Comparative Analysis of Classifier Performance on MR Brain Images

Akila Thiyagarajan and UmaMaheswari Pandurangan
Anna University, India
Department of Computer Science and Engineering, Info Institute of Engineering, India

Abstract: *This paper, aims to reveal a comparative analysis of classifier performance of MR brain images, particularly for the brain tumor detection and classification. The detection of brain tumor stands in need of Magnetic Resonance Imaging (MRI). The moment invariant feature extraction has been evaluated to categorize the MRI slices as normal, benign and malignant by Neural Network (NN) classifier. In our comparative study, we examine the precision rate of aforementioned classification with extracted features and the classification of brain images with selected features by Association Rule (AR) based NN classifier. The results are then analyzed with Receiver Operating Characteristics (ROC) curve and compared to illustrate the method producing higher accuracy rate in tumor recognition. Factually, our analysis proves that the classifier works below feature extraction followed by rule pruning method affords better accuracy rate.*

Keywords: *Binary association rule, brain tumor, feature extraction, MRI, pruning.*

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1. Introduction

Earlier detection and classification of brain tumor is substantial in clinical practice. Myriad researches have been proposed with varying techniques for the classification of brain tumors based on different features. Henceforth, we proposed a comparative analysis to state a better methodology for brain tumor classification with a high precision rate. We focus on the examination of Magnetic Resonance (MR) brain images, which are high in providing tissue contrast. In this comparison scenario, the Neural Network (NN) classifier classifies the images in three categories, normal, benign and malignant based on two aspects 1. Extracted features with moment invariant functions and 2. Selected features through pruning. The adduced works have the potential of supporting the MR brain images.

The input bestowed to our criticism is the MR brain images, which provides good disparity between the soft tissues of the brain to determine the tumor apparently. We engage moment invariant feature extraction methods in our work since it involves in shape discrimination based on some unique features of brain images. According to the Euclidean distance, which is used to measure of similarity between different shapes of the brain images, the moment invariants are determined [1]. The significant part of this diagnosis is to train the NN for classifying brain images according to its characteristics.

Association Rule (AR) based method is involved in selecting typical features of Magnetic Resonance Imaging (MRI) images by combining low level features extracted from images and high level acquaintance from specialists [14]. The AR subsumes in supporting better decision making on medical image diagnosis. In this method of tumor detection, each training image is combined with a set of keywords, which are the representative terms preferred by the specialists for accurate results.

Due to the discrepancy and complexity of tumors, the classification of brain tumor image is considered a difficult task [6]. Basically, the NN technique constitutes two stages, namely, classification and feature extraction. In our proposed work, we incorporate the rule pruning methods based on binary ARs to feature selections from extracted features of brain images before doing classification. The comparison between the results obtained from both approaches is studied.

AR mining involves in efficient classification of MR brain images into three categories, normal, benign and malignant [11]. Mining can be done based on the integrated collection of brain images, termed as associated data. The binary AR method proposed in this paper is to select unique features of distinctive images and reduces the number of features considerably through rule pruning methods.

As we mentioned, the method proposed to categorize the MR brain images under normal, benign and malignant stages. Normal once are those specifying a healthy patient, benign case represents MR brain images illustrating a tumor that are non-cancerous, and malignant cases are those brain images showing tumors that are formed by cancerous cells. MR brain images are among the most peculiar medical images to be read since it shows high contrast and differences in the type of tissues that makes the diagnosis process more facile and accurate. This paper illustrates the results of comparative study for discriminating an accurate MR brain images scheme, which tremendously decreases the computation time and increases precision rate for image classification.

The remainder of this paper is structured as follows: section 2 confers about the related works, section 3 summarizes our proposed analysis about classifier performance, both based on a feature extraction scheme and feature selection method for brain image classification in tumor diagnosis, section 4 discussed the experiments and results achieved. Finally, in section 5, we present the conclusion and future work of the adduced work.

2. Related Works

Zaiane *et al*. [20] developed a classification method based on AR mining that works under three phases: Preprocessing phase, mining phase and the final phase of organizing the resulted AR in a classifier. They formulated an algorithm for AR based classification and pruning. Some authors described about image classification based on moment invariants. They reviewed efficient numerical algorithms, used for moment computation and demonstrated some practical examples of moment invariance based real-time applications. They explained the construction methodologies of moment invariant functions, which can be used in medical image diagnosis. Invariant-based approach is an apparent step provided robustness and reliability in pattern recognition methods. Damodharan *et al*. [2] proposed an effective brain tumor detection mechanism based on NN. In this paper, the efficiency was attained with brain tissue and tumor segmentation, feature extraction of the segmented regions.

