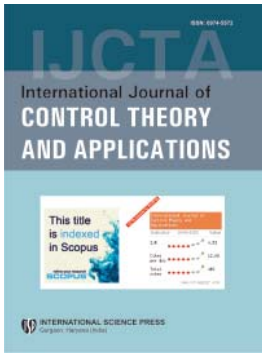

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Improving Feature Selection through Global Discretization for Content-based Image Retrieval and Classification

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Abstract: Content Based Image Retrieval (CBIR) and Computer Aided Diagnosis (CAD) system use a mathematical representation (feature vector) of an image in the image retrieval process. The feature vector-based description of an image in CBIR system generates semantic gap problem. An image represented by a large size feature vector shows to be a solution for the semantic gap problem but it directs to the dimensionality curse problem. It does not assist executing image retrieval process and makes the classification process enormously slow down. To raise the performance of the CBIR system, Feature selection methods are used. Here, we suggest a new supervised feature selection algorithm called IICBMergeFS (Interval InConsistency Based Merge for Feature Selection) to enhance the result of medical image diagnosis. IICBMergeFS is an easy and ordinary algorithm that employs the inconsistency rate to discretize numeric features continually until some irregularities are found in the data. Furthermore, the performance of the classification and retrieval method is processed in terms of Precision, Sensitivity, and Specificity. The test result shows that the proposed method provides an accurate classification result and helps in retrieval of relevant images from the image database.

Keywords: *Feature extraction, Dimensionality Reduction, Discretization, Feature Selection, Feature vector, Image Classification.*

1. INTRODUCTION

Content Based Image Retrieval (CBIR) and Computer Aided Diagnosis(CAD) systems have been effectively used in many hospitals and specialized health centers to recommend speedy access to viewing. CAD system refers to techniques that diagnosis the test image based on the image content automatically extracted from the image and high-level data got from experts [1]. In the medical field, the aim of the CBIR System is to help the radiologist in the medical diagnosis process, retrieving relevant past cases with images and other information. The CAD system development is based on the training process and the test process [2]. The classification of medical images requires the automatic image segmentation and the drawing out of image attributes without human intervention in the Region of Interests (ROIs) with a definite criterion [3]. The image processing techniques are applied to identify the ROIs in the images and extract pertinent features from the ROIs and organize them as feature vectors. The feature vectors are used in place of the images in the form of transaction which is then used on the classification or retrieval processes. The features of the images such as color, contour and texture are described as independent feature vectors with thousands of elements. The presence of irrelevant and redundant features in the feature vector may effect in low efficiency, overfitting and poor prediction performance in learning functions. So, the dimensionality reduction step is required in such applications. There are two dimensionality reduction techniques named feature transformation and feature selection can be used to practice feature vectors, selecting the most relevant features, removing the irrelevant ones [4]. This improves the performance of the retrieval process.

Here, we present an improved supervised feature selection and discretization technique called IICBMergeFS (Interval InConsistency Based Merge for Feature Selection). The IICBMergeFS technique carries out feature Discretization and selection of most significant features from the feature vector in a single step. This supports dimensionality reduction and improves the accuracy of the image retrieval process through data mining techniques. This approach has a considerable advantage that the data has to discretize once and can then be used as the input to any data mining algorithms that accepts categorical data. The rest of the paper is prearranged as follows: Section II shows the related works. Section III presents the proposed work. Experimental Result and Discussion are displayed in Section IV. Finally, the conclusion is described in Section V.

2. RELATED WORKS

Recently, many researchers have applied Data Reduction technique to decrease the dimensionality of high-dimensional data and construct new robust classifiers [5] [6]. During the image classification process, they take out collections of features from medical images, select a set of low dimensional features using data reduction techniques and use them as the input to the classifier or predictive model. The feature selection methods are typically presented in three classes based on Filter, Wrapper and Embedded techniques to select the relevant features from the feature vector space.

