Abstract— An improved image mining technique for brain tumor classification using pruned association rule with MARI algorithm is presented in this paper. The method proposed makes use of association rule mining technique to classify the CT scan brain images into three categories namely normal, benign and malignant. It combines the low-level features extracted from images and high level knowledge from specialists. The developed algorithm can assist the physicians for efficient classification with multiple keywords per image to improve the accuracy. The experimental result on pre-diagnosed database of brain images showed 96% and 93% sensitivity and accuracy respectively.

Keywords-Data mining; Image mining; Association rule mining; Medical Imaging; Medical image diagnosis; Classification.

I. INTRODUCTION

In health care centers and hospitals, millions of medical images have been generated daily. Analyses have been done manually with an increasing number of images. Even after analyzing a minimal number of images, radiologist becomes more tiresome. Nowadays, physicians are providing with computational techniques in assisting the diagnosis process. In the recent past, the development of Computer Aided Diagnosis (CAD) systems for assisting the physicians for making better decisions have been the area of interest [1]. This has motivated the research in creating vast amount of image database. In CAD method, computer output has been used as a second opinion for radiologist to diagnose the information more confident and quicker mechanism as compared to manual diagnosis.

Pathologies are clearly identified using automated CAD system [2]. It also helps the radiologist in analyzing the digital images to bring out the possible outcomes of the diseases. In the last few years, inexpensive and available means of database containing rich medical data have been provided through the internet for health services globally. It has been reported that the brain tumor is one of the major cause leading to higher incidence of death in human. Physicians have faced a challenging task in extracting the features and decision making. The Computerized Tomography (CT) has been found to be the most reliable method for early detection of tumors because this modality is the most used in radiotherapy planning for two main reasons.

The first reason is that scanner images contain anatomical information which offers the possibility to plan the direction and the entry points of the radiotherapy rays which have to target the tumor and to avoid some risk organs. The second reason is that CT scan images are obtained using rays, which is the same physical principle as radiotherapy. This is very important because the radiotherapy rays intensity can be computed from the scanner image intensities. Due to the high volume of CT [3] images to be used by the physicians, the accuracy of decision making tends to decrease. This has further increased the demand to improve the automatic digital reading for decision making [4]. It also significantly improves in the field of conservative treatment of CAD diagnosis. It is an interdisciplinary field that combines techniques like data mining, digital image processing, radiology and usability among others.

In this paper image mining concepts have been used. It deals with the implicit knowledge extraction, image data relationship and other patterns which are not explicitly stored in the images. This technique is an extension of data mining to image domain. It is an inter disciplinary field that combines techniques like computer vision, image processing, data mining, machine learning, data base and artificial intelligence [5]. The objective of the mining is to generate all significant patterns without prior knowledge of the patterns [6]. Rule mining has been applied to large image data bases [7]. Mining has been done based on the combined collections of images and it is associated data. The essential component in image mining is the identification of similar objects in different images [8].

The method proposed in this paper classifies the brain CT scan images into three categories: normal, benign and malignant. Normal ones are those characterizing a healthy patient, benign cases represents CT scan brain images showing a tumor that are not formed by cancerous cells, and Malign cases are those brain images that are taken from patients with cancerous tumors. CT scan brain images are among the most difficult medical images to be read due to their low contrast and differences in the type of tissues. This paper illustrates the importance of data cleaning phase in building an accurate data mining architecture for image classification [9, 10, and 11].
The method presented here is based on the associative classification scheme. This approach has an advantage of selecting only the most relevant features during mining process and obtaining multiple keywords when processing a test image [12].

II. SYSTEM DESCRIPTION

Overview of the proposed system is shown in Fig 1. The proposed system is mainly divided into two phases: the training phase and the test phase. Data cleaning and feature extraction are common for both the training set of brain images and the test set [13, 14]. In the training phase, features are extracted from the images, represented in the form of feature vectors. Next, the features are discretized into intervals and the processed feature vector is merged with the keywords related with the training images [15]. This transaction representation is submitted to the MARI (Mining Association Rule in Image database) algorithm for association rule mining, which finally produces a pruned set of rules representing the actual classifier [16, 17]. In the test phase, the feature vector obtained from the test images are submitted to the classifier which makes use of the association rules to generate keywords to compose the diagnosis of the test image. These keywords have been used to classify the three categories of CT scan brain images as normal image, benign (tumor without cancerous tissues) image and malignant (tumor with cancerous tissues) image.