Wang *et al*. [18] proposed a paper for classifying the brain tumors regarding the information from MRI and Magnetic Resonance Spectroscopy (MRS). Segmentation, feature selection, feature extraction, and classification model conception were the steps included in this paper for brain tumor classification. Moreover, they used Region of Interest (ROI) to feature extraction process and Concentric Circle (CC) method for selecting peculiar features. The classification accuracy of this work could be improved by incorporating more specific information such as spatial details about the tumor.

Zacharaki *et al*. [19] portrayed a pattern-based classification method to differentiate the types and grades of brain tumors using MRI shapes and textures. With this, feature extraction was based on the shape and intensity characteristics of MRI. Following, feature selection was made with Support Vector Machine (SVM) by the elimination of recursive features. The extension works had a plan to develop a framework that performs automatic segmentation and classification of brain neoplasm. They attained their intent by assessing the descriptive ability of MRI acquired in most clinical facilities, in practice.

A pruned associative classification technique for medical image diagnosis was demonstrated in [13]. They used Computerized Tomography (CT) scan brain images in their classification system. The accuracy rate, sensitivity rate and specificity rate were determined with the number of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) cases. Li *et al.* [7] proposed a meticulous classification of MR-brain images using both textures and shape features. They applied statistical AR miner algorithm to evaluate weight coefficient of each characteristic. The brain images were definitely under 14 categories with respect to distinctive anatomical structure and contents, and developed a scrupulous classifier for the brain image retrieval system.

A predictive technique called perceptron based feed forward NN for early detection of brain tumor was introduced in [4]. Region Severance Algorithm (RSA) was developed for abnormality identification, which was prevalently used for the study of hemorrhages. There was a comparative study between the data mining algorithms such as apriori, close+, charm and AR, given in [8] to extract the feature-oriented view of 3D models that could be used in medical simulations for adequate diagnostic methods. In a different way, Tech *et al*. [17] proposed RSA for abnormality identification that effectively performs the quantization of CT scanned image characteristics.

An adept AR-based method for medical image diagnosis, specifically to classify kidney images, described in [3]. Herewith, discretization and feature selection was accomplished on the extracted features to minimize the mining complexity. Semantic ARs [5] were used to produce high-level concepts, which were extracted from visual content. The approach forwarded a modality for learning the medical image diagnosis using low-level features. AR mining reveals all the consuming relationships in a conceivably large image database. A framework formed by the combination of associative rule mining and classification rule mining in medical image diagnosis called NN association classification system [15, 16]. This system is used for the construction of accurate and efficient classifiers, and the classification methods could be further enhanced with the predictive apriori algorithm. The trained NN is used to classify the esoteric data. Back propagation NN technique was used for acquiring adequate results. The decision tree classification with AR classification technique affords a better option to classify the benign and malignant images [12]. The ARs in the training image have been associated with the maximum frequent items of the test image and diagnosis can be made easily. In addition, AR mining used here to analyse the medical images and inevitably produce implications of the diagnosis.

In this section, we analyzed the advancements and shortcomings of aforementioned paper works and we propose a comparative study to enhance the diagnosis of MR brain images apparently.

3. Proposed Work

The proposed work concerns with an eminent comparison between the classifier performances on MR brain images, specifically for brain tumor revelation and classification. Our motive is to conclude the best classification technique that supports effective decision making in clinical practice. As is well known, the examination constitutes the procedures of training and test phases. The training phase involves in drilling the NN with variant brain images, whereas the test phase rivets in the inspection of unseen images for tumor cells. The MR brain images are grabbed as the input here since it provides good contrast, among distinctive soft tissues of the brain, which fosters result accuracy. The overview of the proposed work is revealed in Figure 1. The comparison commences by snagging the MRI images from the database. Subsequently, moment invariant feature extraction is being evaluated. Then, the descriptive analysis is made by bearing extracted features onto a trained NN classifier directly and it is also made by giving up selective features for classification through pruned ARs. Moreover, the results of precision rate are compared with Receiver Operating Characteristics (ROC) performance analysis. Hence, suggests a best classification technique for medical image diagnosis.

