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Comparative Analysis of Classifier Performance on Medical Image Diagnosis

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Abstract: This study aims to reveal a comparative analysis of classifier performance on medical image diagnosis, particularly for 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 Classifier. In the comparative study, researchers examine the precision rate of aforementioned classification with extracted features and the classification of brain images with selective features by association rule based neural network 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, the analysis proves that the classifier research under feature extraction followed by rule pruning method affords better accuracy rate.

Key words: Brain tumor, MRI, feature extraction, classification, binary, association rule, pruning

INTRODUCTION

Earlier detection and classification of brain tumor is substantial in clinical practice. Myriad researches have been proposed with variant techniques for the classification of brain tumors based on different features. Henceforth, researchers proposed a comparative analysis to state a better methodology for brain tumor classification with high precision rate. Researchers focus on the examination of magnetic resonance brain images which are high in providing tissue contrast. In this comparison scenario, the neural network classifier classifies the images on three categories, normal, benign and malignant based on two aspects: extracted features with moment invariant functions and selected features through pruning. The adduced research has the potential of supporting medical image diagnosis.

The input bestowed to the criticism is the magnetic resonance brain images which provides good disparity between the soft tissues of brain to determine the tumor apparently. Researchers engage moment invariant feature extraction methods in the research 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 (Torres and Falcao, 2006). The significant part of this diagnosis is to train the neural network for classifying brain images according to its characteristics.

Association Rule (AR) based method is involved in selecting typical features of MRI images by combining low-level features extracted from images and high-level acquaintance from specialists (Ribeiro *et al*., 2008). 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 as a difficult task (Kharat *et al*., 2012). Basically, the neural network technique constitutes two stages namely, feature extraction and classification. In the proposed research, researchers incorporate the rule pruning methods based on binary association rule for feature selection from extracted features of brain images before doing classification. The comparison between the results obtained from both approaches is studied.

Association rule mining involves in efficient classification of magnetic resonance brain images into three categories, normal, benign and malignant (Rajendran and Madheswaran, 2009a, b). Mining can be done based on the integrated collection of brain images, termed as associated data. The binary association rule method proposed in this study is to select unique features of distinctive images and reduces the number of features considerably through rule pruning methods.

As researchers mentioned, the method proposed to categorize the MR brain images under normal, benign and malignant stages. Normal ones are those specifying a healthy patient, benign case represents MR brain images illustrating a tumor that are non-cancerous and malignant

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cases are those brain images showing tumors that are formed by cancerous cells. Magnetic resonance 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 study illustrates the results of comparative study for discriminating an accurate medical image diagnosis scheme which tremendously decreases the computation time and increases precision rate for image classification.

LITERATURE REVIEW

Zaiane *et al*. (2002) developed a classification method based on association rule mining that research under three phases: preprocessing phase, mining phase and the final phase for organizing the resulted association rule in a classifier. They formulated algorithm for association rule based classification and pruning. There is a description about image classification based on moment invariants (Flusser, 2005). They reviewed efficient numerical algorithms used for moment computation and demonstrated some practical examples of moment invariance based real-time applications. The 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.

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

Zacharaki *et al*. (2009) 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 shape and intensity characteristics of MRI. Following, feature selection was made with Support Vector Machine (SVM) by the elimination of recursive features. The extension work had a plan to develop a framework that performs automatic segmentation and classification of brain neoplasm. They attained their intent by assessing the description ability of MRI acquired in most clinical facilities, in practice.

A pruned associative classification technique for medical image diagnosis was demonstrated by Rajendran and Madheswaran (2009a, b). 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. The study by Li *et al.* (2010) proposed a meticulous classification of MR-brain images using both textures and shape features. They applied statistical association rule miner algorithm to evaluate weight coefficient of each characteristics. The brain images were defined under 14 categories with respect to it’s distinctive anatomical structure and contents and developed a scrupulous classifier for brain image retrieval system.

