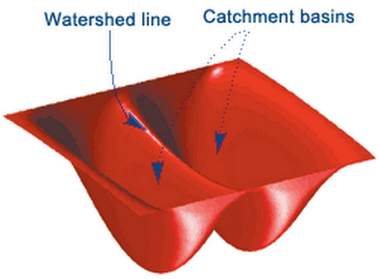


Figure 3. Principal of Watershed Segmentation

b) Stage Two: Feature Extraction

To connote any image big pack of information is needed. This information consumes lots of space in memory. The number of features is extracted from an image. These features provide relevant information about the image. The extracted features are provided as an input to the classifier for classification. The GLCM algorithm has been implemented for textural information extraction. The multi-resolution of image is performed using DWT method. The wavelet decomposed features in four sub bands: (i) Approximated (LL), (ii) Horizontal (LH), (iii) Vertical (HL) and (iv) Diagonal (HH) are extracted with the help of DWT. Contrast, correlation, energy, homogeneity, variance, standard deviation, Inverse Difference Moment (IDM), Entropy, Mean, skewness, cluster prominence, cluster shade, inertia features are extracted using GLCM. This feature helps classifier for more accurate decision making i.e. tumor classification.

c) Stage Three: Deep Neural Network using Stack Autoencoder

Deep Learning with Convolutional Neural Network (CNN) used for classification & regression, and autoencoders utilized for features learning. Autoencoders are straightforward learning circuits which aim to transform input to its output with least possible distortion. They assume essential part in machine learning. As of late autoencoder has obtained an imperative part in the "deep-learning" approach where autoencoders act as Restricted Boltzmann Machines (RBMS) [8].The number of autoencoders are stacked and trained up in unsupervised manner, trailed by a supervised learning stage. These deep architectures have been used to lead to state-of-the-art results on number of challenging classification and regression problems.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

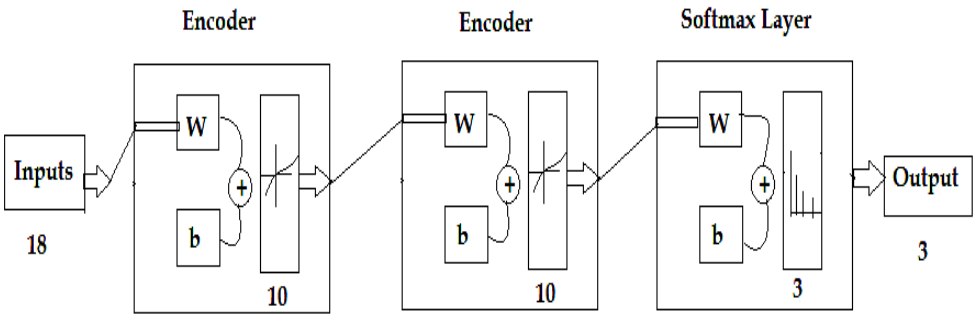


Figure 4. Our Autoencoder Deep Neural Network Consist of two Autoencoders and one softmax layer. Both the autoencoders has 10 hidden layers.

Neural network with multiple hidden layers can be helpful for solving classification problems with complex information, for example, images. Each layer can learn features at different level of abstraction. Notwithstanding, training a neural system with various hidden layers can be troublesome practically speaking. One approach to successfully prepare a neural system with numerous layers is via train one layer at given moment. In our work we have accomplished this via training exceptional kind of system known as an autoencoder for desired hidden layer. To start with we have prepared the hidden layers independently in an unsupervised manner using autoencoders Then we prepared a last softmax layer and combine the layers to shape a deep system as appeared in fig. 3 above. At long last DNN with stack autoencoders has been trained one last time in supervised fashion. The softmax layer utilized as yield layer in supervised fashion. The main function of softmax layer is classification and autoencoders are used for feature learning and feature representation

V. RESULTS

The developed application software efficiently performed on the input MRI images of brain cancer affected patients. The system successfully classifies the tumor into pituitary, glioma & meningioma type of cancer. The system first extracts the tumor abnormal cells from rest of the normal cells i.e tumor segmentation. The textural and wavelet features are extracted from segmented cerebrum. The extracted features are used as an input to train the classifier. Finally the DNN classifies the tumor in to three types of brain cancer: Pituitary, Glioma & Meningioma.

a) Stage One: Training the first Autoencoder

Training the first autoencoder on the training data. It learn & returns the smaller representation of input training data i.e. features. The performance of the first autoencoder is shown in fig. 5 The Mean Squared Error (MSE) is 1.0397e+22 which represent the learning accuracy of the autoencoder. Lesser the value of MSE more is the learning accuracy.