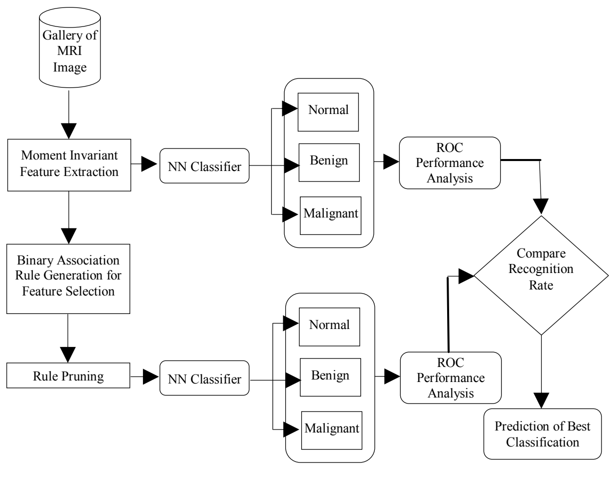

Figure 1. Block diagram for the description of proposed work.

3.1. Moment Invariant Feature Extraction

An analysis of object classification or recognition methods is based on image moments. The various types of moments are complex moment, geometric moment and moment-based invariants with respect to various image degradations and distortions, which can be used as shape descriptors for classification. There is a description about image classification based on moment invariants [8]. They reviewed efficient numerical algorithms, used for moment computation and demonstrated some practical examples of moment invariance based real-time applications.

The feature extraction of MR images is done with the consideration of moment invariant functions. Generally, moments are given as a projection of the image function into a polynomial basis. Such projections are known as image moments and the respective functions are called moment invariants. In practice, the interpretation of an image obtained by the MRI system provides the degraded version of the original scene. Those degradations have occurred during image acquisition by factors like lens aberration, the motion of the scene, imaging geometry, wrong focus and random sensor error. The dexterity of invariants with respect to these factors is a crucial part. In our proposed work, we provide a moment invariant mechanism in feature extraction. Images under each moment are too sensitive to local changes, but they are very robust to noise. Accordingly, invariants are applied to intensity changes, convolution, rotational images and contrast images.

During MRI, brain is scanned to give distinctive brain images for accurate prediction and classification of brain tumor. Through differentiating the intensity values of images in increasing order, we evaluate the moment invariance.

$$\varphi_1 = \mu_{20} + \mu_{02} \quad (1)$$

$$\varphi_2 = (\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2 \quad (2)$$

$$\varphi_3 = (\mu_{30} - 3\mu_{12})^2 + (3\mu_{21} - \mu_{03})^2 \quad (3)$$

$$\varphi_4 = (\mu_{30} + \mu_{12})^2 + (\mu_{21} + \mu_{03})^2 \quad (4)$$

$$\begin{aligned}\varphi_5 = {} & (\mu_{30} - 3\mu_{12})(\mu_{30} + \mu_{12})((\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2) + \\ & (3\mu_{21} - \mu_{03})(\mu_{21} + \mu_{03})(3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2)\end{aligned} \quad (5)$$

$$\begin{aligned}\varphi_6 = {} & (\mu_{20} - \mu_{03})((\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2) + \\ & 4\mu_{11}(\mu_{30} + \mu_{12})(\mu_{21} + \mu_{03})\end{aligned} \quad (6)$$

$$\begin{aligned}\varphi_7 = {} & (3\mu_{21} - \mu_{03})(\mu_{30} + \mu_{12})((\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2) - \\ & (\mu_{30} - 3\mu_{12})(\mu_{21} + \mu_{03})(3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2)\end{aligned} \quad (7)$$

Where φ represents an invariant value of extracting feature of a particular brain slice, which is obtained by μ value, differential values of image intensities.

From the above equations, the distinctive features of images are extracted based on 7 invariants of rotation using 3rd order differentiations. In our first classification method, the outcome will be given for classification precisely to the trained NN classifier and preceded with the section 3.4. The next method proceeds with the following section and classifies the brain images into normal, benign and malignant.