The filter methods are depending on the features of the image and process the features without any learning algorithms. Generally used algorithms like F-score [7], maximal Relevance and Minimal Redundancy criterion (mRMR)[8][9], Relief Feature selection (RelieF) [10], cluster-based feature selection[11] and correlation-based feature selection[12] are called filter based approaches. Wrapper methods evaluate subsets of variables which allows, unlike filter approaches, to detect the possible interaction between variables. A variety of wrapper-based methods, including sequential forward selection [13], genetic algorithms [14] and kernel methods [15] are useful for image classification. Embedded methods search an optimal feature subset for the classification process.

The filter-based feature selection approach named max-min-association index (MMAIQ)[16], selects features concurrently satisfying the criteria of a statistically maximum relationship between target labels and features and a minimum relationship between selected features with respect to the Cramer's V-test(CV-test) coefficient. For the CV-test value calculation, the MMAIQ approach takes on the Simple Equal Width (EQW) algorithm to discretize continuous feature without taking class labels [16]. Thus, MMAIQ could be more advanced if a good discretization scheme was developed.

In statistics and machine learning, discretization refers to the process of converting features or variables to discretized or nominal features. The trouble concerned to discretization is to search suitable cut points in the feature domains. The discretization method based on CV-test coefficient (CVD) was proposed to make the most of the class feature interdependence and to create the least number of discrete intervals [17]. The Cramer's V-test value produces two association-based feature indices named CVD-based association index (CVDAI) and class-attribution interdependence maximization (CAIM) based association index (CAIMAI) to select the optimal feature subset from the large dimensional feature space. It takes up a lot of CPU time, memory or both compared with other methods. Moreover, the method employs an incremental forward selection procedure. The forward selection has drawbacks, including the fact that each addition of new feature may render one or more of the already included features non-significant.