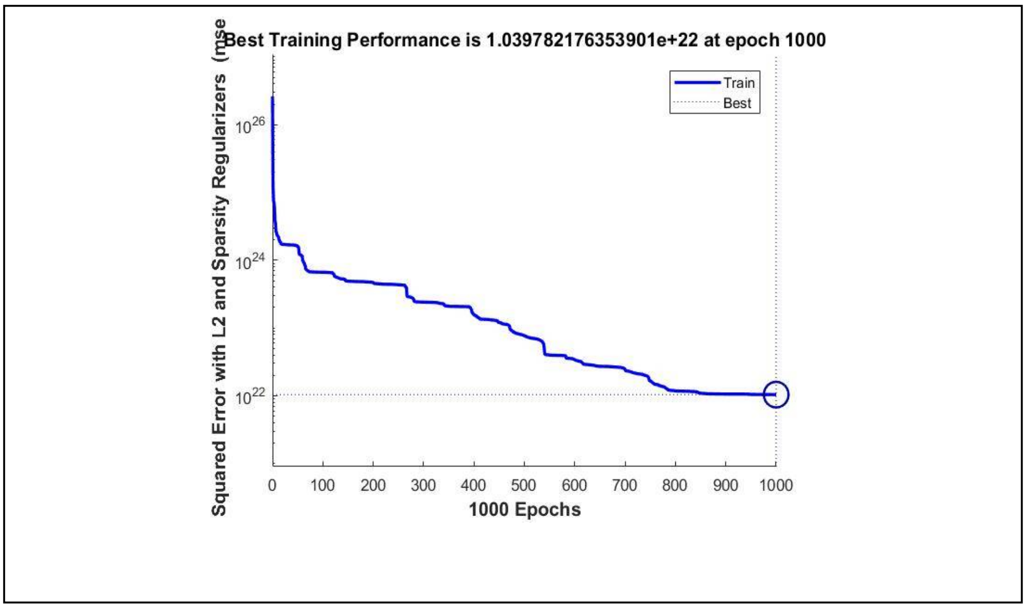
ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017



b) Stage Two: Training the Second Autoencoder

After training the first autoencoder, we trained the second autoencoder in similar way. The main difference is that we used the features that were obtained from the first autoencoder. This Autoencoder learns even smaller representation of the input data.

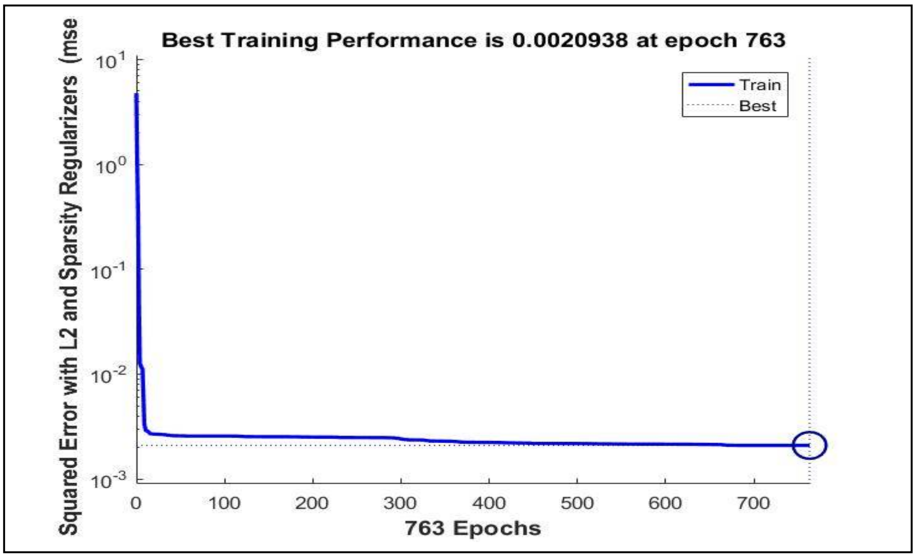


Figure 6. Training performance of second autoencoder.
The performance of second autoencoder shown in fig. 6. MSE value is 0.0020938.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering
(An ISO 3297: 2007 Certified Organization)
Website: www.ijircce.com
Vol. 5, Issue 5, May 2017

c) Stage Three: Training the Softmax layer & stacking the network.