3.2. Binary AR Generation

The conceit of feature selection involves in reducing he inputs to an endurable size for effective processing and analysis. A quality pattern has been discovered with substantial features from large training dataset using binary AR. The rule pursues in discovering the association among features extracted from the MRI image gallery. Moreover, it contrives strong rules in a database for analysis using different measures of intrusiveness. The problem of binary AR generation is given as: Let $D= \{t_1, t_2, \ldots, t_m\}$ be a set of transactions and $I= \{i_1, i_2, \ldots, i_n\}$ be a set of items. It is conspicuous that each transaction has a subset of the items in I [10]. Inherently, the aforementioned rule is defined as an implication of the form $X \Rightarrow Y$, where X, $Y \subseteq I$ (X is the antecedent of the rule and Y is the consequent of the rule). The ARs are confined such that the antecedent of the rules is comprised conjunction of features from the MR brain image whereas the consequent of the rule is constantly the class label to which the brain image concerns. The method draws in finding rules that provide minimum confident and minimum support values specified by the user.

3.3. Rule Pruning Technique

Employing rule pruning techniques has become necessary since the number of rules produced in the preceding phase is very large. The rule pruning, technique eliminates the rules that are conflicting. Pruning the specific ARs can be performed with the following cases:

- *Case* 1: Consider two rules $X_1 \Rightarrow Y$ and $X_2 \Rightarrow Y$, the first rule is a general rule if $X_1 \subseteq X_2$. To accomplish this, the ARs must be ordered, according to case 2.
- *Case* 2: In the given two rules X_1 and X_2, X_1 is higher ranked than X_2 if:

  a. X_1 has higher confidence value than X_2.
  b. If the confidences are equal, support of X_1 must exceed support value of X_2.
  c. If both confidence and support values are equal, but X_1 has less number of attributes in left hand side than X_2.

  The next case is for eliminating the conflicting rule.

- *Case* 3: The rules $X_1 \Rightarrow C_1$ and $X_2 \Rightarrow C_2$ are conflicting in nature. Based on the above cases, duplicates have been eliminated. The set of rules that are chosen after pruning represents the actual classifier. These cases have been used to predict which class the new test image belongs in an adept manner.

  After applying the rule pruning technique, the number of features for brain tumor diagnosis is considerably reduced. Thus, the process tremendously reduces the computation time and increases the result accuracy.

3.4. Classification of Test Image

Following the training phase, a NN classifier with a pruned set of ARs can be developed for training the brain images. Each training image is associated with a set of keywords, which are the representative words given by a specialist to use in the medical imaging diagnosis. The selective features obtained from the rule pruning method are submitted to the NN classifier that uses the set of keywords and ARs to categorize the given image. The MR brain image is classified under three stages namely, normal, benign and malignant.

3.5. Performance Evaluation Criteria

ROC graphs are prevalently used to evaluate the cutoff value for a clinical diagnosis. The outcome of a medical image diagnosis is either positive or negative. The possible outcomes related to accuracy are *TP*, *TN*, *FP* and *FN* and a complete sensitivity/specificity report is generated for diagnostic test evaluation. *TP* specifies the instance classified as positive, if it is positive. *FN* represents the results classified under negative, when the instance is positive. The result specified as *TN*, the instance is negative and classified as negative. Then, the *FP* ratio is mentioned as the positive classification with negative instance. The precision rate is calculated by considering the aforesaid values. The performance analysis also based on:

- *Precision Rate*: which is defined as the accuracy rate of results in tumor diagnosis. The precision rate is calculated as:

$$Precision\ rate = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{8}$$

- *Sensitivity Rate*: Which is defined as the probability that a test result will be positive when the tumor is present. It is evaluated by:

$$Sensitivity\ rate = \frac{TP}{TP+FN} \tag{9}$$

- *Specificity Rate*: Which is defined as the probability that a test result will be negative when the tumor is not present. It is determined by:

$$Specificity\ rate = \frac{TN}{FP+TN} \tag{10}$$

In our adduced work, we compare the results of two classification procedures using a ROC curve graph. It gives that Area Under ROC Curve (AUC) is a metric that can be used to compare different analysis, in accuracy aspects. The results are considered more precise, when the *AUC* is large. Consequently, the value of *AUC* satisfies the following inequality.

$$0 \leq AUC \leq 1$$

In order to, determine the performance of the classification procedure, the confusion matrix is formed by the values of *TP*, *TN*, *FP*, *FN*, *precision*, *sensitivity* and *specificity rate*.

Due to the variation and complexity of tumors, the classification of brain tumor image is considered a difficult task. Hence, the intention of our proposal is to suggest a better classification methodology for clinical image diagnosis, which is accomplished with the comparison of the ROC curve, produced by both procedures.

