An Improved Classification Algorithm for Content Based Image Retrieval using Fuzzy and Genetic Optimization

[1]C Ramesh Babu Durai, [2] G Sai Prashanth
[1]Professor, Sri Sai Ram Engineering College, Chennai, India
[2] Sri Sai Ram Engineering College, Chennai, India

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Abstract-
Medical information systems are going to play an important role in clinically related decisions in future by rendering similar disease or pathological effects in a medical image and thereby helping physicians view noteworthy images to form improved decisions. For retrieval of images CBIR is used successfully from the databases with respect to an input query, which could be in an compartmentalize the human body image or a behavior of the pathological image. Methods suggested for CBIR include features of description of images with respect to low intensity level like histogram, texture, color, shape, and frequency domain analysis. Classifiers include algorithms such as Support Vector Machine, Neural Network, Naïve Bayes classifier and Decision Tree algorithm. In this work, it is proposed to image features can be extracted by using DCT, to extract similar features using the characteristics. For classification algorithm, Neural Network with feed forward algorithm is proposed. The optimization of learning rate by using Genetic Optimization. The proposed method of classifier is simple and it can be implemented easily in discrete frequency domain. This proposed classifier is best suited for extracted features and the computation process is for CBIR systems.

***Keywords:** , DCT, Neural Network, Fuzzy classifier, CART*

INTRODUCTION

The rapid modern development of Internet and the popularization of medical analysis in the recent research technology, the number of image data increased in huge manner, but the difficult problem is how the image can be retrieved quickly in the image processing and retrieval application. Content – based is nothing but search tool engines that retrieve contents present in image themselves, also providing human metadata input like caption and /or search queries.

A CBIR is a tools of simulation that describes image retrieval technique. In CBIR system, the input features of the image has to be stored in main database is called image database. It can be extracted from image data base and compared with query image related to the features. It includes two levels. The first level is the extraction of the features of the images into a impossible to judge as being different when compared to another similar images. Then the process of extraction to transforms high level content of images into different features content. The processing of low intensity level features can be used in the selection process and classification is known as Feature extraction. The extracted features in the image are likely to categories of the different images. It can be selected and used in the classification tasks. The main objective of an content based retrieval system is to retrieve a group

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of input images from the image data base and classified according to the quires.

CBIR system is the coherence between a high intensity level system like human brain and a low intensity level system like a computer. In the recent trend for CBIR technique implies to add Image Retrieval in the form of text based. The CBIR has developed in an effective way to represent the image by creating data models, intelligent interfaces, query-processing algorithms, and system architecture in frequency domain.

The CBIR has been focused as one of the prime research areas in image processing domain. For CBIR, frequency image representation offers higher levels of ratio between invariance and noise, and the researchers prefer it in content based image retrieval [9].

Suhasini (2008) [10] forward an approach based on graph segmentation to differentiate the low and high range of image sectors to extract the features from various image segments. Classifications depending on Self organizing maps [8], Bayesian network [3] [4] Support vector machine [12] and Regression models [9] have been proposed for feature extraction with various classification accuracy. Ghrare (2009) [5] proposed a coding with lossless algorithm to perform image retrieval search by employing lossless compression having good accuracy.

CBIR PROCESS

In the generic CBIR process is divided into three level of stages. In first stage describes image features can be extracted from the images stored in the database. The extracted features are further indexed and compiled into the database. In the next level, the features of input query image is also extracted. In the last stage compare the extracted features from query with the test image stored in database, and the image is retrieved. The block diagram represent CBIR process as shown in Figure 1.

Image Database: Images are uploaded into database from which the relevant images has to be retrieved.

Feature Extraction: All the stored images are processed to extract features. The extracted features like color, shape and texture are used as low level features.

Feature Indexing: The features extracted are further indexed for easy comparison.

