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Supporting content based visual information retrieval for medical imaging with lenient relevance feedback

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Abstract:-

The objective of CBIR is to retrieve relevant medical images from the medical database with reference to the query image in a shorter span of time. All the proposed approaches are different, yet the research goal is to attain better accuracy in a reasonable amount of time. The initial phase of this research presents a feature selection technique that aims to improvise the medical image diagnosis by selecting prominent features. The second phase of the research extracts features and the association rules are formed by the proposed Classification Based on Highly Strong Association Rules (CHiSAR). Finally, the rule subset classifier is employed to classify between the images. The final phase of the research extracts the features from the kidney images and the association rules are reduced for better performance. The image relevance inference is performed and finally, binary and the best first search classification is employed to classify between the images. The system was effectively prepared for 10 classes of CT scan image and in the proposed IICBMergeFS based CNN classifier provide high accuracy of 97.24% is obtained by comparing with the state of arts in MATLAB software.

Keywords:

1-Content Based Information Interval in Consistency Based Merge
2- Feature Selection
3- Feature extraction
4- Classification
5- Image analysis

INTRODUCTION

Recently, with the advent of Picture Archiving and Communication Systems (PACS), there is an increasing trend in the incorporating all patient-related content, such as text, pictures, maps, temporal details, etc., into coherent systems. PACS should incorporate techniques that allow the retrievals of medical image in a timely manner to increase the quality and effectiveness of care process. In fact, in order to offer appropriate support to the practitioner with their examination and treatment, the collection will provide photographs that follow the requirements set forth by the specialists. Add CBIR capability to PACS allows it more effective to aid diagnosis, making it simpler and more productive to access and arrange processed images in hospitals. CBIR system is the retrieval system that takes the features of the system into account for distinguishing between the images. This work focuses only on the ultrasound images of the kidneys. The aim of CBIR system is to retrieve similar images from the database with respect to the query image [14]. Here, the goal is to find the similar images and it is achieved by means of image properties. This helps the healthcare professional to make decision by referring the similar case [19]. Traditional CBIR systems work in the following way and the basic functionality of the CBIR system relies on two important phases, which are training and testing. In the training phase, the input database is processed by means of advanced image pre-processing and feature extraction activities. The discrimination ability of the CBIR system relies on the effectiveness of the features being extracted. However, the feature set must be crispy and precise, such that the time consumption can be reduced. The feature vector is formed from the extracted features and saved for future reference [13]. During the testing phase, when the test image is passed, the features of the test image are extracted and are matched against train feature vector. The top matching images are listed as the result to the user. The main challenges being faced by the CBIR systems are retrieval time and efficiency. A CBIR system is considered to be effective only when the better results are achieved in a short span of time [12]. Some of the noteworthy applications of CBIR systems are biometric systems, medical applications, textile industry and so on. The biometric applications utilize finger print, palm print, face images as input for retrieving the matching entity. This kind of applications can be employed to ensure security [15]. The CBIR

systems in medical field support the healthcare professional in relating between the similar cases. Thus, the medical CBIR systems help in achieving better diagnosis. Textile industries employ CBIR systems for finding the related fabric images, which are rich in texture. A new content-based image retrieval method in that texture and color feature used. In the color image two types of information is extracted such as color and texture feature, in which it is more accurate for image retrieval based upon their query request [1]. By comparing to the conventional moments, the Zernike moments has less sensitive to noise in the descriptor for ideal region-based shape. RGB image converted from the spot where his opponent's chromaticity space, the contents of the characteristics of the color of an image caught using distribution moments of Zernike chromaticity [2]. The margin of variation of the rotation and scale invariant image domain description of the system features are extracted and has less feature vector dimension. The low level image features depend on texture, shape and color in the CBIR system. One of the main drawbacks of the CBIR system uses images of similar low-level features to vary the query image based on the objects that the user is predicting, and the complexity is identified as this type of semantic space. In recent times, CBIR research effort in the low-level visual features and high-level semantic gap is reducing between objects in the image [3]. The survey paper discusses Color histograms, invariant color histograms, color moments, and dominant color system features are the color features extracted from Gabor Transform, Tamura features and the GLCM [4]. Spatial communication aspect, approximation polygon-shaped features, moments, shape-space patterns and change the size are extracted using space feature. The similarity of images is to be calculate the various distance measures for semantic gap, and discuss about the retrieval of invariant image. The similarity of two images can be obtained by measuring the distance value between them [5]. One of the unsupervised learning technique is image clustering. For any particular problem cannot be separated on the basis of a novel multi-dimensional lifting schematic structure of the bandwidth filter bank discussed [6]. The content-based retrieval is worked with types of images, patterns of use, the sensory gap and the role of semantics. Object and shape features. Each feature types the similarity of objects and pictures are reviewed, through interaction with the feedback of the users of the systems and methods are capable of producing in close contact with it. Content-based retrieval applications are discussed in three broad categories: association search, target search, and category search [7]. The influence of computer vision, unity and the role of communications, the demand for databases, estimates are made of the issue and reviewed the role of the semantic gap [8]. Content-based image retrieval system, the retrieval process of leaf color, shape and texture features are used and which is mainly implemented in the medical industry, cosmetic industry and botanical gardening [9] [10]. CBIR system discuss about the requirement of indexing, classification, image retrieval, clustering, etc. images are the most important requirements for efficient features are extracted from the color features [11]. Quad-tree decomposition is used for films and Wide Color histogram image retrieval results compared to the same blocks as represented in different sizes.