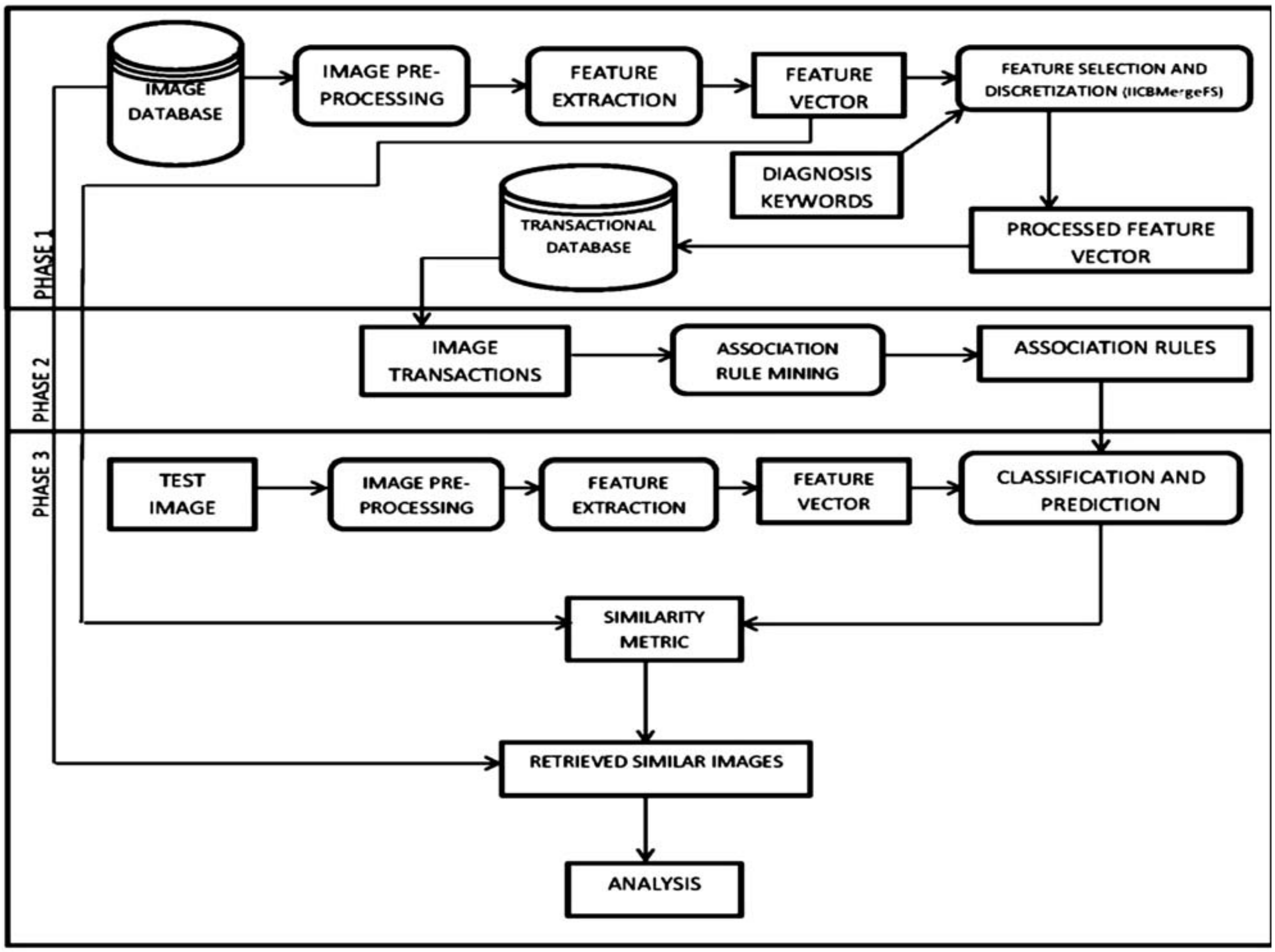


Figure 1: Overall structure of the proposed CBIR system

Texture based image descriptors are widely used in pattern recognition to detain the well detail of the image. A new image texture feature descriptor based on Local Wavelet Pattern (LWP) is used for image retrieval in medical CT data bases. The performance of the LWP feature vector is better than other feature descriptors in terms of both feature extraction and image retrieval time. The performance of the LWP is similar over the databases having images from the same body part while it is slight different over the data base of different body part [18]. The automatic classification of CT result of lung lesions in CT scan is achieved through FIsher criterion and Genetic optimization (FIG) feature selection method. In the FIG feature selection method, the FIG criterion is applied to evaluate the feature subset and genetic optimization algorithm is developed to find out optimal feature subset from the candidate features [19]. Discretization of data is a process of transforming numerical attributes into discrete ones. This will improve the speed and accuracy of data mining algorithms. An evolutionary multivariate dicretization algorithm for selecting optimal cut points was proposed in [20]. The objective of this algorithm was to maximize the accuracy of the subsequent classification process and simplify the solution by using wrapper fitness function. An effective discriminative feature selection method was proposed in [21]. This method is the combination of the popular transformation-based dimensionality reduction method named Linear Discriminant Analysis (LDA) and sparsity regularization. In the biomedical image retrieval applications, the standard Local Binary Pattern (LBP) encodes the relationship between the reference pixel and its surrounding neighbors but the proposed Local Mesh Pattern encodes the relationship among the surrounding neighbors for a given referenced pixel in an image [22]. The objective of this method is to improve the accuracy of the image retrieval process.

In this paper, we propose a new backward selection method based on an interval Inconsistency rate for feature selection. This provides a maximum benefit for medical image classification and medical image retrieving applications. This would speed up the diagnosis and classification process. Our experiment built over classification performance measures shows that the proposed method improves the classification accuracy than all the other methods.