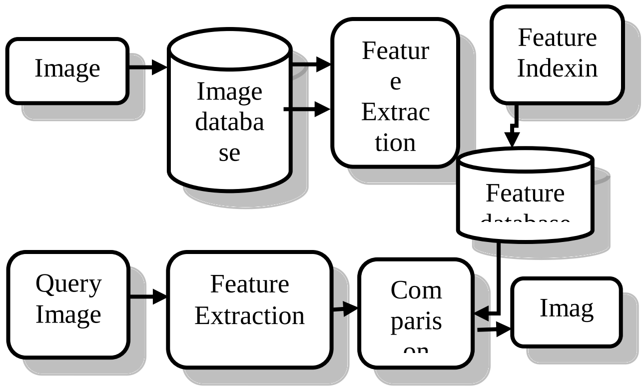

Figure 1 Block diagram of CBIR process

Feature Database: The indexed features are stored in a feature database. Any new image included in the database is processed and its feature is indexed in stored database.

Query image: In retrieved images from the stored database with respect to the image content, a query image for which similar content are required to assign as input.

Comparison: To compare query image and extracted features of the images in the image database. Then the image similarity is compared using distance metrics, decision tree and Neural Networks.

Image Retrieval: If the similar images feature contents equal to the query image features then it is to be retrieved from the database of images.

GENERAL ISSUES IN CBIR

Incorporating adaptable techniques to process images of varied characteristics and classes is the biggest issue for CBIR systems. Factors like image resolution, illumination variation, and occluded

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objects affect the performance of the systems. The low intensity level features doesn't coincide with the high intensity level features example: emotions, events conveyed by an image. This is termed as semantic gap (Smeulders et al 2000), which gives the difference between the low intensity level concepts and high intensity level concepts. Bridging the semantic distance between the low-level features and semantics of the given image is a challenge process in CBIR systems. Memory and disk capacity requirements needed for storing the images processing are problems faced by the CBIR systems. High intensity pixel of feature vectors gives large computation time which affects the usability and efficiency of the systems.

UNSUPERVISED LEARNING

In unsupervised learning system, clustering of feature vectors in feature space is obtained on the basis of similarity measured. Each vector belongs to a particular class in a group of featured vectors. The unsupervised learning extracts the features and characteristics from the image input and matching with the feature vector. In an unsupervised classifier comprising different problems like the unknown number of classes. The similarity measurement between two feature vectors can be measured. The problem for selecting the optimal algorithm that will group the vectors on the basis of similarity distance measure. (Cordon et al 2006).

SUPERVISED LEARNING

In supervised training, a training data set and group of class labels are identified and it is given to the classifier. The classifier uses this previous information (Haykin 1999). In contrast to the unsupervised learning, the number of training set of classes and location of point. The feature in the class label are well known in supervised learning. Many different techniques are used to design a classifier with the help of supervised learning.

Neural Network:

Artificial networks consist of a huge set of connected neurons, operated simultaneously to perform according to the learning tasks. Multi Layer Perceptron is one of the important learning network model. It consists of input layer, one or more connected hidden layers and output layer. The connections between layers established with the help of connecting different nodes of a specific layer to in the next layer of neurons.

Every connection contains a scalar weight which is trained during the training phase. The outputs get it from the output nodes. In the neural network, each connection has a training phase adjustable scalar weight with outputs from nodes at the output. The input layer the feature vectors are applied as a input with the output representing a discriminator between its class and other classes. During training, test data are fed, predicted outputs computed with the latter being compared to the target output. Errors if any are measured and propagated and feedback through the network, and weights adjusted. Soo Beom Park et al 2004 used color features based neural classification.

Support Vector Machines

Support Vector Machines (SVM) are machine learning algorithms, which gives better performance in classification algorithms. Support Vector Machines is used to find beneficial training data sets from the hyperplane between classes (Vapnik 1998) with the former classes. The optimal hyperplane leaves the maximum margin from classes and to locate the hyperplane with respect to maximum margin of a sample object. In other words, if the margin is greater then the possibility about misclassification of any feature vector is lesser. The image classification of the input vectors are mapped into high dimensional feature vector space from the nonlinear transformation method. The support vector Kernel function is used to obtain the favorable hyperplane using kernel function. The

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former SVMs methods are implemented between each classes versus other classes and in the present SVMs are implemented between pairs of classes.