A predictive technique called preceptron based feed forward neural network for early detection of brain tumor was introduced by Flusser (2005). 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 association rule, given by El-Far *et al.* (2011) to extract the feature-oriented view of 3D Models that could be used in medical simulations for adequate diagnosis methods.

An adept association rule-based method for medical image diagnosis, specifically to classify kidney images, described by Dhanalakshmi and Rajamani (2010). Herewith, discretization and feature selection was accomplished on the extracted features to minimize the mining complexity. Semantic association rules (Ion and Udristoiu, 2011) 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. Associative rule mining reveals all the consuming relationships in a conceivably large image database. A framework formed with the combination of associative rule mining and classification rule mining in medical image diagnosis called neural network association classification system (Shekhawat and Dhande, 2011a, b). This system is used for the construction of accurate and efficient classifiers and the classification methods could be further enhanced with predictive apriori algorithm. The trained neural network is used to classify the esoteric data. Backpropagation neural network technique was used for acquiring adequate results. A computer-aided decision support system (Jose *et al.*, 2012) developed based on association rule mining for effective classification of kidney images that could be further extended for other image diagnosis process. The association rule mining, used here to analyze the medical images and inevitably produce implications of diagnosis.

In this study, researchers analyzed the advancements and shortcomings of aforementioned study research and researchers propose a comparative study to enhance the diagnosis of brain images apparently.

PROPOSED RESEARCH

The proposed research concerns with an eminent comparison between the classifier performances on medical image diagnosis, specifically for brain tumor revelation and classification. The 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 neural network with variant brain images whereas the test phase rivets in the inspection of unseen image for tumor cells. The magnetic resonance 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 research is revealed in Fig. 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 on to a trained neural network classifier directly and it is also made with giving up selective features for classification through pruned association rules. Moreover, the results of precision rate are compared with ROC performance analysis. Hence, suggests a best classification technique for medical image diagnosis.

Moment invariant feature extraction: The feature extraction of MR images is done with the consideration of moment invariant functions. Generally, moments are given as projection of the image function into a polynomial basis. In practice, the interpretation of an image obtained by MRI System provides the degraded version of the original scene. Those degradations have occurred during image acquisition by factors like lens aberration, imaging geometry, motion of the scene, wrong focus and random sensor error, etc. The dexterity of invariants with respect to these factors is a crucial part. Henceforth, researchers 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, contrast images, convolution and rotational images.

During MRI, brain is scanned in various positions to give distinctive brain images for accurate prediction and classification of brain tumor. By differentiating the intensity values of images in increasing orders, researchers evaluate the moment invariance:

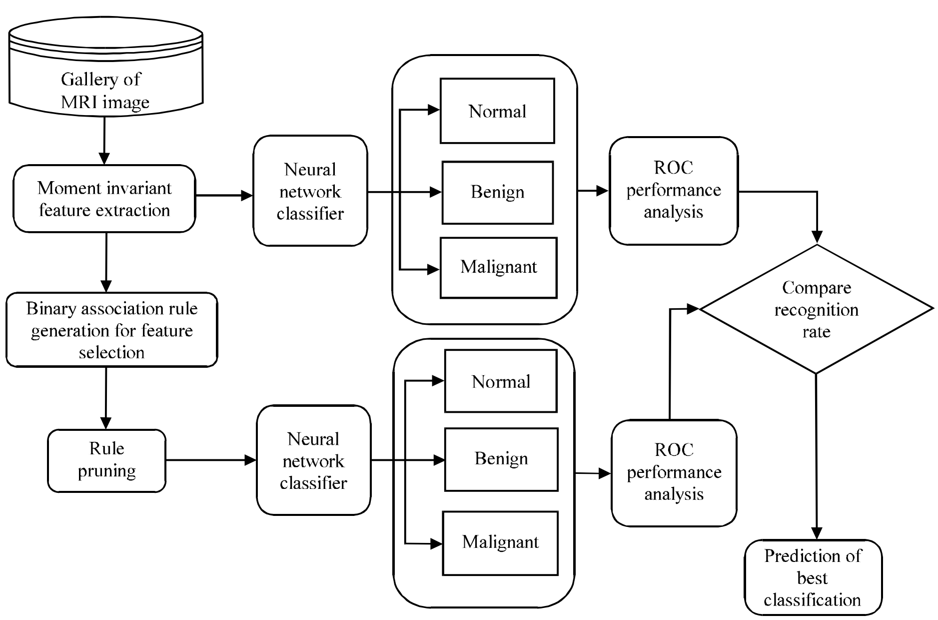

Fig. 1: Block diagram for the description of proposed research

$$\varphi_1 = \mu_{20} + \mu_{02} \tag{1}$$

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

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

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

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

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

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

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

From Eq. 1-7, the distinctive features of images are extracted based on 7 invariants of rotation using 3rd order differentiations. In the first classification method, the outcome will be given for classification precisely to the trained neural network classifier. The next method proceeds with the following section and classifies the brain images into normal, benign and malignant.

Binary association rule generation: The conceit of feature selection involves in reducing the 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 association rule. The rule pursues in discovering the association among features extracted from MRI image gallery. Moreover, it contrives strong rules in database for analysis using different measures of intrusiveness. The problem of binary association rule generation is given as: Let D = $\{t_1, t_2,..., t_m\}$ be a set of transactions and I = $\{i_1, i_2,..., i_n\}$. It is conspicuous that each transaction has a subset of the items in I (Olukunle and Ehikioya, 2002). 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 association rules are confined such that the antecedent of the rules is comprised conjunction of features from the magnetic resonance 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.

Rule pruning technique: Employing rule pruning techniques becomes necessary since the number of rules produced in the precedent phase is very large. The rule pruning technique eliminates the rules that are conflicting. Pruning the specific association rules can be performed with the following cases.

Case 1: Consider two rules $X1 \Rightarrow C$ and $X2 \Rightarrow C$, the first rule is a general rule if $X1 \Rightarrow X2$. To accomplish this, the association rules must be ordered, according to case 2.

Case 2: In the given two rules X1 and X2, X1 is higher ranked than X2 if:

- X1 has higher confidence value than X2
- If the confidences are equal, support of X1 must exceed support value of X2
- If both confidences and support values are equal but X1 has less number of attributes in left hand side than X2

The next case is for eliminating the conflicting rule.

Case 3: The rules $X1 \Rightarrow C1$ and $X2 \Rightarrow C2$ 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 to 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.

Classification of test image: Following the training phase, a neural network classifier with pruned set of association rules 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 image diagnosis. The selective features obtained from the rule pruning method are submitted to the neural network classifier that uses the set of keywords and association rules to categorize the given image. The magnetic resonance brain image is classified under three stages namely, normal, benign and malignant.

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 True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) and a complete sensitivity/specificity report is generated for diagnostic test evaluation. TP specifies the instance classified as positive, if it is positive. FP 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:

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

Sensitivity rate which is defined as the probability that a test result will be positive when the tumor is present. It is evaluated by:

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

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:

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

In the adduced research, researchers compare the results of two classification procedures using ROC curve graph. It is given 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 variance and complexity of tumors, the classification of brain tumor image is considered as a difficult task. Hence, the intention of the proposal is to suggest a best classification methodology for clinical image diagnosis which is accomplished with the comparison of ROC curve, produced by both procedures.

EXPERIMENTAL RESULTS

Researchers have tested the classification approach with the IBSR dataset (http://www.cma.mgh.harvard.edu/ibsr/) which contains multiple scan images of patients with and without brain tumor. Dataset was partitioned into three sets -80% for training, 10% for validation and 10% for testing. All the computations are implemented using MATLAB V 7.9 with learning rate of 0.001. For the sake of providing experimental results, researchers have analyzed with 172 brain images.