2. OBJECTIVES OF THE RESEARCH

The main objective of the research is to present CBIR systems for the ultrasound images of the kidney. In order to attain this objective, the entire research work is divided into three separate phases and each phase works towards achieving the research goal. The objectives of each and every phase are listed below.

- To propose a CBIR system with better feature selection model for ultrasound images of kidney. The idea of this phase is to reduce the computational complexity and time consumption of the CBIR system [16] [17].
- To present a CBIR system for ultrasound images of kidney by means of association rule mining classification technique. In this phase, the association rules are generated, organized and then utilized to perform classification [18] [20].
- To introduce a CBIR system based on lineant relevance feedback mechanism, which works by considering the search pattern of the user.
- To evaluate the performance of the proposed CBIR systems with the standard performance measures for justifying the efficiency of the proposed approach.

Hence, the objectives of the research work are presented and the following section presents the overall flow of the proposed approach. Figure 2.1 overall structure of the proposed CBIR System.

3. PROPOSED CBIR SYSTEM

This proposes a new Feature Selection Method called "IICBMergeFS". This helps to improve the performance of the CBIR system by using stable feature selection through discretization for ultrasound kidney image diagnosis. The proposed approach extracts the low level features based on the high level knowledge (keywords) given by the user, in order to suggest a better diagnosis for the query images. The algorithm of this work is presented as follows. The overall structure of the new CBIR system is presented in algorithm 1. The proposed approach is subdivided into three phases, as listed below. Feature Selection Based on IICBMergeFS ii)IICBMergeFS Based Association Rule Mining iii)Classification using CNN algorithm

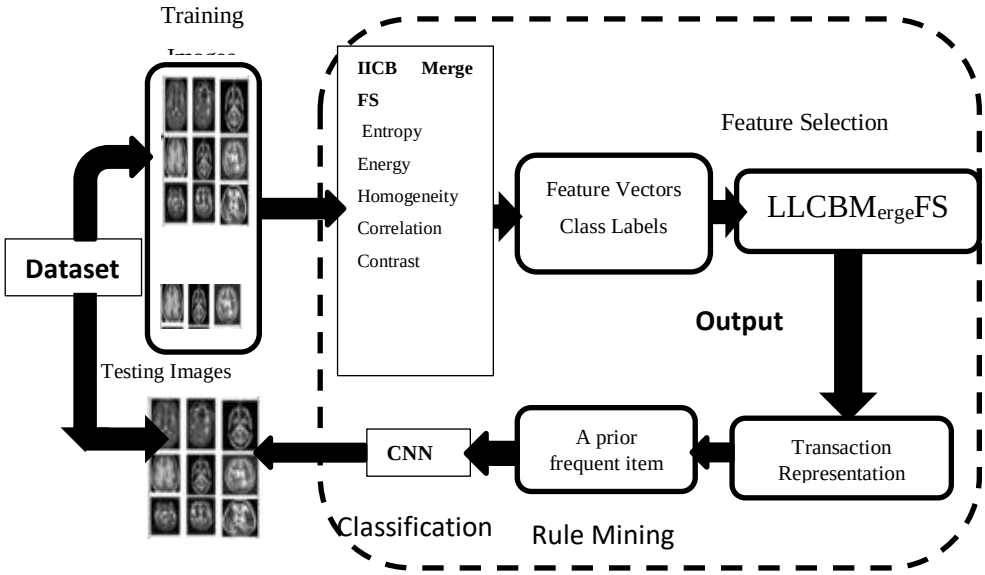

Figure 2.1 Overall Structure of the Proposed CBIR System

following subsections describe the details explanation of these modules.