3. PROPOSED SYSTEM

In this section, we propose a new Interval Inconsistency Based Merge algorithm for feature selection called IICBMergeFS. This helps to improve the performance of the CBIR system by using stable feature selection through discretization for Ultra Sound Kidney image diagnosis. The overall structure of the new CBIR system is shown in figure 1. It can be noticed that the system includes three phases.

1. Feature selection based on IICBMergeFS
2. IICBMergeFS based Association rule mining
3. Building Hybrid Associative Classification Engine(HyACE)

This paper focuses on the overall function of phase 1. The aim of phase1 is to build a transaction representation of images. This is achieved through image pre-processing, feature extraction and feature selection modules. The following subsections describe the detail explanation of these modules.

3.1. Image pre-processing

In our work, image pre-processing technique is used to enhance the visual appearance of US(Ultra Sound) kidney image by removing the unnecessary information other than kidney. It is necessary to make the feature extraction process more reliable. The image pre-processing procedure involves two steps: Identifying ROI (Region-Of-Interest) and removing Speckle noise.

1. **Identifying Region-Of-Interest (ROI):** The first step in image preprocessing is Image Cropping. The cropping function removes the unwanted details from the image and focuses on the image region of interest. It improves the speed and accuracy of the image classification and retrieval process. In our work, the ROI is obtained by applying MATLAB function to reduce the possibility of errors and simplify the process. Figure 2 shows the output of ROI.

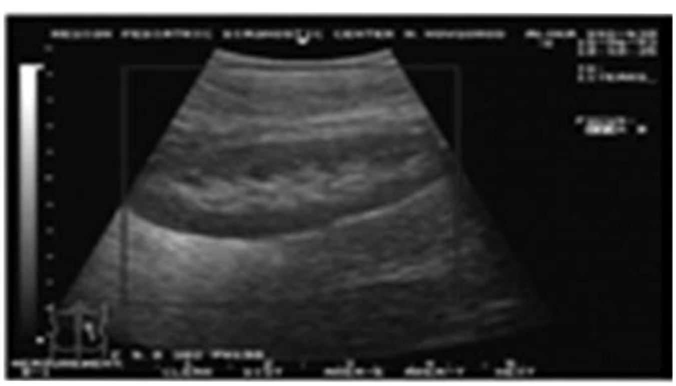
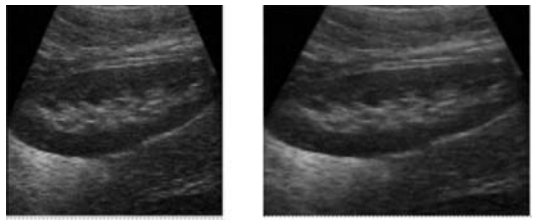


Figure 2: ROI of Normal kidney image

2. **Speckle noise Removal:** In this step, the noise occurred in our images that are removed. Noise is an undefined information that contaminates the images. These noises are removed using some types of filter methods. Here, we have used the median filter to reduce speckle and salt-pepper noise. Figure 3(*b*) shows the result of original image after applying the median filter.



(*a*) (*b*)

Figure 3: ROI (*a*) Normal image (*b*) after applying Median Filter

3.2. Feature Extraction

The most significant stage of content-based image retrieval and classification process is feature extraction. In our work, Center Symmetric Local Binary Pattern Gray Level Co-occurrence Matrix (CSLBPGLCM) algorithm is employed for the extraction of texture features from the given image. During the process, the image is converted into a collection of gray values ranging from 0 to 16. Next, the GLCM (Gray Level Co-occurrence Matrix) matrices are generated for each of the four directions of 0^o, 45^o, 90^o, 135^o and a distance of 1,2,3 and 4. Using this co-occurrence matrix, the texture features namely, entropy, energy, contrast, correlation and homogeneity are computed using MATLAB 14A and put it in the feature vector form. These features are then fed into the medical image retrieval system.