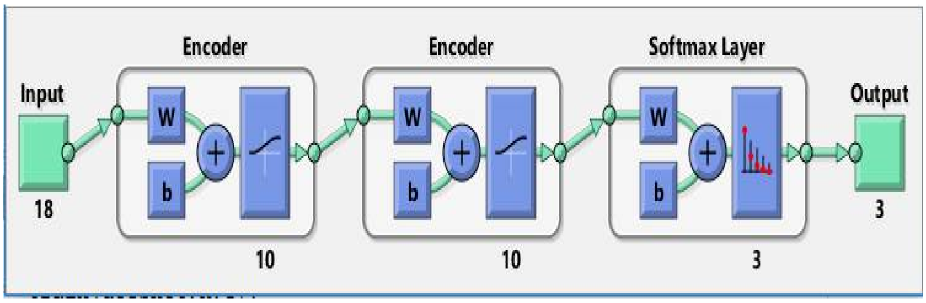


Figure 7. Stack of Autoencoders & Softmax Layer.

We trained the softmax layer for classification using the learned features obtained from autoencoders. Finally, to form a Deep Neural Network (DNN) we stacked autoencoders & softmax layer as shown in fig. 7 above. This forms a deeper architecture in supervised fashion.

d) Stage Four: Testing of DNN architecture.

With the full deep network formed in figure 7, we computed the final result in the form of confusion matrix shown in figure 8 below.

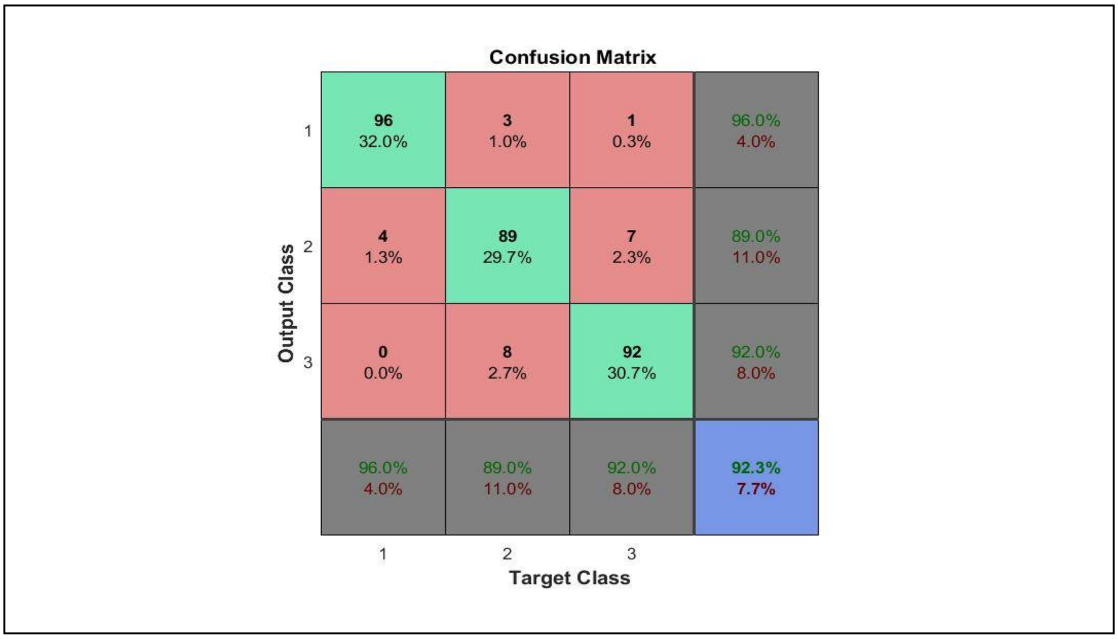


Figure 8. Visualize the final result with confusion matrix.

The numbers in the blue color bottom right-hand square of the matrix give the overall accuracy. We achieved the final accuracy of 92.3% as shown in fig. 8 above.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering
(An ISO 3297: 2007 Certified Organization)
Website: www.ijircce.com
Vol. 5, Issue 5, May 2017

e) Stage Five: Graphical User Interface (GUI).