Algorithm 1 Proposed CBIR System

Procedure OVERALL Input: Image database
Result: Relevant images with classes Training Phase:

For all Images **do**
Pre-Process the images

Extract texture features from the training images

End for

Execute IICBMergeFS algorithm Mine Association Rules

Test Phase:

Extract texture features from the test image

Classify the images by applying K-Nearest Neighbour (CNN) algorithm

return the relevant images and class name found

End procedure

3.1 Kidney Image Feature Extraction

The most significant stage of CBIR and classification process is feature extraction. This work employs Gray Level Co-occurrence Matrix (GLCM) algorithm introduced by Haralick for the extraction of texture features from the given image. During the process first, the image is converted into a collection of gray values ranging from 0 to 4. Secondly, the GLCM matrices are generated for each of the four directions of 0°, 45°, 90°, 135°and a distance of 1, 2, 3 and 4. Therefore, sixteen matrices of 4x4 integer elements per images are generated. GLCM is a second order statistic dimension which holds details about the number of occurrence of two gray levels.Several statistical features known as Harlick textures features as described by Deserno [2011] are extracted by the GLCMs. For each image, GLCMs are calculated in four directions such as Horizontal: 0°or 180°, Vertical: 90°or 270°, Right Diagonal: 45°or 225°, Left Diagonal: 135°or 315°. The GLCM directions utilized for the analysis is denoted as D0°, D45°, D90°and D135°respectively.

. The following algorithm summarizes the process of image feature extraction.

Algorithm 2 Image Feature Extraction Using GLCM

procedure IMAGE FEATURE EXTRACTION Input: Gray scale Image

Output: Image Features f1,f2,f3,f4,f5.

for each Image I, is IDB Where IDB is the collection of image Begin

For all image I, i s IDB **do**

Calculate the grey level Co-occurrence matrices $M_{(i, j)}^{K}$ in an N neighbourhood of the current pixel a_k

$M_{(i, j)}^{K}$ =Graycomatrix (Image1, Distance, Angle θ)

End for

For all $M_{(i, j)}^{K}$ extract the five Haralick features **do end procedur.**

3.2 Feature Selection

Feature selection is the process of selecting pertinent features from images that are important for differentiating between different classes. This work selects better features from the feature set by employing an enhanced feature selection algorithm namely 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.

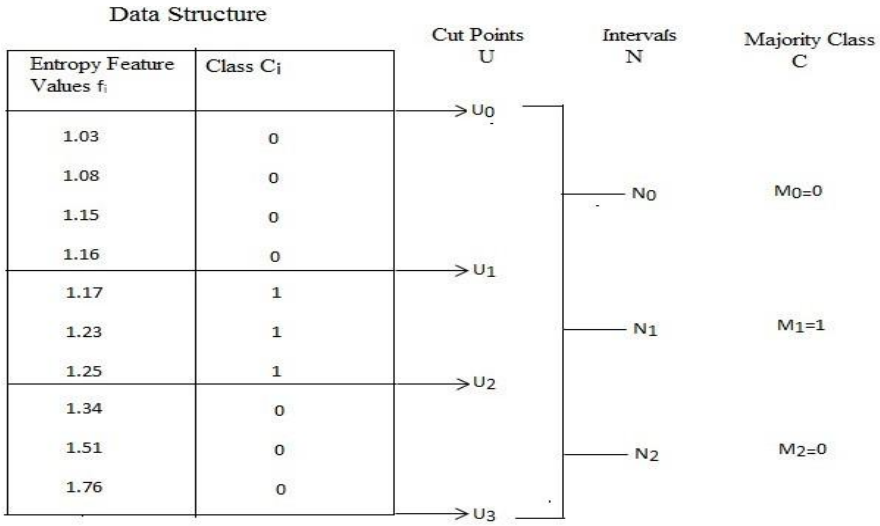

Figure 3.2 Data Structure of IICBMergeFS Algorithm

The definitions related with the IICBMergeFS algorithm are as follows. 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 processes each feature separately. Definition 4: An Instance Ii belongs to an interval Ni of its feature value fi is between two continuous cutpoints Ui and Ui+1, i.e., fis Ni =Ui, Ui+1 The IICBMergeFS algorithm uses the following input thresholds for discretization.