4. Simulation Results Brain Tumor Classification

We have tested our classification approach with the IBSR dataset [9], which contains multiple scan images of patients with and without brain tumor. The data set was partitioned into three sets 80% for training, 10% for validation and 10% for testing. All the computations are implemented using MATLAB V7.9 with learning rate of 0.001. For the sake of providing experimental results, we have analyzed with 172 brain images. The files contain 126 multiple scans a patient with a tumor approximately taken scan at 6 month intervals over three and a half years. In MRI image acquisition, the T1+Gadolinium MRI scans were acquired for this 59 years old (age at first scan) female at the NMR center of the Massachusetts General Hospital with a 1.5 Tesla General Electric Signal.

Initially, MRI images are fed up to moment invariant feature extraction process to excerpt the decisive features that are approving effective brain tumor diagnosis. The process derives 7 distinctive characteristics of brain images from MRI gallery. According to that, NN classification takes place and categorizes the images under normal, benign and malignant stages. The NN based classification results are shown in Table 1. The performance of the classifier is analyzed with respect to *sensitivity*, *specificity* and *precision*.

Table 1. Results of NN classification.

Performance Analysis Metric	Normal	Benign	Malignant
TP	49	0	77
FP	4	22	20
FN	32	0	14
TN	87	150	61
Precision	0.9245	0	0.7938
Sensitivity	0.6049	NaN	0.8462
Specificity	0.9560	0.8721	0.7531

It is observed from Table 1, the precision of detecting 'normal' cases is the highest, whereas detecting 'benign' tumors is not at all precise. Detection of 'normal' cases is the overall best compared to other two cases.

Figure 2 exemplifies the performance of a NN classifier with the given dataset. The NN classification affords regression rate of 0.60721 and gives the best evaluation performance 0.090714 at epoch 7. The best evaluation rate is determined by plotting the graph against Mean Squared Error (MSE) and number of epochs needed. The accuracy rate produced by this analysis is 73.3%. TP rate and FP rate provide ample impact in performance analysis. Figure 3 shows the confusion matrix for the results obtained with NN classification. The confusion matrix is determined between target class and output class. The diagonal values represent the appropriate classification results and the final diagonal value shows the accuracy rate of the classification. The rest of confusion matrix exhibits the misclassification results.

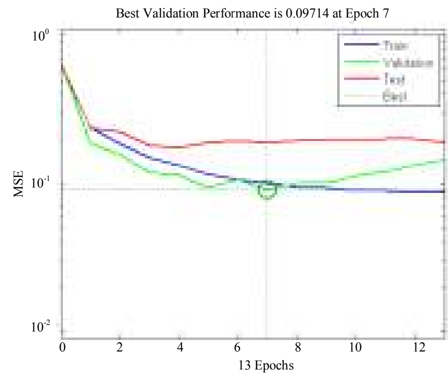

Figure 2. NN Classification.

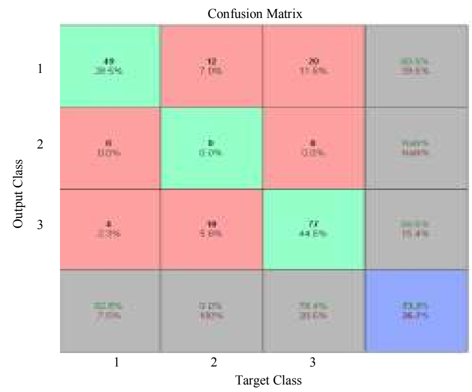

Figure 3. Confusion matrix-NN classification.

Receiver operating characteristic curve graph for NN classification is represented in Figure 4. In order to, predict the accuracy rate of diagnosis, the graph is plotted between *TP* rate and *FP* rate. As we mentioned, the AUC varies from 0 to 1.

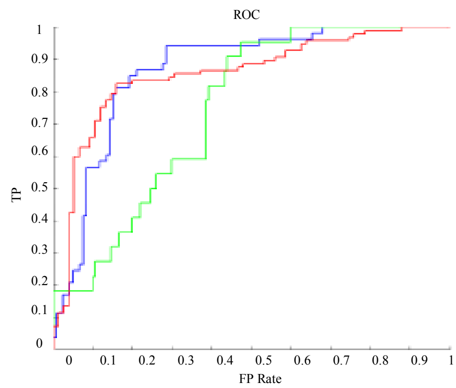

Figure 4. ROC graph-NN classification.

