



Deep learning for enhanced brain Tumor Detection and classification Using Hybrid Method

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Abstract

Brain tumor classification plays an important role in clinical diagnosis and effective treatment. In this work, we propose a method for brain tumor classification using an ensemble of deep features and machine learning classifiers. In our proposed framework, we adopt the concept of transfer learning and uses several pre-trained deep convolutional neural networks to extract deep features from brain magnetic resonance (MR) images. The extracted deep features are then evaluated by several machine learning classifiers. The top three deep features which perform well on several machine learning classifiers are selected and concatenated as an ensemble of deep features which is then fed into several machine learning classifiers to predict the final output. To evaluate the different kinds of pre-trained models as a deep feature extractor, machine learning classifiers, and the effectiveness of an ensemble of deep feature for brain tumor classification, we use three different brain magnetic resonance imaging (MRI) datasets that are openly accessible from the web. Experimental results demonstrate that an ensemble of deep features can help improving performance significantly, and in most cases, support vector machine (SVM) And ANN kernel outperforms other machine learning classifiers, especially for large datasets.

Keywords: Deep learning; ensemble learning; brain tumor classification; machine learning; transfer learning

I. INTRODUCTION

The theme of this thesis is varied strategies of image segmentation applied on medical pictures. This chapter can begin by outlining the essential drawback of segmentation and inspire its importance in several applications. Fashionable medical imaging modalities like magnetic resonance imaging and CT scans generate larger and bigger pictures that can not be analyzed manually. This drives the need for additional economical and study image analysis strategies, tailored to the issues encountered in medical pictures. The aim and motivation of this thesis area unit directed towards the matter of segmenting brain magnetic resonance imaging pictures.

Image segmentation is that the drawback of partitioning a picture into significant regions on the premise of grey-level, color, texture. this means the generality of the problem-segmentation may be found in any image-driven method, e.g. fingerprint/text/face



recognition, trailing of moving people/cars/airplanes, etc. for several applications, segmentation reduces to finding associate in nursing object in a picture. This involves partitioning the image into two categories of regions - either object or background. It's merely not possible in apply to manually method all the pictures (like magnetic resonance imaging and CT scan), owing to the overwhelming quantity of data it provides. Therefore, we have a tendency to style algorithms that search for bound patterns and objects of interest and place them to our attention. To Illustrate, area unit centre standard application is to look and match illustrious faces in your photograph library that makes it attainable to mechanically generate photograph collections with a precise person. a crucial a part of this application is to section the image into "Face" and "background". this may be tired variety of the way, and it's well accepted that no general purpose segmentation rule exists, or that it ever are going to be made-up. Thus, once planning a segmentation rule, the appliance is often of primary focus: ought to we have a tendency to section the image supported edges, lines, circles, faces, cats or dogs [1].

II. ISSUES OF OLD ARTICLES

Diagnostic imaging is a useful tool in drugs nowadays. The technologies like resonance imaging (MRI), X-radiation (CT), and alternative imaging modalities have relieved data of traditional and pathological anatomy for medical analysis and area unit an important part in identification and treatment coming up with [2].

The potential of intelligent knowledge analysis techniques has up with the increasing quantity of knowledge on the market digitally. With enhancements in laptop performance and development of the digital devices opportunities are created to use multimedia system knowledge, admire pictures and voice. In existing storage systems, a amount of information that our system is ready to store associated an index entry is created once information is keep. once users wish to retrieve some item of data, they use the index to seek out the specified item. it's tough to seek out one thing accurately and quickly from among the various complicated things in an exceedingly information due to the massive index house for the info being searched.

III. FUNDAMENTAL OF SEGMENTATION TECHNIQUE:

Segmentation technique may be divided roughly into the subsequent categories:

- (1) Thresholding approaches,
- (2) Region growing approaches,
- (3) Classifiers,
- (4) Bunch2 approaches,
- (5) Andrei Markov random field models,
- (6) Artificial neural networks,
- (7) Deformable models, and
- (8) Atlas guided approaches.

Different notable ways conjointly exist of the various approaches expressed above; thresholding, classifier, clustering, and Andrei Markov random field approaches may be thought of component classification ways. [3]

IV. BASIC OF ALGORITHMS

Three normally used agglomeration algorithms are:

- 1) k-means,
- 2) The fuzzy c-means algorithmic rule,
- 3) The expectation-maximization (EM) algorithmic rule.