Initially, MRI images are fed up for moment invariant feature extraction process to excerpt the decisive features that approving effective brain tumor diagnosis. The process derives 7 distinctive characteristics of brain images from MRI gallery. According to that, neural network classification takes place and categorizes the images under normal, benign and malignant stages. The classification results are shown in Table 1. Performance of the classifier is analyzed with occurrence of true positive, false positive, false negative and true negative rates. Also, the accuracy rate has been determined in terms of precision, sensitivity and specificity ratios.

Figure 2 exemplifies the performance of neural network classifier with given dataset. The NN (Neural Network) 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%. True positive rate and false positive rate provides ample impact in performance analysis. Figure 3 shows the confusion

Table 1: Results of neural network 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

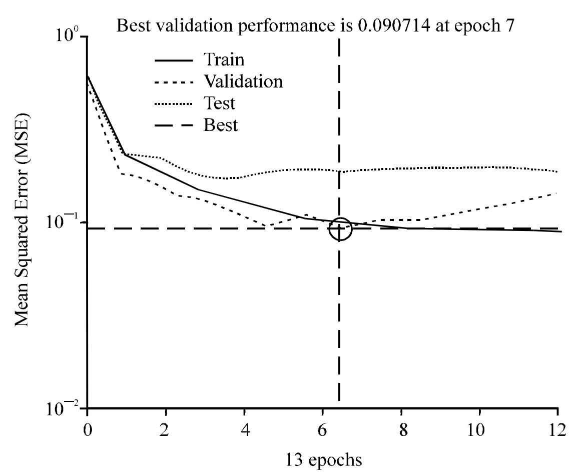

Fig. 2: Neural network classification

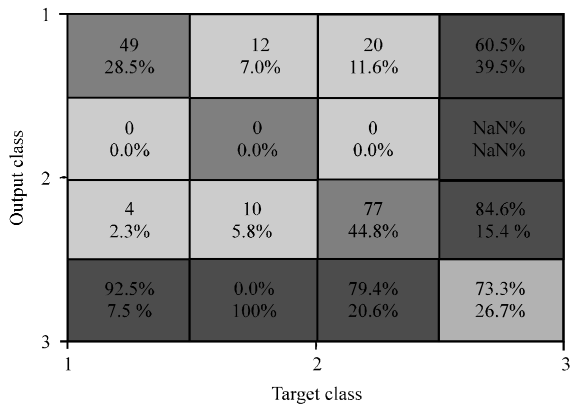

Fig. 3: Confusion matrix-NN classification

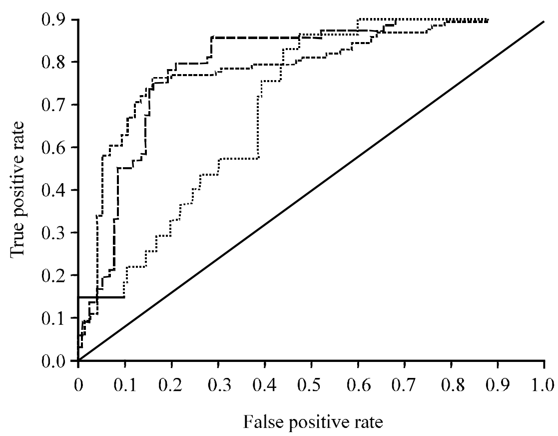

Fig. 4: ROC graph-NN classification

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.

Receiver operating characteristic curve graph for NN classification is represented in Fig. 4. In order to predict the accuracy rate of diagnosis, the graph is plotted between true positive rate and false positive rate. As researchers mentioned, the AUC varies from 0-1.