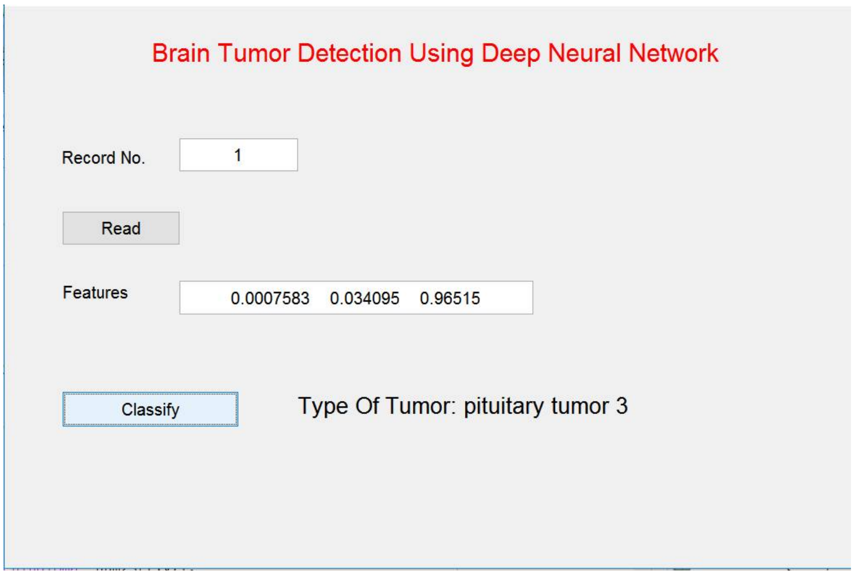


Figure 9. Result of Classification

The final Classifier is represented by using GUI as shown in fig 9. The above results describes that the system works efficiently for classification of brain tumor. Test result is in the agreement with the opinion of doctors and provides a confirmation test for cancer detection.

VI. CONCLUSION

The Brain Tumor classification system is implemented using Deep Neural Network using Stack Auto Encoders. The design based on image processing techniques, DNN and Graphical User Interface was successfully completed and used in the system to detect and classify the tumor. The watershed transform technique is used for tumor detection. Texture and Wavelet features are used in the training of the classifier. We trained our architecture on three different categories of brain MR images. In this experiment, the MRI samples are collected from Radiology department of SKN hospital, Pune. The system has been tested only with the above sample images. We have achieved promising results in automatic brain abnormality classification by using Deep learning with 92.3% accuracy.

REFERENCES

1. Meena Razaei, Haojin Yang and Christoph Meinel, “Brain Abnormality Detection by Deep Convolutional Neural Network”, unpublished.
2. Dipali M. Joshi, Dr.N. K. Rana, V. M. Misra,”Classification of Brain Cancer Using Artificial Neural Network“, IEEE-2nd International Conference on Electronic Computer Technology (ICECT), 2010, pp. 1-5.
3. Ramya K, Joshila Grace L. K., “Brain Tumor Detection Based on Watershed Transformation”, IEEE-International Conference on Communication and Signal Processing, pp. 0049-0054, 2016.
4. Sergio Pereira, Adriano Pinto, Victor Alves, and Carlos A. Silva, “Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images”, IEEE TRANSACTION ON MEDICAL IMAGING, VOL 35, MAY 2016.
5. Carlos Arizmendi, Alfredo Vellido, Enrique Romero, “Binary Classification of Brain Tumors Using a Discrete Wavelet Transform and Energy Criteria”, IEEE 2011, 2011, pp. 1-4.
6. P. Dhage, M. Phegade, S. K. Shah, “Watershed Segmentation Brain Tumor Detection”, IEEE International Conference on Pervasive Computing (ICPC), 2015
7. Komal Sharma, Akwinder Kaur and Shruti Gujral, “A review on various brain tumor detection techniques in brain MRI images”, IOSR Journal of Engineering (IOSRJEN), Vol. o4, Issue 05, May-2014
8. Pierre Baldi, “Autoencoders, Unsupervised Learning and Deep Architectures” , Workshop on Unsupervised and Transfer Learning, JMLR: Workshop and Conference P roceedings 27:37-50,2012.