Within the k-means agglomeration algorithmic rule, clusters mean is iteratively computed and a mean intensity for every category is assigned and image is segmented by assigning each component within the category with the nearest mean. The fuzzy c-means algorithmic rule generalizes the k-means algorithmic rule, giving soft segmentations supported by fuzzy mathematics. Clustering knowledge isn't needed by agglomeration algorithms, however they do need an initial segmentation (or equivalently, initial parameters). Therefore, not like classifier ways, agglomeration algorithms may be sensitive to noise and intensity inhomogeneities. This lack of special modelling, however, will give important benefits for quick computation.

K-means agglomeration algorithmic rule is additionally an unsupervised technique for the segmentation of the image in a very noisy image of the target area into several regions that are of comparable intensities, that lead to several local minima that will increase over-segmentation. The coarse area units are smoothed within the segmentation by k-means technique.

K-means agglomeration is employed as a result of it's straight forward and has comparatively low procedure quality. Additionally, it's appropriate for medical specialty image segmentation because the range of clusters (K) is sometimes glorious for pictures of specific regions of human anatomy.

V. PROPOSED METHOD SUPPORT VECTOR MACHINES

Support Vector Machines or SVM in-short, is one of the most popular and talked about algorithms, and were extremely popular around the time they were developed and refined in the 1990s, and continued to be popular and is one of the best choices for high-performance algorithms with a little tuning and it presents one of the most robust prediction methods.

SVM is implemented uniquely when compared to other ML algorithms. An SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier.

SVM is a Supervised Learning algorithm, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification as well using a trick or parameter called as Kernel, which implicitly maps their inputs into high-dimensional feature spaces. Will see the details about the Kernel soon.

SVM is also an Unsupervised Learning algorithm. When data is unlabelled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data into groups, and then map new data to these formed groups.

The support-vector clustering algorithm, created by Hava Siegelmann and Vladimir Vapnik, applies the statistics of support vectors, developed in the support vector machines algorithm,

to categorize unlabeled data, and is one of the most widely used clustering algorithms in industrial applications.

In machine learning, support-vector machines (SVMs, also support-vector networks[1]) are supervised learning models with associated learning algorithms that analyze data for classification and regression analysis. Developed at AT&T Bell Laboratories by Vladimir Vapnik with colleagues (Boser et al., 1992, Guyon et al., 1993, Vapnik et al., 1997), SVMs are one of the most robust prediction methods, being based on statistical learning frameworks or VC theory proposed by Vapnik (1982, 1995) and Chervonenkis (1974). Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). SVM maps training examples to points in space so as to maximise the width of the gap between the two categories. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

When data are unlabelled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups. The support-vector clustering[2] algorithm, created by Hava Siegelmann and Vladimir Vapnik, applies the statistics of support vectors, developed in the support vector machines algorithm, to categorize unlabeled data, and is one of the most widely used clustering algorithms in industrial applications [4].

Proposed Method: Hybrid ANN–SVM for Brain Tumor Classification

Step 1: Preprocessing and Feature Extraction

Brain MRI images are first pre-processed to remove noise and improve contrast using techniques such as median filtering and histogram equalization. The tumor region is then segmented using thresholding or region-based segmentation. From the segmented region, discriminative features such as texture (GLCM features), shape, and intensity-based features are extracted to represent tumor characteristics effectively.

Step 2: Feature Learning Using Artificial Neural Network (ANN)

The extracted features are fed into an Artificial Neural Network to perform high-level feature learning. The ANN automatically captures complex and non-linear patterns present in brain tumor data. Instead of final classification, the ANN is used as a feature optimizer, and the learned feature vectors from the hidden layer are forwarded to the next stage.

Step 3: Final Classification Using Support Vector Machine (SVM)

The optimized feature vectors obtained from the ANN are classified using a Support Vector Machine. SVM is employed due to its strong generalization ability and effectiveness in handling high-dimensional data. The final output classifies MRI images into tumor and non-

tumor (or different tumor types), achieving improved accuracy compared to individual ANN or SVM models.