Thus, researchers have analyzed the performance evaluation of neural network classifier with its accuracy rate in brain tumor diagnosis. The second procedure, researchers have admitted for the comparative analysis is association rule based neural network classification. With this method, researchers give the results of future extraction to binary association rule generation to select adroit features from extracted results. Following, rule

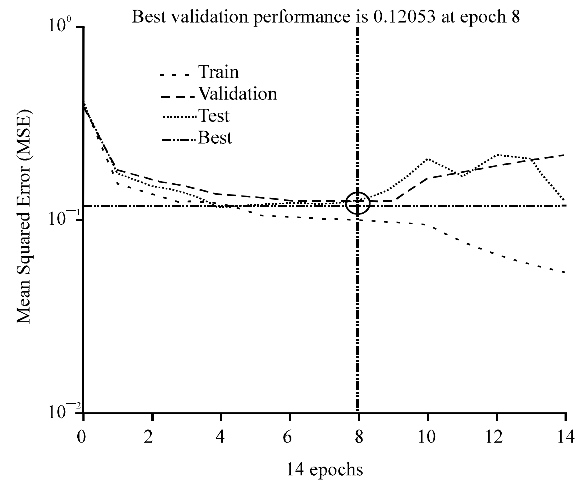

Fig. 5: Association rule based NN classification

Table 2: Results of association rule 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	0.9072
Sensitivity	0.7586	0.7059	0.9072
Specificity	0.9211	0.9355	0.8800

pruning method is applied to eliminate the redundant and feeble features. As per the testing criteria, the 7 extracted decisive features are further reduced to 3 features, adequately. Then, the neural network classification is performed to categorize the brain images by the selective features. Table 2 proffers the classification results of association rule based neural network classification. Comparing this with NN classification, it is obvious that precision, sensitivity and specificity rate are considerably higher and absence of NaN (Not as a Number results). Hence, the accuracy rate is also significantly greater. The performance of association rule based neural network classification is represented in Fig. 5. The regression rate is evaluated as 0.76411 and the best evaluation performance is 0.12053, attained at 8th epoch. The accuracy rate of diagnosis by this method is 83.72%. It also reduces the computation time tremendously.

Figure 6 portrays the confusion matrix for association rule based NN classification. It is apparent from the matrix that the misclassification rate is lesser than previous procedure. It produces higher true negative and true positive rates and abates the occurrence rates of false positive and false negative. The ROC curve graph in Fig. 7 evinces the accuracy rate of this classification approach. The curve plotted against the correlation between false positive and true positive rate. As alleged

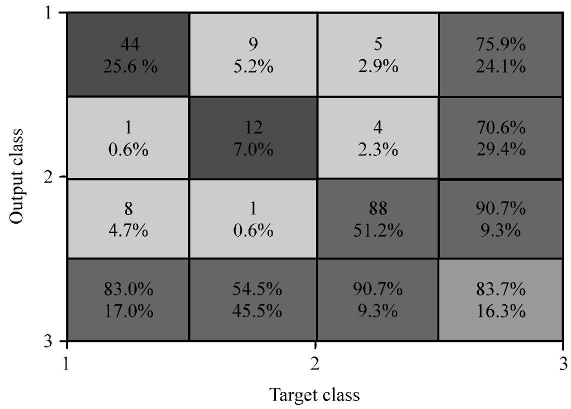

Fig. 6: Confusion matrix-association rule based NN classification

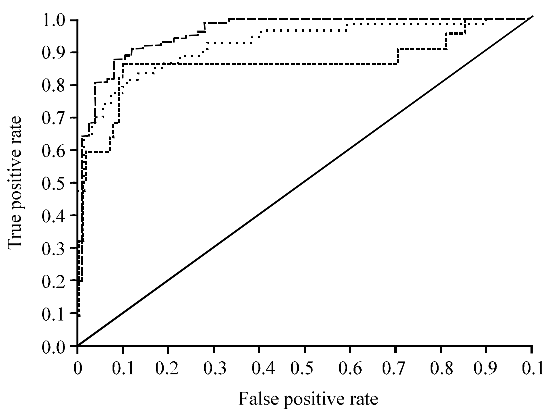

Fig. 7: ROC graph-association rule based NN classification

before, the area under the curve is larger which shows the prediction of more accurate classification results in medical image diagnosis. On comparing the results of two classification system, the more accuracy rate is obtained by the latter 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 association rule based neural network classification method affords factual classification results.