The Support Vector Machines algorithm is described below:

Any linear SVMs, consider K is linear; and the output can be expressed in Equation (1) as

Output, O = (w*x) - b …………………. (1)

and weight $w = \sum_i \alpha_i y_i x_i$ ………………….. (2)

where

b is the value of threshold.

α_i can be used to training SVMs. It can used to minimize the dual quadratic form of Equation (2).

$$\min_\alpha \psi_{(\alpha)} = \min_\alpha \tfrac{1}{2} \sum_i \sum_j y_i y_j K(x_i, x_j) \alpha_i \alpha_j - \sum_i \alpha_i$$

Subject to box constraint $0 \le \alpha_i \le C$

The linear equality constraint is also expressed in Equation (3) as

$\Sigma_i y_i \alpha_i = 0$ …………………………. (3)

Where α_i is the Lagrange multipliers.

TYPES OF CLASSIFIERS

IB1 Classifier

IB1 classifier is an instance-based learning algorithm. The class of the nearest training instances k is classified with a set of attribute in the test instances class. IB1 classifier is used to measure a euclidean distance measure of training instance very closest to a given test instance. It determines the similar class as training instance with a set of attribute value pairs which correspond to category and predictor attributes. The similarity function of the equation is given by,

Similarity (x,y) = -√Σf(x,y) for a n attributes.

IB1 is similar to the closest neighbor algorithm with a difference that it normalizes the attribute's range. The IB1 algorithm (Aha et al 1991) is as follows:

Concept description $CD \leftarrow 0$
for each $x \in$ TS

1. for each $y \in CD$ do $Sim[y] \leftarrow Similarity(x,y)$
2. $y_{max} \leftarrow some\ y \in CD$ with maximal Similar[y]
3. if $class(x) = class(y_{max})$ then classification is correct, otherwise it is incorrect.
4. $CD \leftarrow CD \cup \{x\}$

1. Naive Bayes

Naïve Bayes classifier is one of the probabilistic method. It is depends on applying Bayes' theorem (or Bayes' rule) with strong independent (naive) assumptions (Choochart 2008). The Naïve Bayes' rule for 'n' number of evidences is given by mathematically in Equation.

$$P(H|E_1, \ldots, E_n =) = \frac{P(E_1, \ldots, E_n|H)P(H)}{P(E_1, \ldots, E_n)}$$

where

E and H are the events.

Random Forest

A random forest technique is a collection of unpruned decision trees (Rong Zhao and William 2006). Random forests are applied successfully to input variables and very large training datasets. The random forest has lower generalization error rate when compared to other boosting approaches. The advantage of random forest is more robust to noise. It is not affected by the ratio of sensitivity to noise in a complete dataset. The random forest model builder is very more successful with nonlinear

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classifiers, like Support Vector Machines and Artificial Neural Networks.

Each decision tree of the training dataset in the random forest is constructed using a subset of the training dataset randomly, which are bagging. Some instances will be added more often in the test instance sample and others are not used at all. Generally, two thirds of the instances from the training dataset will be added in the subset and one third of the training dataset will be left out. The available variable for a random subset, the best possibility to partition at each node can be chosen. Each decision tree of random forest is constructed to its maximum size, with no cut off branches from a tree is performed. Thus, the evaluation result decision trees represent the final random forest model, with each and every decision tree voting for the final evaluation result and the majority to be wins.

Classification and Regression Trees(CART)

CARTs are generally used for building statistical approach models from simple selected feature data [2]. The main advantages of CART are that it can distribute with incomplete data, features multiple data, and the common rules produced in the tree are easily readable. The decision trees are made of nodes, which answer a binary form of some feature. Based on the training data the leaves in each and every tree contain the best determination. Usually, the CART tree is built using the Greedy algorithm, which chooses at every stage the locally best discriminatory feature. Decision trees, which are used in computer and data mining operation, are of two main types:

- Classification tree analysis: where the class to which the data belongs is predicted.
- Regression tree analysis: where the outcome is mostly a real number.