VI. SIMULATION AND RESULT

SIMULATION AND IMPLEMENTATION WORK

Image properties

Size of the images taken are:

- Brain1 : 746X 644
- Brain2 : 746X 644
- Brain3 : 746X 644
- Colored image1 : 169X243
- Colored 2 : 189X269
- Colored 3 : 186X274
- Watershed image 1 : 170X190
- Watershed image 2 : 170X190
- Watershed image 3 : 170X190

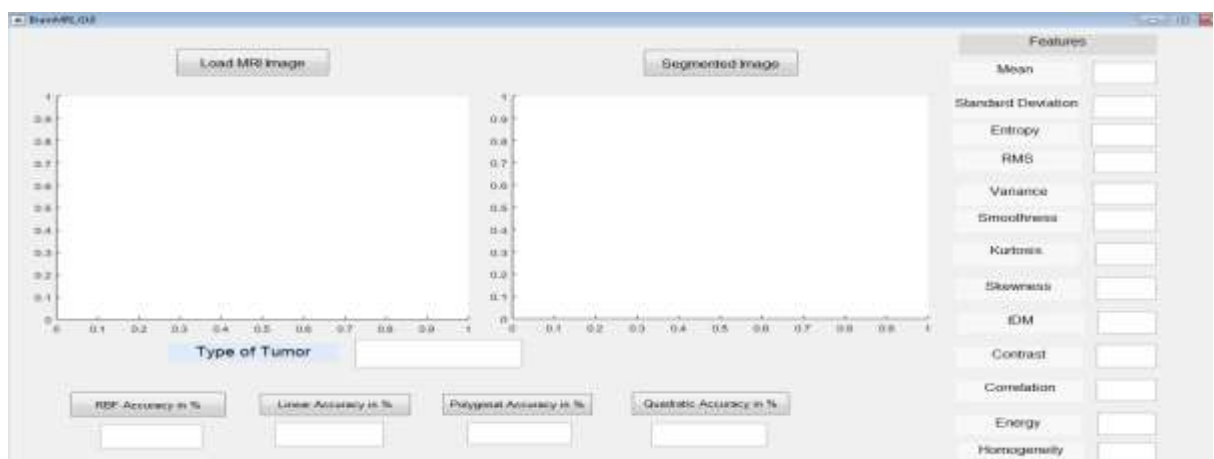


Fig.6.1 Input Image.

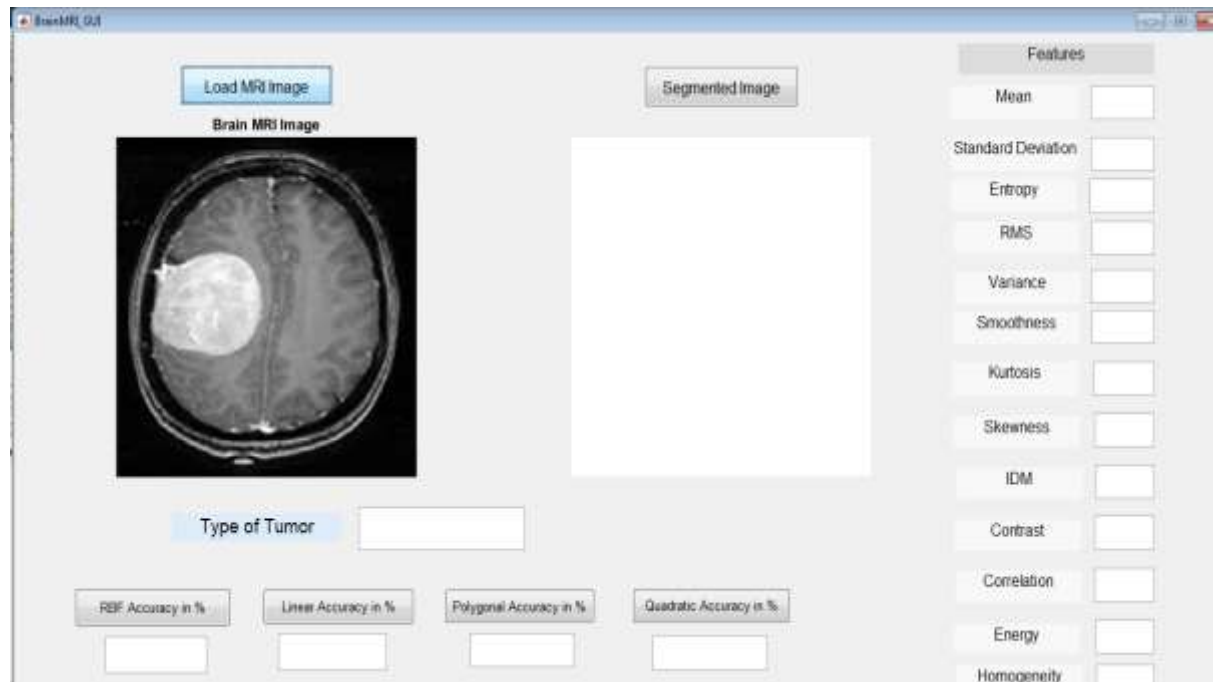


Fig.6.2 Image Selection (a).