A. Pre-Processing

Since most of the real life data is noisy, inconsistent and incomplete, preprocessing becomes necessary [18]. The cropping operation can be performed to remove the background, and image enhancement can be done to increase the dynamic range of chosen features so that they can be detected easily. In general, most of the soft tissues have overlapping gray-levels and the condition of illumination at that time of CT scan taken is also different. The histogram equalization can be used to enhance the contrast within the soft tissue of the brain images and also hybrid median filtering.

Figure 1. Overview of the proposed system
technique can be used to improve the image quality. Good texture feature extraction can be done by increasing the dynamic range of gray-levels using the above mentioned technique [19].

**B. Texture Feature Extraction**

As the tissues present in brain are difficult to classify using shape or intensity level of information, the texture feature extraction is found to be very important for further classification [20,21, and 22]. The analysis and characterization of texture present in the medical images can be done using several approaches like run length encoding, fractal dimension, and discrete wavelet transform and co-occurrence matrices [23, 24].

Though many texture features have been used in the medical image classification, Spatial Gray Level Dependent Features (SGLDF) can be used to calculate the intersample distance for better diagnosis [25, 26]. In order to detect the abnormalities in medical images association rule mining is built based on estimation of the second-order joint conditional probability density function for the pixel (i, j), P[i,j|d,θ] for θ = 0°, 45°, 90° and 135°. The function is the probability that two pixels which are located with an inter sample distance d and a direction θ. The estimated joint conditional probability density functions are defined as

\[
P[i,j|d,θ] = \frac{\# ((k,l),(m,n)) \in [L_x \times L_y] \times [L_x \times L_y] ; S(k,l)=i, S(m,n)=j}{T(d,θ)}
\]

where # denotes the number of elements in the set, \(S(x, y)\) is the image intensity at the point (x, y) and \(T(d, θ)\) stands for the total number of pixel pairs within the image which has the intersample distance d and direction θ.

Co-occurrence matrices can be calculated for the directions 0°, 45°, 90°, 135° and their respective pixels are denoted as 1, 2, 3 and 4. Once the co-occurrence matrix is calculated around each pixel, the features such as entropy, energy, variance, homogeneity and inverse variance can be obtained for each matrix with respect to the intersample distance. From the co-occurrence matrices the feature vectors can be calculated and stored in the transaction database. Next, the continuous valued features are discretized into intervals, where each interval represents an item in the process of mining association rules [15].

\[
\text{Entropy} = -\sum_{i,j} P[i,j] \log P[i,j]
\]

\[
\text{Energy} = \sum_{i,j} P^2[i,j]
\]

\[
\text{Contrast} = \sum_{i,j} (i-j)^2 P[i,j]
\]

\[
\text{Homogeneity} = \sum_{i,j} \frac{P[i,j]}{1 + |i-j|}
\]

\[
\text{SumMean} = \frac{1}{2} \sum_{i,j} i \cdot P[i,j] + j \cdot P[i,j]
\]

\[
\text{Variance} = \frac{1}{2} \sum_{i,j} (i-μ)^2 P[i,j] + (j-μ)^2 P[i,j]
\]

\[
\text{Maximum Probability} = \max_{i,j} P[i,j]
\]

\[
\text{Inverse Difference Moment} = \sum_{i,j} \frac{P[i,j]}{|i-j|^k}
\]
III. BUILDING THE CLASSIFIER

The extracted features can be stored in transaction database for classification using the trained brain images. The image mining techniques can be applied to match the extracted features with trained sets for proper classification [29].

A. Association Rule Mining

Association rule mining aims at discovering the associations between items in a transactional database [8, 27, and 30]. Given a set of transactions \( D = \{t_1, t_2, ..., t_n\} \) and a set of items \( I = \{i_1, i_2, ..., i_m\} \) such that the transaction \( T \) in \( D \) is a set of items in \( I \), an association rule is an implication of the form \( X \Rightarrow Y \), where \( X \) is called body or antecedent of the rule, and \( Y \) is called as head or consequent of the rule [31]. The problem of mining association rules involves finding rules that satisfy minimum support and minimum confidence specified by the user. In this approach, modified version of ARC-AC algorithm [32] can be used for mining the association among the features from the transactional database. The proposed algorithm named MARI has been explained as follows.

**Algorithm:** MARI Find association on the training set of the transactional database.

**Input:** A set of Image patches \( P_1 \) of the form \( \{k_1, k_2, ..., k_m, f_1, f_2, ..., f_n\} \) where \( k_i \) is a keyword attached to the patches and \( f_j \) are the selected features for the patches, a minimum support threshold \( \sigma \).