CONCLUSION

The predominant intention of the research is to suggest a congruous procedure for effective medical image diagnosis in clinical practice. Researchers accomplished the comparative analysis with two procedures. Neural network classification which is performed with extracted features of MRI brain images in terms of moment invariance and association rule based neural network classification, enforced with binary association rule 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, researchers suggest that association rule based neural network classification system affords better decision making in discriminating brain tumors and reduces complexity.

In future research, researchers intend to apply association rule based neural network 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 the suggested procedure for other medical images is of great interest.

REFERENCES

Dhanalakshmi, K. and V. Rajamani, 2010. An efficient association Rule-based method for diagnosing ultrasound kidney images. Proceedings of the Conference on Computational Intelligence and Computing Research, December 28-29, 2010, Coimbatore, pp: 1-5.

El-Far, M., L. Moumoun, M. Chahhou, T. Gadi and R. Benslimane, 2011. Comparing between data mining algorithms: Close+, Apriori and CHARM and Kmeans classification algorithm and applying them on 3D object indexing. Proceedings of the International Conference on Multimedia Computing and Systems, April 7-9, 2011, Ouarzazate, Morocco, pp: 1-6.

Flusser, J., 2005. Moment invariants in image analysis. World Acad. Sci. Eng. Technol., 11: 376-381.

Ion, A.L. and S. Udristoiu, 2011. An experimental framework for learning the medical image diagnosis. Proceedings of 33rd International Conference on Information Technology Interfaces, June 27-30, 2011, Dubrovnik, pp: 465-470.

Jose, J.S., R. Sivakami, N.U. Maheswari and R. Venkatesh, 2012. An efficient diagnosis of kidney images using association rules. Int. J. Comput. Technol. Electron. Eng., 2: 14-20.

Kharat, K.D., P.P. Kulkarni and M.B. Nagori, 2012. Brain tumor classification using neural network based methods. Int. J. Comput. Sci. Inform., 1: 2231-5292.

Li, W., Z. Lu, Q. Feng and W. Chen, 2010. Meticulous classification using support vector machine for brain images retrieval. Proceedings of the International Conference on Medical Image Analysis and Clinical Application, June 10-13, 2010, Guangdong, pp: 99-102.

Olukunle, A. and S.A. Ehikioya, 2002. A fast algorithm for mining association rules in medical image data. Electr. Comput. Eng., 2: 1181-1187.

Rajendran, P. and M. Madheswaran, 2009a. An improved image mining technique for brain tumour classification using efficient classifier. Int. J. Comput. Sci. Inform. Secur., 6: 107-116.

Rajendran, P. and M. Madheswaran, 2009b. Pruned associative classification technique for the medical image diagnosis system. Proceedings of the 2nd International Conference on Machine Vision, December 28-30, 2009, Dubai, pp: 293-297.

Ribeiro, M.X., A.J. M. Traina, C. Traina and P.M. Azevedo-Marques, 2008. An association Rule-based method to support medical image diagnosis with efficiency. Multimedia, 10: 277-285.

Shekhawat, P.B. and S.S. Dhande, 2011a. A classification technique using associative classification. Int. J. Comput. Appli., 20: 21-28.

Shekhawat, P.B. and S.S. Dhande, 2011b. Building an iris plant data classifier using neural network associative classification. Int. J. Adv. Technol., 2: 491-506.

Torres, R.S. and A.X. Falcao, 2006. Content-based image retrieval: Theory and applications. Revista Informatica Teorica E Aplicada, 13: 161-185.

Zacharaki, E.I., S. Wang, S. Chawla, D.S. Yoo, R. Wolf, E.R. Melhem and C. Davatzikos, 2009. Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme. Magn. Reson. Med., 62: 1609-1618.

Zaiane, O.R., M.L. Antonie and A. Coman, 2002. Mammography classification by an association rule based classifier. Proceedings of the International Workshop on Multimedia Data Mining with ACM SIGKDD, July 23, 2002, Edmonton, Alberta, Canada, pp: 62-69.