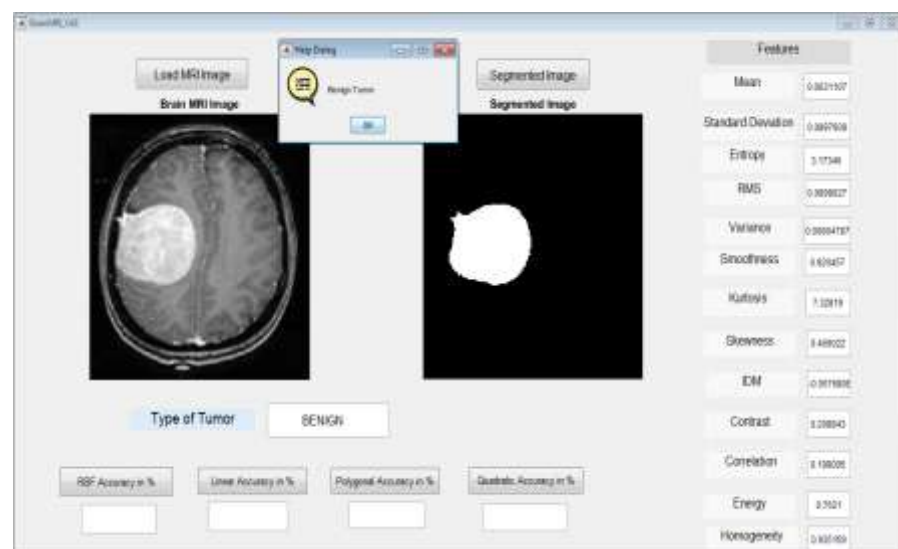


Fig.6.3 Segmentation image (b).

Features	
Mean	0.0031107
Standard Deviation	0.0897608
Entropy	3.17346
RMS	0.0898027
Variance	0.00804787
Smoothness	0.920457
Kurtosis	7.32819
Skewness	0.469022
IDM	-0.057689E
Contrast	0.208843
Correlation	0.199005
Energy	0.7621
Homogeneity	0.935159

Fig.6.4 Output parameters.

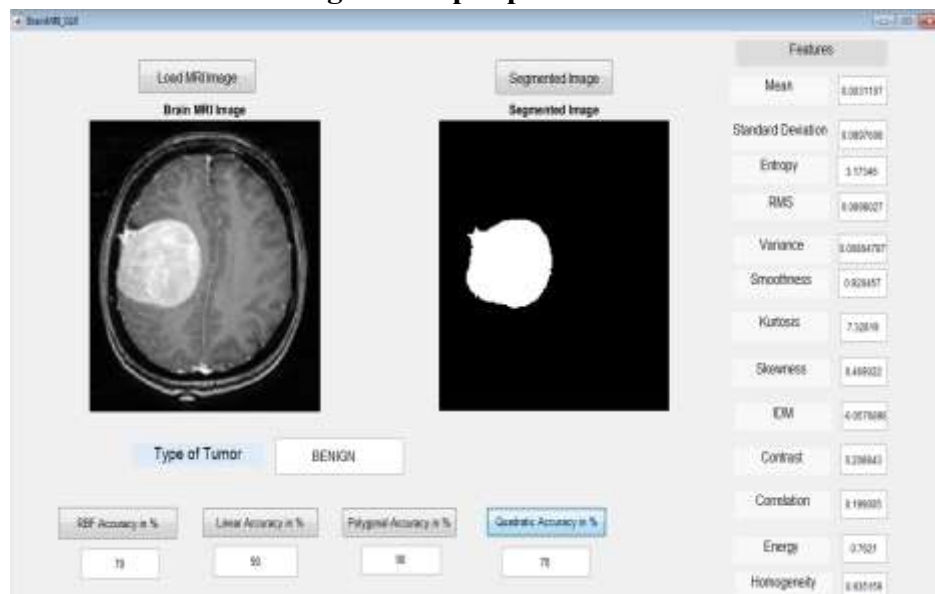


Fig.6.5 Test Image 1.