**Output:** A set of association rules of the form \( f_1 \land f_2 \land ... \land f_n \Rightarrow k_i \) where \( k_i \) is a keyword, \( f_j \) is a feature and \( kw \) is a class category.

**Method:**

1. \( C_0 \leftarrow \{ \text{candidate keywords and their support} \} \)
2. \( F_0 \leftarrow \{ \text{frequent keywords and their support} \} \)
3. \( C_1 \leftarrow \{ \text{candidate keyword 1 item sets and their support} \} \)
4. \( F_1 \leftarrow \{ \text{frequent 1 item sets and their support} \} \)
5. \( C_2 \leftarrow \{ \text{candidate pairs } (k, f), \text{such that } (k, f) \in P_1 \text{ and } k \in F_0 \text{ and } f \in F_1 \} \)
6. For each patches \( p \) in \( P_1 \) do {
   (8) \( \text{kw.support} \leftarrow \text{kw.support. count}(k, p) \)
   (9) \}
   (10) \( F_2 \leftarrow \{ \text{kw} \in C_2 | \text{kw.support} \geq \sigma \} \)
   (11) \( P_2 \leftarrow \text{Filter Table}\left(P_1, F_2\right) \)
   (12) \( \text{For } (i \leftarrow 3; F_{i-1} \neq \phi; i \leftarrow i + 1) \) do {
   (13) \( C_i \leftarrow \{ \text{kw} \mid \text{Item-set of kw} \notin F_{i-1} \} \)
   (14) \( P_i \leftarrow \text{Filter Table}\left(P_{i-1}, F_{i-1}\right) \)
   (15) \( \text{For each Patches } p \text{ in } P_i \) do {
   (16) \( \text{If kw in } C_i \) do {
   (17) \( \text{kw.support} \leftarrow \text{kw.support} + \text{count}(kw, p) \)
   (18) \}
   (19) \}
   (20) \( \text{kw.support} \leftarrow \text{kw.support} + \text{count}(kw, p) \)
   (21) \}
   (22) \}
   (23) \( F_i \leftarrow \{ \text{kw} \mid \text{kw.support} \geq \sigma \} \)
   (24) \}
   (25) \}
   (26) \text{for each item set } I \text{ in sets do } \right\}
   (27) \text{Rule} \leftarrow \{ \text{kw} \mid \text{kw.support} \geq \sigma \}
   (28) \}

The association rules are constrained such that the antecedent of the rules is composed of conjunction of features from the brain image while the consequent of the rule is always the class label to which the brain image belongs [33].

B. Pruning Techniques

The rules generated in the mining phase are expected to be very large. This could be a problem in applications where fast responses are required. Hence, the pruning techniques become necessary to eliminate the specific rules and which are conflicting with the same characteristics pointing different categories [34, 35].

This can be achieved using the following conditions:

Condition 1: Given two rules \( R_1 \Rightarrow C \) and \( R_2 \Rightarrow C \), the first rule is a general rule if \( R_1 \subseteq R_2 \). To attain this, ordering the association rules must be done as per condition 2.

Condition 2: Given two rules \( R_1 \) and \( R_2 \), \( R_1 \) is higher ranked than \( R_2 \) if:

1. \( R_1 \) has higher confidence than \( R_2 \),
2. If the confidences are equal, support of \( R_1 \) must exceed support of \( R_2 \).
(3) If both confidences and supports are equal, but R1 has less attributes in left hand side than R2.

Condition 3: The rules R1 \(\Rightarrow\) C1 and R1 \(\Rightarrow\) C2 , represents are conflict in nature. Based on the above conditions, duplicates have been eliminated. The set of rules that are selected after pruning represents the actual classifier. These conditions have been used to predict to which class the new test image belongs.

C. Classification Of Test Image

After the completion of training phase, an actual classifier with pruned set of association rules can be built for training the brain images [36]. Each training image is associated with a set of keywords. Keywords are representative words chosen by a specialist to use in the diagnosis of a medical image. The knowledge of specialists should also be considered during the processing of mining medical images in order to validate the results. The extracted features of the test image and the feature vector generated can be submitted to the classifier, which uses the association rules and generates set of keywords to compose the diagnosis of a test image.