Consequently, we have analyzed the performance evaluation of a NN classifier with its accuracy rate in brain tumor diagnosis. The second procedure, we have admitted for our comparative analysis is AR based NN classification. With this method, we give the results of future extraction to binary AR generation to select adroit features from extracted results. Following, rule pruning method is applied to eliminate the redundant and feeble features. Since, our testing criteria, the 7 extracted decisive features are further reduced to 3 features, adequately. Then, the NN classification is performed to categorize the brain images by the selected features.

Table 2 proffers the classification results of AR based NN classification. Comparing this with NN classification, it is obvious that precision, sensitivity and specificity rates are considerably higher for 'benign' and 'malignant' tumors. The absence of NaN (not as a number) results in AR based NN classification does not result in complexity as in NN based classification. The detection of 'normal' cases using association based NN classification is better in terms of sensitivity alone compared to NN based classification.

Table 2. Results of AR based NN classification.

Performance Analysis Metric	Normal	Benign	Malignant
TP	44	12	66
FP	9	10	9
FN	14	5	9
TN	105	145	66
Precision	0.8302	0.5455	0.9027
Sensitivity	0.7586	0.7059	0.9027
Specificity	0.9211	0.9355	0.8800

The performance of AR based NN classification is represented in Figure 5. The regression rate is evaluated as 0.76411 and the best evaluation performance is 0.12053, attained at 8^{th} epoch. The accuracy rate of diagnosis by this method is 83.72%. It also reduces the computation time tremendously.

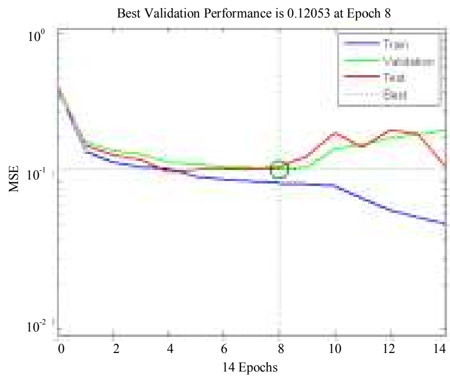

Figure 5. AR Based NN classification.

Figure 6 portrays the confusion matrix for AR based NN classification. It is apparent from the matrix that the misclassification rate is lesser than previous procedures. It produces higher *TN*, *TP* rates and abates the occurrence rates of *FP* and *FN*. The ROC curve graph in Figure 7 evinces the accuracy rate of this classification approach. The curve plotted against the correlation between *FP* and *TP* rate. As alleged before, the AUC is larger, which shows the prediction of more accurate classification results in medical image diagnosis. On comparing the results of two classification systems, the more accuracy rate is obtained by the latter classification.

Figure 6. Confusion matrix-AR based NN classification.

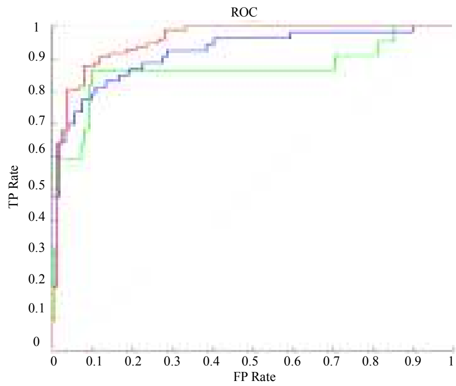

Figure 7. ROC graph AR based NN classification.

The efficacy rate of the classification approach is determined via less MSE and higher accuracy rate in accordance with reduced time consumption. Hence, analyzing the results, it is conspicuous that AR based NN classification method affords factual classification results.

A classification accuracy graph of NN with and without AR feature selection is depicted in Figure 8. In order to, predict the accuracy rate of diagnosis, the graph is plotted between *TP* and *FP* rate. As we mentioned, the AUC varies from 0 to 1. Therefore, we have analyzed the performance evaluation of a NN classifier with its accuracy rate in brain tumor diagnosis.