i) minfperInt: The minimum frequency per Interval (minfperInt) threshold limits the minimum number of existences of the majority class allowable in an interval.

ii) maxInCon: The maximum InConsistency (maxInCon) threshold restricts the maximum Inconstancy rate allowed within an interval.

iii) maxAvgOCP: The maximum average Overall Cut Point (maxAvgOCP) threshold restricts the maximum average global cut point rate allowed for every attribute

iv) maxAvgOI: The maximum Average Overall Inconsistency (maxAvgOI) threshold restricts the

maximum average Inconsistency rate allowed for every attribute.

Algorithm 3 Classification based on CNN

Procedure CLASSIFICAtion BASED on CNN

Input: Training data set D; a set of rules R, Test instance T. Output: class name assigned to T.

Begin

For all rules R that matches T **do**

if all best t rules predict the same class name C **then**

assign C to T

Else

accumulate all training instances D_1 ε D enclosed by best n rules and moved into d

For all d s D_1 **do**

compute the distance between d and T

End for end

if

End for

for arrange D_1 by distance ascending order **do**

choose K nearest neigbours by lowermost distance categorize K nearest neighbors according to class name compute average distance for every group

allot the class name C of the group having the lowest average distance to T **end procedure**

4. Expermental result and Discusion

All the picture cuts accessible in database are under pivotal point of view with the framework size of (256 × 256) or (512 ×512) and 16 bits for every pixel. These pictures are gotten from Brain Web Database at the McConnell Brain Imaging Center of the Montreal Neurological Institute, McGill University. As the enthusiasm for the PC helped, the quantitative investigation of medicinal picture information is developing, the requirement for the approval of such systems is likewise expanding. Tragically, there exists no `ground truth' or best quality level for the investigation of procured information. These pages give a response for the endorsement issue, as a Simulated Brain Database (SBD). The SBD contains an arrangement of reasonable MRI information volumes created by a MRI test system. These data can be used by the neuroimaging gathering to survey the execution of various picture examination procedures in a setting where the truth is known. At the present time, the SBD contains emulated mind MRI data in perspective of two anatomical models: normal and multiple sclerosis (MS). For both of these, full 3-

dimensional information volumes have been reenacted utilizing three arrangements (T1-, T2-, and Proton-Density (PD-) weighted) and an assortment of cut thicknesses, clamor levels, and levels of power non-consistency. This information is accessible for review in three orthogonal perspectives (transversal, sagittal, and coronal), and for downloading.