Algorithm:
Input: Feature vector F of the test image, threshold
Output: set of keywords S
Method:
(1) for each rule r \(\in\) R of the form body \(\rightarrow\) head do
(2) { 
(3) for each itemset h \(\in\) head do
(4) { 
(5) if body matches F then 
(6) increase the number of matches by 1 
(7) Else 
(8) increase the number of non matches by 1 
(9) } 
(10) } // to generate keywords
(11) for each rule r \(\in\) R of the form body \(\rightarrow\) head do
(12) { 
(13) for each item set h \(\in\) R head do
(14) { 
(15) if \((n(Mh) \div (n(Mh) + n(Nh))) \geq T\) then
(16) if h \(\notin\) S then
(17) add h in S 
(18) } 
(19) } 
(20) return S
This classifier returns the multiple classes when processing a test image. The algorithm developed has been employed to generate suggestions for diagnosis. This algorithm stores all item sets (i.e. Set of keywords) belonging to the head of the rules in a data structure. An item set h is returned in the suggested diagnosis if the condition is satisfied as the given equation

\[
\frac{n(M)}{n(M) + n(N)} \geq T
\]

where, \(n(M_h)\) is the number of matches of the item set h and \(n(N_h)\) is the number of non-matches. Threshold T is employed to limit the minimal number of matches required to return an item set in the suggested diagnosis. A match occurs when the image features satisfy the body part of the rule.

D. Performance evaluation criteria

The confusion matrix can be used to determine the performance of the proposed method and is shown in Fig 2. This matrix describes all possible outcomes of a prediction results in table structure. The possible outcomes of a two class prediction be represented as True positive (TP), True negative (TN), False Positive (FP) and False Negative (FN). The normal and abnormal images are correctly classified as True Positive and True Negative respectively. A False Positive is when the outcome is incorrectly classified as positive (yes) when it is a negative (no). False Positive is the False alarm in the classification process. A false negative is when the outcome is incorrectly predicted as negative when it should have been in fact positive.

From the confusion matrix, the precision and recall values can be measured using the formula. Precision: It is defined as the fraction of the classified image, which is relevant to the predictions. It is represented as

\[
\text{Precision} = \frac{TP}{TP + FP}
\]

Recall: It is defined as the fraction of the classified image for all the relevant predictions. It is given as

\[
\text{Recall} = \frac{TP}{TP + FN}
\]

![Figure 2.Confusion matrix](http://sites.google.com/site/ijcsis/)

| Actual | Identified |
|--------|------------|
|        | Yes        | No         |
| Yes    | TP         | FN         |
| No     | FP         | TN         |
IV. RESULT AND DISCUSSIONS

An experiment has been conducted on a CT scan brain image data set based on the proposed flow diagram as shown in Fig 1. The pre-diagnosed databases prepared by physicians are considered for decision making. Fig 3(a) represents the original input image and Fig 3(b) shows the result of histogram equalization and hybrid median filtered original image, which is used to reduce the different illumination conditions and noises at the scanning phase.

After preprocessing, feature extraction has been done to remove the irrelevant and redundant content of the information present in the input image [23]. Haralick co-occurrence method has been used to determine the discrimination of the tissue level variations and shown in Fig.4. In Fig 4(a) pixel 1 represents $0^\circ$, pixel 2 represents $45^\circ$, pixel 3 represents $90^\circ$ and pixel 4 represents $135^\circ$ from the centered pixel, at a distance value of one. Fig 4(b) shows the preprocessed CT scan brain image merged with angle representation. Fig 4(c) represents the pixel representation matrix for distance one and degree zero, similarly the pixel representation matrix have to be calculated for the remaining degrees. From the pixel representation matrix, the co-occurrence matrices are also calculated and represented in the Fig 4(d).

![Figure 3(a). Input CT scan brain image](image1)

![Figure 3(b). Histogram equalized image](image2)

![Figure 4(a). Matrix representation for center pixel and all around pixels](image3)

![Figure 4(b). Preprocessed CT scan brain image merged with angle representation](image4)

![Figure 4(c). Pixel representation matrix for Zero Degree](image5)
Fig 5 represents the flow of texture feature extraction and object segregation process. For each object co-occurrence matrix has been calculated and texture features are extracted. Four different directions $0^\circ, 45^\circ, 90^\circ, 135^\circ$ generate 16 co-occurrence matrices. The texture features are then calculated for each co-occurrence matrix and stored in the database. The feature vectors have calculated and the obtained vectors are stored in the transaction database from the co-occurrence matrix values.