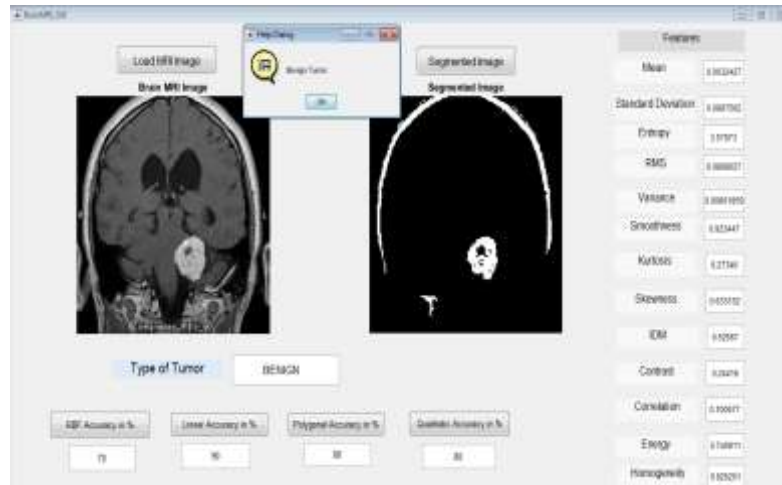


Fig.6.6 Test Image 2.

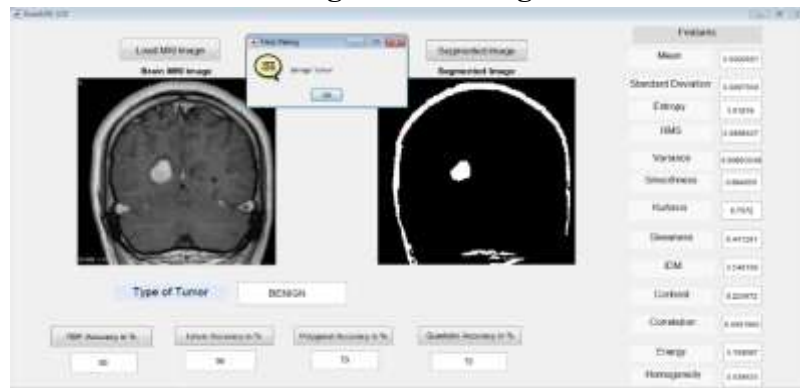


Fig.6.7 Test Image 3.

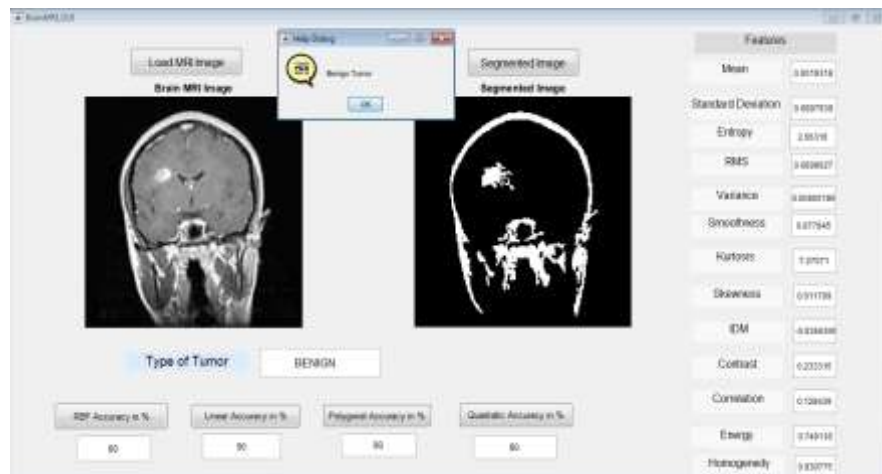


Fig.6.8 Test Image 4.