3.3. Feature Selection

Feature selection is the process of selecting pertinent features from images that are important for differentiating one class of objects from another. Here, we have presented an enhanced feature selection algorithm named IICBMergeFS for speeding up the process of classification and image retrieving from medical image database. IICBMergeFS is an enhanced supervised algorithm that reads the input vector and reduces the irrelevant features by discretizing the continuous values of the feature and selects the most relevant ones. This algorithm describes the interval Inconsistency rate which is considered as the merged standard in the process of discretization. The definitions related with the IICBMergeFS algorithm are:

Definition 1: Cut point: cut point refers to a boundary of an interval of real values.

Definition 2: Class:class refers to an important diagnosis keyword given by a specialist.

Definition 3: Majority class: It refers to a most frequently occurred class in an interval.

IICBMergeFS is a novel supervised algorithm that computes feature selection and discretization of continuous values. IICBMergeFS perform each feature separately and discretize the set of N sorted values in 4N steps. In the first step, the IICBMergeFS algorithm sorts the continuous values using quick sort algorithm and creates the cut points based on the changes in the class label of the instance. In the second step, IICBMergeFS eliminates the right cut points of the intervals that do not satisfy the minimum occurrence limit given by an input threshold minfperInt. In the third step, the algorithm merges successive intervals measuring the inconsistency rate to determine which intervals should be merged. Let N_i and N_{i+1} be the two successive intervals. Let M_{N_i} be the majority class of an interval N_i. The inconsistency rate ∂_{N_i} of an interval N_i is computed according to equation (1).

$$\partial_{N_i} = \frac{|N_i| - |MN_i|}{|N_i|} \quad (1)$$

Where $|N_i|$ number of instances in the interval N_i and $|M_{N_i}|$ is the number of majority class of an interval N_i. The algorithm merges the two successive intervals that have same majority class and also have inconsistency rates below or equal an input threshold ∂_{max} $(0 \le \partial_{max} \le 0.5)$. In the fourth step, the IICBMergeFS algorithm executes the feature selection process. Let N be the set of intervals in which feature is discretized. For each feature f, the algorithm computes the overall inconsistency ∂_G value according to equation (2).

$$\partial_G = \frac{\sum N_{i \in N}(|N_i| - |MN_i|)}{\sum N_{i \in N}|N_i|} \quad (2)$$

Let Cp_n be the set of cut points $(c_p, c_{p+1}, \ldots c_{p+n})$ in which feature is selected. For each feature f, the algorithm computes the overall cut point φ_G value according to equation (3).

Finally, the algorithm computes average overall inconsistency $\overline{\partial_G}$ value and average overall cut point $\overline{\varphi_G}$ value by using equations (4) and (5).

$$\overline{\partial_G} = \frac{1}{k}\sum_{i=1}^{k}\partial_G \quad (4)$$

$$\overline{\varphi_G} = \frac{1}{k}\sum_{i=1}^{k}\varphi_G \quad (5)$$

Where, k is the total number of overall inconsistencies and overall cut points. For each feature The IICBMergeFS algorithm removes from the set of feature each feature, whose average overall inconsistence rate $\overline{\partial_G}$ is greater than the input threshold $\overline{\partial_{Gmax}}$ $(0 \le \overline{\partial_{Gmax}} \le 0.5)$ and average overall cut point rates greater than the input threshold $\overline{\varphi_{Gmax}}$ $(0 \le \overline{\varphi_{Gmax}} \le 0.5)$.

Algorithm (The IICBMergeFS algorithm):

Input : Feature vector (FV), diagnosis keywords(Classes), minfperInt, ∂_{max}, $\overline{\varphi_{Gmax}}$, $\overline{\varphi_{Gmax}}$.

Output : Processed Vector (V).