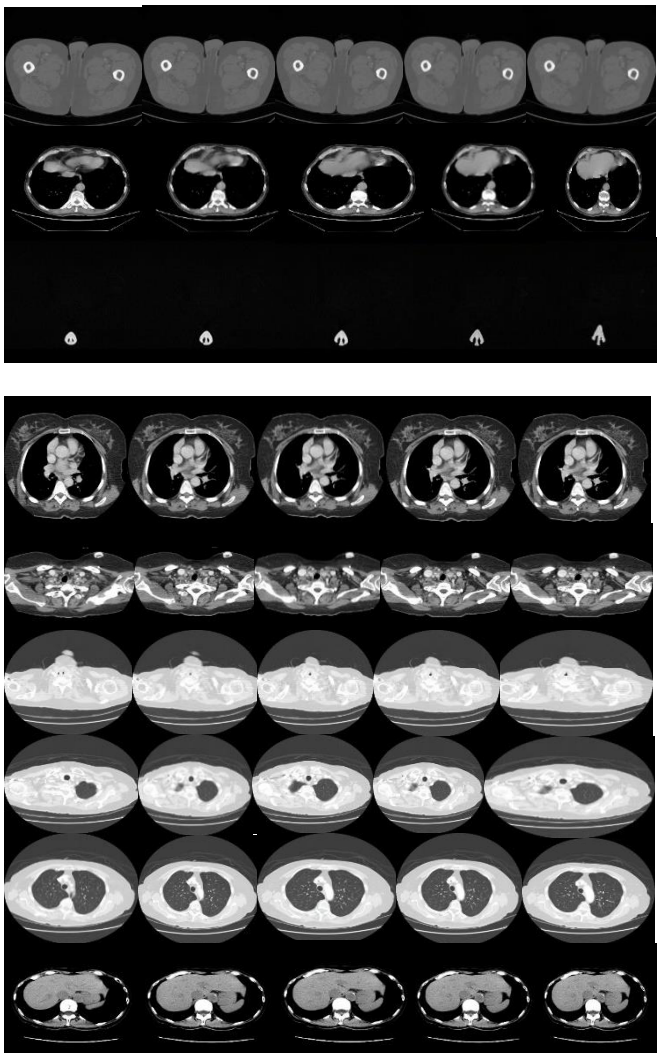

Figure 4.1 Sample 10 classes if CBIR images

In figure 4.1 indicated the 10 classes of CBIR images like Abdomen, Bladder, Brain,, Chest, Head-neck, Liver, Lung and rectum

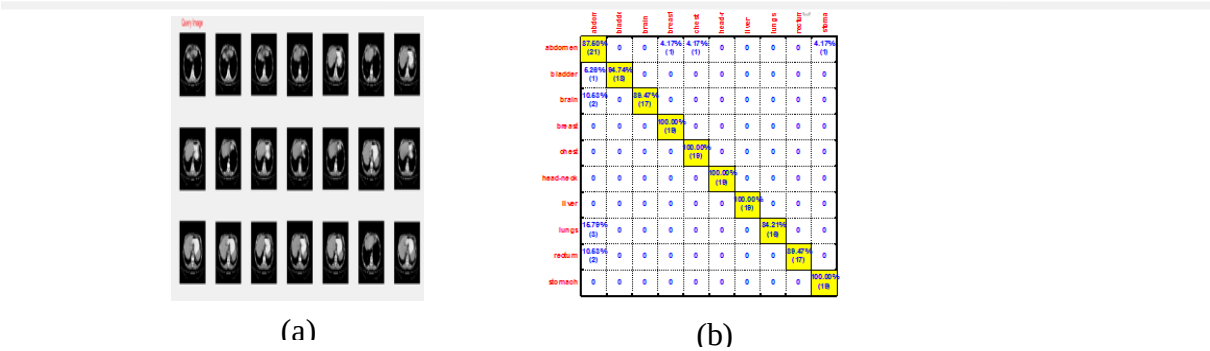

Figure 4.2 Retrieved image with conclusion matrix for CBIR lung image

From figure 4.2 shows that the retrieved image based on the query image and the 10 class CBIR medical image confusion matrix. Here, lung image is used to the query image. Based on the query image features are extracted. 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 RoI of ultrasound kidney images are shown in Table 4.1. As the number of irrelevant and inconsistent features arise in the vector affects 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. The IICBMergeFS algorithm selects the significant features for efficient classification. The selected features and the diagnosis keywords are submitted to the apriori algorithm, which generates lesser amount of rules. The minimum support threshold is set to 10% and minimum confidence threshold is set to 98%. As IICBMergeFS feature selection procedure is utilized, the generation of redundant rules is restricted. In this experiment, the classifier CNN is trained for classifying ultrasound kidney images based on Levenberg-Marquardt proced.

Table 4.1: Extracted Features and Positions

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

During the test phase, the query image is classified by the CNN classifier as normal, CC or a 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. Accuracy is the proportion of the correctly diagnosed cases to the total number of cases. The measure Accuracy is defined in Equation 4.1.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4.1)$$

Sensitivity measures the ability of the method to identify abnormal (positive) cases, it is used in Equation 4.2.

$$Sensitivity = \frac{TP}{TN + FN} \quad (4.2)$$

Specificity measures the ability of the method to identify normal cases, it is used in Equation 4.3.

$$Spicificity = \frac{TN}{TP + FP} \quad (4.3)$$

Where

TP = The number of True Positive cases (abnormal cases correctly classified). TN = The number of true negatives (normal cases correctly classified). FP = The number of false positives (normal cases classified as abnormal by the method). FN = The number of false negatives (abnormal cases classified as normal by the method). Additionally, overall accuracy rates using discretized features are compared with the four well known classifiers like J48-DT, Native-Bayes (NB), SVM and CNN for five feature selection schemes. The result shows that the discretized feature set minimizes the complexity of the subsequent processes and improves the accuracy of the classification process. The comparison of accuracies using discretized features by classifiers for five feature selection schemes with kidney image database. The performance of the proposed CBIR system is determined by Precision and Recall (P&R) rates. The measures precision and recall are calculated in Equations 4.4 and 4.5.