MARI algorithm has been applied on the transaction database which consists of the feature vectors and the diagnosis information about the training CT scan images. Fig 6 represents the images of the sample dataset and their diagnosis information.

In Fig 7 the precision and recall values of the proposed method, Association Rule Mining (ARM) method and Naïve Bayesian method are plotted in the graph. It shows that the performance of proposed method is better compared to the existing methods.

The effectiveness of the proposed method has been estimated using the following measures:

\[
\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN},
\]

\[
\text{Sensitivity} = \frac{TP}{TP+FN},
\]

\[
\text{Specificity} = \frac{TN}{TN+FP}
\]

where, TP, TN, FP, and FN are the number of True Positive cases (abnormal cases correctly classified), the number of True Negatives (normal cases correctly classified), the number of False Positives (normal cases classified as abnormal), and the number of False Negatives (abnormal cases classified as normal) respectively. Accuracy is the proportion of correctly diagnosed cases from the total number of cases. Sensitivity measures the ability of the proposed method to identify abnormal cases. Specificity measures the ability of the method to identify normal cases. The value of minimum confidence is set to 97% and the value of minimum support is set to 10%. The features of the test images and the association rules have been generated using the threshold value=0.001. The results show that the proposed classifier gives higher values of sensitivity, specificity and accuracy such as 96%, 90% and 93% respectively. In order to validate the obtained results, the algorithmic approach has been compared with the well known classifier, a naive bayesian classifier and associative classifier [37, 38 and 39].
Recall

Table 1 illustrates the sensitivity, accuracy, specificity, area under the curve (Az), standard error (SE) and execution time of naive bayesian classifier, association rule mining and proposed method. The experimental results have shown that the proposed method achieves high sensitivity (up to 96%), accuracy (up to 93%) and less execution time and standard error in the task of support decision making system.

Table 2 represents the results of the classifiers, here 150 images are taken for training and 95 images are taken for the testing in both benign and malignant categories, which are classified using different classifiers. The results show that the proposed system gives better percentage of correct classification as compared to naive bayesian classifier and association rule based classifier.

### TABLE 1 PERFORMANCE COMPARISON FOR CLASSIFIERS

| Classes | No. of data Training/Testing | Naive Bayesian classifier | Association rule based classifier | Pruned Association rule with MARI Algorithm based classifier | No. of correctly classified data | Percentage of correct classification |
|---------|-----------------------------|--------------------------|-----------------------------------|-------------------------------------------------------------|--------------------------------|------------------------------------|
| Benign  | 150/95                      | 84                       | 91                                | 93                                                          | 88.4                          | 95.78                              |
|         |                             | 96                       | 94                                | 94                                                          | 89.4                          | 96.84                              |
| Malignant | 150/95                     | 85                       | 92                                | 94                                                          | 89.4                          | 96.84                              |
|         |                             | 96                       | 90                                | 93                                                          | 96.84                         | 98.95                              |
| Average |                             | 89.9                     | 96.31                             | 98.42                                                       |                               |                                    |

### TABLE 2 RESULTS OF THE CLASSIFIERS

| Approach                                      | Sensitivity (%) | Specificity (%) | Accuracy(%) | Az  | SE  | Time (ms) |
|-----------------------------------------------|-----------------|-----------------|-------------|-----|-----|-----------|
| Naive Bayesian classifier [22]                | 75              | 63              | 70          | 0.89| 0.08| 30.91     |
| Association rule based classifier [22]        | 95              | 84              | 91          | 0.91| 0.03| 9.75      |
| Pruned Association rule with MARI Algorithm based classifier | 96              | 90              | 93          | 0.98| 0.02| 2.15      |

Figure 7. P & R graph using naive bayesian, association rule mining and MARI association rule mining

Figure 8. Tumor classification by ROC analysis
The Receiver Operating Characteristic (ROC) curves are plotted with respect to sensitivity and specificity. The area under the ROC plays a vital role since it has been used to determine the overall classification accuracy. Fig 8 shows the comparison of the ROC curve for various classifiers. It clearly shows that the proposed mining based classification with pruned rules has higher value of the ROC curves as compared to other methods.

V. CONCLUSION
An improved image mining technique for brain tumor classification using pruned association rule with MARI algorithm has been developed and the performance is evaluated. The proposed algorithm has been found to be performing well compared to the existing classifiers. The accuracy of 93% and sensitivity of 96% were found in classification of brain tumors. The developed brain tumor classification system is expected to provide valuable diagnosis techniques for the physicians.

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