1. For each feature f of the image i
2. Sort f values with classes C
3. For each transaction i, create an Image instance I_i as (f_i, c_i)
4. To create cut points C_p do
5. Place a cut point before the smallest value and place another cut point after the highest value.
6. A new cut point is created when the changes in the class label occur.
7. For each Cp do
8. Remove the right cut points as per the number of occurrences of the majority class in an interval N_i must be $|MN_i| \ge$ minfperInt threshold.
9. Remove the cut points as per the consecutive intervals N_i and N_{i+1} that has the same majority class and inconsistency rate ∂_{N_i}, $\partial_{N_{i+1}}$ below or equal to an input threshold ∂_{max}
10. Compute the overall inconsistency measure ∂_G for each feature according to the equation 2.

11. Compute the overall cut point measure φ_G according to equation 3.
12. End for
13. For each ∂_G and φ_G do
14. Compute average overall inconsistency rate $\overline{\partial}$ by using equation 4.
15. Compute average overall cut point $\overline{\varphi_G}$ by using equation 5.
16. Select features according to $\overline{\partial_G}$ and $\overline{\varphi_G}$ is less than the $\overline{\partial_{Gmax}}$, and $\overline{\varphi_{Gmax}}$ thresholds.
17. Write the selected features in V
18. Return V
19. Stop.

3.4. Association Rule Generation

After selecting the relevant features, association rules are generated to reduce the complexity of classification and image retrieval process. The output of the IICBMergeFS algorithm and the diagnosis keywords of the training images are submitted to the Apriori algorithm [23] to mine association rules. Let D = $\{t_1, t_2, \ldots t_n\}$ be a set of transaction and I = $\{i_1. i_2\ldots i_m\}$. Each transaction has a subset of the items in I. The Apriori algorithm generates the association rule of the form $X \Rightarrow Y$, where $X, Y \subseteq I$ and X is the antecedent of the rule which returns the diagnosis keywords and the Y is the consequent of the rule which is composed of indexes of the features and their intervals. Typically, association rules are considered interesting if they satisfy both a minimum support (minsup) threshold and minimum confidence (minconf) threshold. These values are set by the users or experts. The values of minconf are set to be high. The mined rules are employed as input to KNN algorithm.

4. EXPERIMENTAL RESULT AND DISCUSSION

We have tested our proposed CBIR system with the Ultra Sound Kidney images obtained from signal processing laboratory (http://www.splab/en/). The database contains different classes of ultrasound kidney images like Normal, cortical cyst (CC), medical renal diseases (MRD) are taken for experiments. In the pre-processing step, ROIs in the images are identified and pertinent features are extracted from the Region of Interest. Finally, these features are organized into feature vectors. The feature vectors are used in place of the images as transactions which are then used in the classification or retrieval processes. The texture features extracted from the ROIs of US Kidney images are shown in Table 1. As the number of irrelevant and inconsistent features arise in the vector is the issue that contributes to affect the classification and retrieval process, removing the most irrelevant and inconsistent features that can contribute to speed up and improves the accuracy of classification and retrieval process.

In our experiment, IICBMergeFS algorithm selects the significant features for efficient classification. The selected features and the diagnosis keywords are submitted to the apriori algorithm, which generates less amount of rules. The minimum support threshold is set to 10% and minimum confidence threshold is set to 98%. Because of using IICBMergeFS feature selection procedure, the generation of redundant rules is restricted. In this experiment, the KNN classifier is trained for classifying ultrasound Kidney images based on Levenberg-Marquardt procedure. During the test phase, the query image is classified by the KNN classifier either as a normal or a cortical cyst(CC) or a medical renal disease (MRD). Finally, the relevant images are retrieved from the database according to the images have minimum trigonometric distance and maximum correlation coefficient values. The performance of feature selection based classification method is determined by Accuracy, sensitivity, and specificity. The performance measures are defined as:

Table 1
Extracted features and their positions

Feature	*Meaning*	*Position*
Entropy	Suavity	1–16
Contrast	Contrast	17–32
Correlation	Association	33–48
Energy	Uniformity	49–64
Homogeneity	Homogeneity	65–80

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{6}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{7}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{8}$$

Where TP is the number of True Positive cases. TN is the number of true negative cases. FP is the number of false positives and FN is the number of false negatives. We also compare the overall accuracies using discretized features by the four well known classifers like J48-DT, NB, SVM and KNN for five feature selection sechems. Table II describes the experimental result.