Where

$$\text{Precision} = \frac{\text{TSR}}{\text{TS}} \quad (4.4)$$

$$\text{Recall} = \frac{\text{TSR}}{\text{TR}} \quad (4.5)$$

Where TR = the number of relevant images in the database. TS = The total number of retrieved images.
TRS = The number of relevant retrieved images.

The performance of the proposed approach is evaluated in different aspects, such as by varying feature selection techniques and classifiers in terms of accuracy, sensitivity, specificity, precision, recall and computation time. The analysis is processed separately upon normal, CC and MRD images. The performance of the proposed approach isanalyzed and presented in both graphical and tabular formats.

Table 4.2: Comparative Analysis Based on Time Consumption of Various Feature Selection Techniques

Techniques / Performance Metrics	Time Consumption (s)
CAIMAI	5
EQWAI	6
ReliefF	8
F-Score	10
IICBMergeFS	3.4

From Table 4.2, it is concluded that the time consumption of the proposed approach is much lesser than the existing techniques. This in turn makes the training process of the classifier simpler and the time required for the learning process is reduced considerably. The reason is that the feature set is processed and the relevant features alone are provided place. This practise speeds up the learning process and the association rules can easily be formed. As the importance of feature selection is realized, this chapter proposes a new feature selection technique named as IICBMergeFS. The potential of the IICBMergeFS is tested against the standard feature selection techniques such as CAIMAI, EQWAI, ReliefF and F-score in terms of accuracy, sensitivity, specificity, precision and recall. The experimental results are presented in Table 4.3. All these feature selection techniques are tested in combination with CNN classifier.

Table 4.3: Comparative Analysis Based on Accuracy, Sensitivity and Specificity of Various Feature Selection Techniques

Techniques/Performance Metrics	Accuracy (%)	Sensitivity (%)	Specificity (%)
CAIMAI	89.17	86.7	83.26
EQWAI	88.9	81.05	76.1
ReliefF	87.09	80.3	79.5
F-Score	89.04	87.3	81.3
IICBMergeFS	97.24	90.6	96.3

Additionally, the precision and recall rates of the proposed approach are evaluated and the results are presented in Table 4.4. The precision and recall rates are computed by Equations 4.4 and 4.5. The precision and recall rates of any system must be greater, such that the system can be claimed as efficient.

Table 4.4: Precision and Recall Rates Analysis by Varying Feature Selection Techniques

Techniques / Performance Metrics	Precision (%)	Recall (%)	Time Consumption (ms)
CAIMAI	85.1	52	1893
EQWAI	84.28	46	1922
ReliefF	70.34	34	2316
F-Score	69.3	31	2687
IICBMergeFS	89.12	69	1763

From Table 4.4, it is concluded that the proposed approach shows maximum precision and recall rates, when compared to the existing techniques. In addition to this, the time consumption of the proposed approach is much lesser than the existing techniques. This section compares the performance of the proposed approach by varying the classification techniques. The classifiers being considered for performance analysis are J48-DT, NB, SVM and CNN classifiers. The proposed feature selection technique IICBMergeFS is[21,22] utilized for all the classifiers and the results are presented in Table 4.5.

Table 4.5: Comparative Analysis Based on Accuracy, Sensitivity, Specificity, Precision and Recall of Various Classification Techniques

Techniques / Performance Metrics	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Precision (%)**	**Recall (%)**
J48-DT	86.14	78.6	72.3	72.6	49
NB	86.48	76.4	69.1	79.3	53
SVM	88.24	81.3	78.9	83.2	61
CNN	97.24	90.6	96.3	99.12	79

The time complexity of the classifiers with IICBMergeFS is analyzed and the results are presented in Table 4.6.