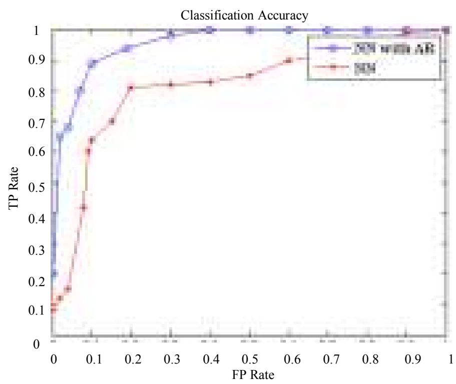

Figure 8. Classification accuracy of existing and proposed.

We incorporate the rule pruning methods based on binary ARs to feature selections from extracted features of brain images before doing classification.

Then, the NN classification with and without AR is performed to categorize the brain images by the selected features.

The Figure 9 represents the performance of training, validation and testing phase and finally, the regression rate of the proposed approach. The graphs plotted in Figure 9 specify the relationship between the target of our classification procedure and the actual output produced.

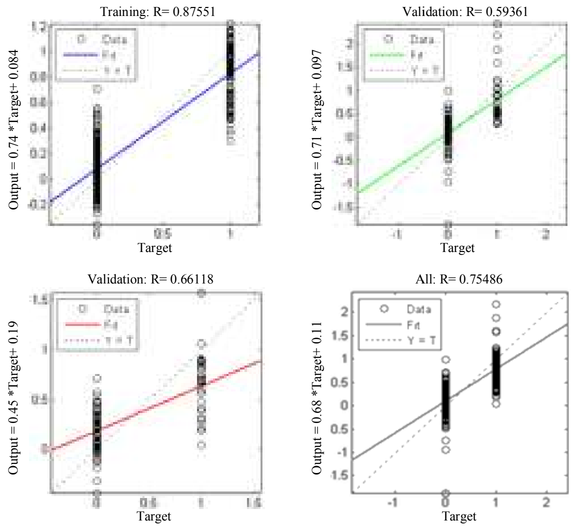

Figure 9. Regression graph.

5. Conclusions and Future Works

The predominant intention of our work is to suggest a congruous procedure for effective MR brain images in clinical practice. We accomplished the comparative analysis with two procedures: NN classification, which is performed with extracted features of MRI brain images in terms of moment invariance, and AR based NN classification, enforced by binary AR based feature selection and rule pruning techniques. The experimental results have shown that the latter method achieves high accuracy, high sensitivity and specificity rates than the NN classification. Hence, we suggest that AR based NN classification system affords better decision making in discriminating brain tumors and reduces complexity.

In future work, we intend to apply AR based NN classification as a pre-classification method for categorizing database images under normal, benign and malignant grades and develop a content based medical image retrieval system by sorting the query image. Investigating the applicability of our suggested procedure for other medical images is of great interest.

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Akila Thiyagarajan ME is presently being an Assistant professor and Head in the department of Information Technology at Trichy Engineering College, Trichy. She received her master degree in computer science and Engineering from JJ College of engineering, Trichy. Presently she is pursuing her PhD in Anna University, Chennai. She has 12 years of experience in teaching. Her field of interest includes digital image processing, soft computing and data mining.

UmaMaheswari Pandurangan ME, MBA PhD is presently being a Professor and Head of the department of Computer Science and Engineering, at INFO Institute of Engineering, Coimbatore. She completed her BE (Computer Science and Engineering) at Thiagarajar College of Engineering, Madurai, ME degree (Software Engineering) at PeriyarManiammai College of Technology for Women, MBA from Madurai Kamaraj University and PhD (I and C) at Anna University, Chennai in 2009. During her tenure of 17 years of engineering teaching experience she performed various roles and responsibilities as academic coordinator, ISO management Representative, Organizing secretary for National and international Conferences, ISTE chapter secretary and convener for various workshops and faculty development programs. She delivered 33 workshops and seminars for staffs and students. Her research interests are in the field of data Mining, Intelligent Computing and image processing. 14 candidates are pursuing PhD under his guidance at present. From her record, she has published her Research findings in 14 International Journals/National Journals, 21 International Conferences and 10 National Conferences. She has also authored 8 Text Books. She has rendered unblemished services in various categories as member as well as university nominee of Board of Studies, Computer Science and Engineering Course for 5 Autonomous colleges, Member of University level NSS Advisory Council, Co-coordinator of various programs relating to Services to Community and Coordinator of Entrepreneurship development cell sponsored by EDI, India. She is a life member of ISTE, IEEE, CSI, IAENG and ICTACT.