Table 2
Comparison of overall accuracies using entire discretized features by different classifiers for the five feature selection schemes

Classifiers	*Feature selection*	*Accuracy*
	IICBMergeFS	86.14
	CAIMI	84.24
J48-DT	EQWAI	85.08
	ReliefF	82.41
	F-score	83.33
	IICBMergeFS	86.48
	CAIMI	84.48
NB	EQWAI	82.71
	ReliefF	81.01
	F-score	79.59
	IICBMergeFS	88.24
	CAIMI	88.17
SVM	EQWAI	87.9
	ReliefS	86.09
	F-score	88.09
	IICBMergeFS	89.24
	CAIMI	89.17
KNN	EQWAI	88.9
	ReliefF	87.09
	F-score	89.04

The result shows that the discretized feature set minimizes the complexity of the subsequent processes and improves the accuracy of the classification process. Figure 4 shows the comparison of accuracies using discretized features by classifiers for five feature selection schems with kidney image database.

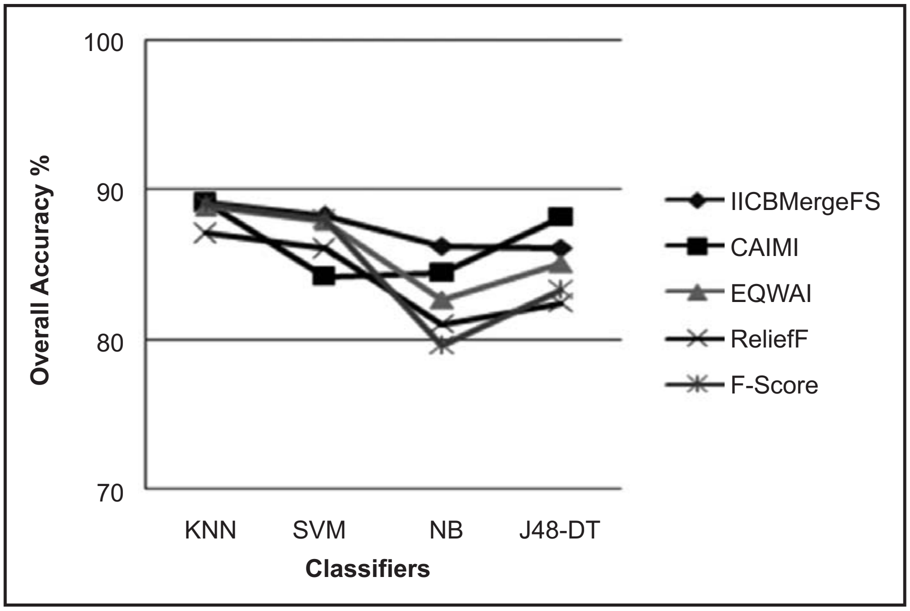


Figure 4: Comparison of overall classification accuracies of the different feature selection approaches

The performance of the proposed content based image retrieval system is determined by P&R rates (Precision and Recall rates). The performance measures are defined as:

$$\text{Precision} = \text{TRS/TS} \quad (9)$$

$$\text{Recall} = \text{TRS/TR} \quad (10)$$

Where TR is the number of relevant images in the database. TS is the total number of retrieved images and TRS is the number of relevant retrieved images. The result of the experiment is shown in Table 3. To analyse the performance of the proposed IICBMerge feature selection method in content based image retrieval system, we have calculated the retrieval precision and recall respectively for the query image. The precision is compared with some other well- known feature selection method used in image retrieval like CAIMI, EQWAI, ReliefF and F-score. The comparison chart figure 5 shows that the proposed feature selection method used in image retrieval provides an high precision than other methods.