Table 4.6: Comparative Analysis Based on Time Consumption of Various Classification Techniques

Techniques/Performance Metrics	**Time Consumption (ms)**
J48-DT	2143
NB	1972
SVM	1738
CNN	1763

Time consumption is the most serious issue of any application, as it conserves more computational power and energy. It is always advisable to minimize the time consumption as much as possible. On analysis, it is observed that SVM consumes lesser than CNN. From the below presented Table 4.7, it is clear that the performance of CNN with IICBMergeFS shows better accuracy rates. The proposed IICBMergeFS shows better accuracy rates on all the classifiers than the other feature selection techniques. However,[23,24] the maximum accuracy rate is registered as 97.24 percent, which is shown by IICBMergeFS in combination with CNN classifier. The second better suitable classifier to the proposed IICBMergeFS technique is [25].SVM and the recorded accuracy rate is 88.24 percent. The NB classifier shows 86.48 percent and the J48-DT classifier shows 86.14 percent as accuracy, with IICBMergeFS technique.

Table 4.7: Overall Performance Analysis by Varying Classifiers and Feature Selection Techniques

Classifiers	**Featur e**	**Accuracy (%)**

	Selection Techniques	
J48-DT	CAIMI	84.24
	EQWAI	85.08
	ReliefF	82.41
	F-Score	83.33
	IICBMergeFS	86.14
NB	CAIMI	84.48
	EQWAI	82.71
	ReliefF	81.01
	F-Score	79.59
	IICBMergeFS	86.48
SVM	CAIMI	88.17
	EQWAI	87.9
	ReliefF	86.09
	F-Score	88.09
	IICBMergeFS	88.24
CNN	CAIMI	90.17
	EQWAI	93.9
	ReliefF	94.09
	F-Score	92.04
	IICBMergeFS	97.24

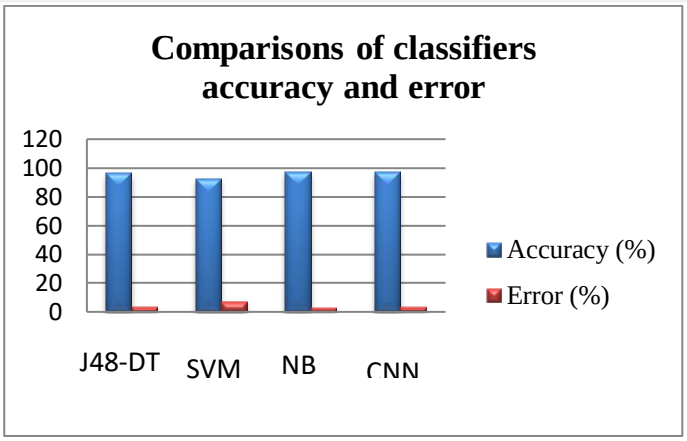

Figure 4.3 classifiers accuracy and error comparisons

From the comparison figure 4.3 the accuracy is high for CNN classifiers. IICBMergeFS based CNN classifier accuracy will be 97.3%. If the error is high, then the accuracy will be low.

Table 4.8: Retrieved result for similarity measures

Method	Similarity measures			
	Euclidean	Manhattan	Spearman	Cosine
EQWAI	0.0817	0.3010	0.0897	0.3944
ReliefF	0.8001	0.4682	0.4342	0.4244
F-Score	0.3696	0.4049	0.2528	0.5672
IICBMergeFS	0.1034	0.3152	0.0917	0.3967

4. Conclusion

Computer aided medical image analysis is strongly influenced by a special application called CBIR. The CBIR application helps in retrieving medical images from the database, which strongly resembles the query image. The resemblance of the image is computed by different means and the effectiveness of relevance determination decides the efficiency of the CBIR system. However, achieving better results in medical CBIR systems is a crucial challenge, as the images share same structure. The final phase of this work proposes a CBIR system for ultrasound kidney images based on Lenient relevance feedback. This CBIR system takes the search pattern of the user into account for presenting better image with greater relevance. The performances of all the proposed works are tested in terms of classification accuracy and relevant image retrieval time. The proposed approaches show better performance and the results are convincing. The network was successfully trained for 10 classes of image with an average classification accuracy of 97.24% is obtained using IICBMergeFS, classifier by comparing with the state of arts in MATLAB software

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