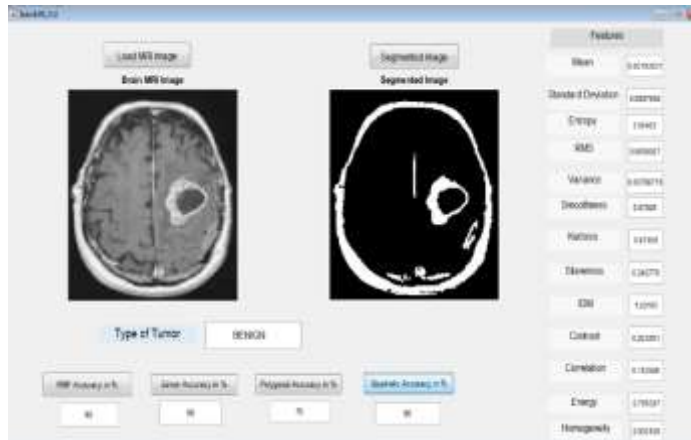


Fig.6.9 Test Image 5.

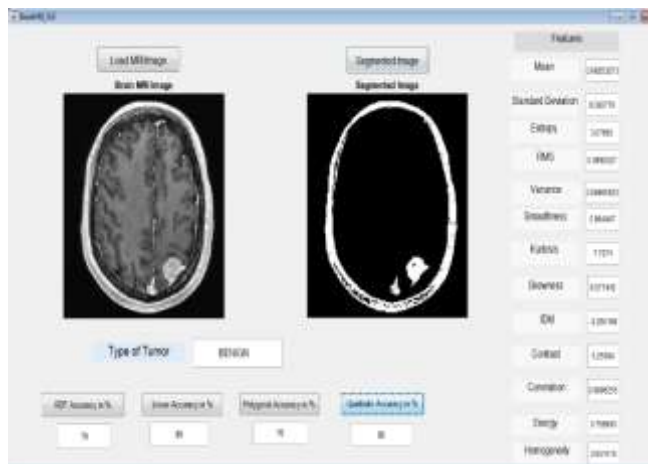


Fig.6.10 Test Image 6.

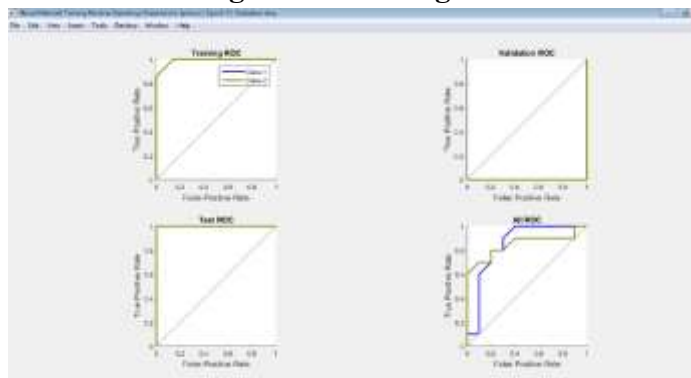


Fig.6.11 ROC curve.

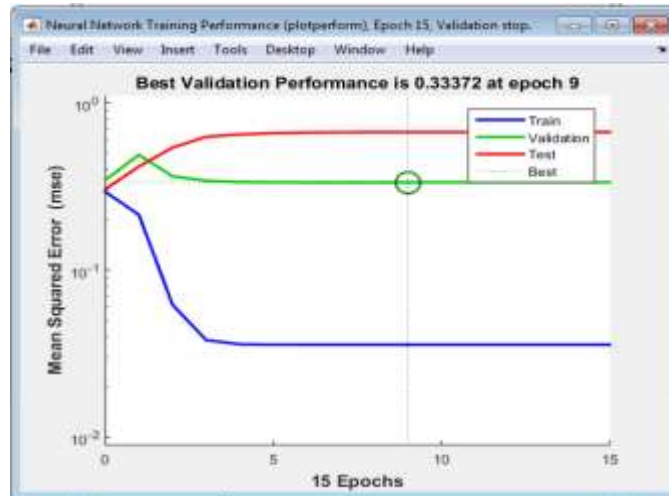


Fig.6.12 Performance curve.

VII. CONCLUSION

This research concludes that machine learning–based approaches provide an effective and reliable solution for automated brain tumor classification and prediction using MRI images. The implemented framework, which integrates feature extraction with Support Vector Machine (SVM) and Artificial Neural Network (ANN) classifiers, demonstrates strong capability in distinguishing tumor-affected and normal brain tissues. The extracted feature set successfully captures the critical characteristics of brain tumors, thereby enhancing the overall classification performance.

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