Table 3
Comparison of precision of CBIR system using five Feature selection methods

Performance	*Feature selection methods*				
	IICBMerge	CAIMI	EQWAI	ReliefF	F-score
Precision %	89.12	85.1	84.28	70.34	69.3

Figure 5 shows the performance comparison of our feature selection method in CBIR with other filter methods in term of Precision rates over kidney image database. The above two experimental result show that the IICBMergeFS feature selection algorithm reduces the dimensions of the feature vector as maximum and improves the performance measures of classification and retrieval process.

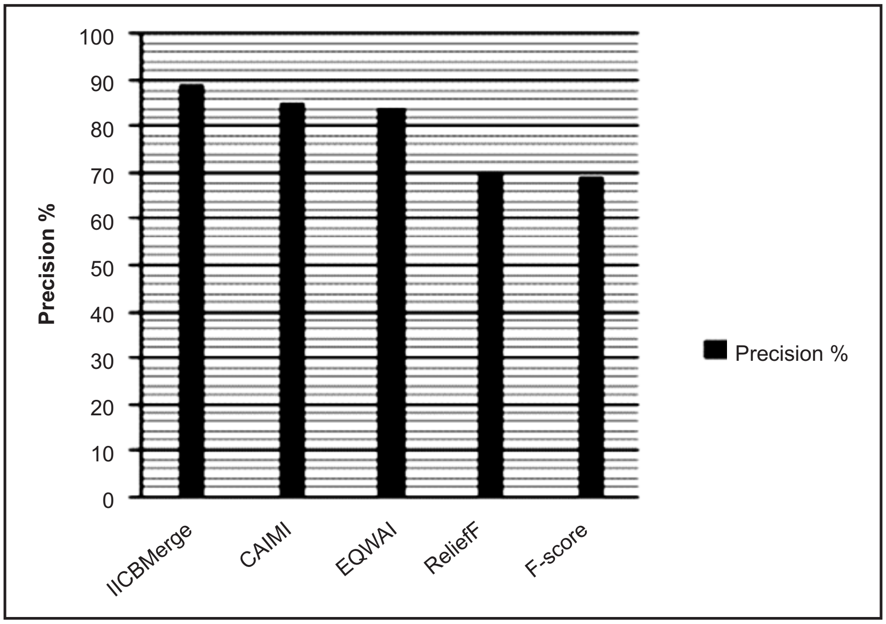


Figure 5: Precision rates of CBIR with various feature selection methods

5. CONCLUSION

In this paper, a supporting content based image retrieval (CBIR) system based on IICBMergeFS feature selection for kidney image diagnosis has been developed. The proposed CBIR system consists of six major steps: identifying Region of interest, image pre-processing, feature extraction, feature selection and discretization, association rule mining, classifying and retrieving kidney images. The ROI segmentation is performed by MATLAB cropping functions. The image pre-processing is carried out by the median filter. Texture features are extracted and stored it in the feature vector. Feature selection and discretization are achieved using a new IICBMergeFS algorithm. The algorithm discretizes the numeric features into discrete ones. Since feature selection and discretization have been performed before the learning stage in the classifiers, they significantly reduce the processing effort of the classification algorithm. The experimental result has proved that the IICBMegeFS algorithm reduces the irrelevant and inconsistency features and produces good classification accuracy when compared with other feature selection methods used in J48-DT, NB, SVM and KNN classifiers. Moreover, the image retrieval test result shows that the CBIR system using the proposed feature selection algorithm provides better precision and recall rates compared with the other well- known feature selection algorithms. Hence, we pose the IICBMergeFS based CBIR system to provide better decision making in selective kidney images and reduces complexity. Future work includes investigating the applicability of the proposed system for other medical images and improving the accuracy of image classification while using a large database.

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