Proposed Scheme Of Neural Network Using Fuzzy Logic

Last five decades have seen many Neural Network models mostly based on Hopfield network [7] and Perceptron [6]. With type of feedback as base, Feed Forward Neural Networks are classified into two models namely feed forward and feedback models. The proposed scheme utilizes feed forward networks with supervised learning. The feature extraction diagram of the proposed methodology is shown in Fig. 2.

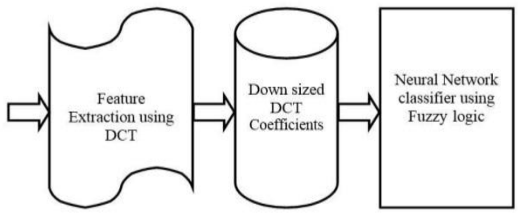

Figure 2: Proposed block diagram

A typical CBIR system using fuzzy logic (as in Fig.3) is divided into 2 stages: feature extraction in on-line image retrieval and off-line image retrieval [2]. In off-line stage, the system extracts the attributes based on its pixel values mechanically of every brain image in the database and stores all the data in a different database within the same system, called as a feature database. In online image retrieval features extraction , the user will identify a query image first .Then the same query image is applied to the retrieval system. The system represents the query image into a different feature vector. The system determines the similarities distances between the feature vectors of the query image and stored images in the feature database. Then it is ranked one by one of the images. The ranking of evaluated images are most similar characteristics to the query examples.

The content based image retrieval system property will creates some issues like [14]:

1. The image contents descriptions typically comprises improper and subjective concepts.

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2. In the visual features, imprecision exist in the image descriptions.
3. It needs to image retrieval can be used naturally fuzzy logic algorithm.

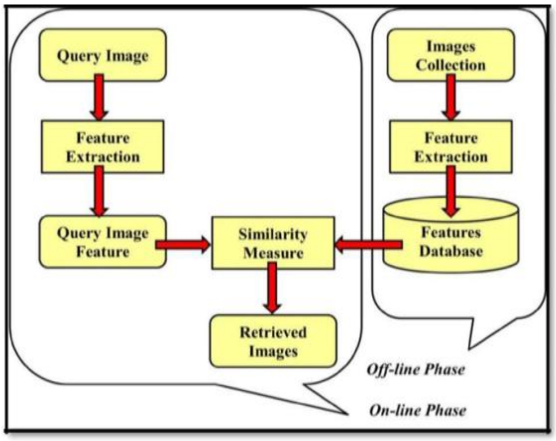

Figure 3: Typical content-based retrieval system

Fuzzy Logic (FL) is a technique used in CBIR system, it posses the nature of human perception, character of image data, and also thinking process. The Fuzzy logic can reduce the semantic gap between low and high intensity level image features. The main advantage is robust to the noise and intensity of the modified images. Fuzzy Logic gives the results according to closeness instead of equality of the images.

A Discrete Cosine Transformation (DCT) shows a sequence of finite amount of sample data points with respect to the sum of series of cosine functions swinging at different range of frequencies in the finite interval. DCTs are used in applications like signal processing , image processing and lossy compression of video and audio images. It can also be used to analyze the spectral analysis in frequency domain. The Cosine function use is of importance in applications: for compression, segmentation. The cosine basis functions are more efficient, while for analysis of differential equations, the function of cosines of Fourier transform represent a specific choice of boundary conditions in the finite size of the image.

The DCT is a Frequency – related transform that is the similar to the standard Discrete Fourier transform (DFT). It uses only real numbers. DCTs are equivalent to Discrete Cosine Fourier Transform but are approximately double the length of the finite duration sequence and operating with even linear symmetry property. But in some limit of variants the input and / or output data are linearly shifted by half of a sample in same variants. Because of its cosine basis functions the Discrete Cosine Transform is shift linear time variant. There are eight standard variants with four of them being common.

The Discrete Cosine Transform (DCT) is a real frequency domain transform that has advantages in energy expansion. The spectral components of DCT DPu,v is expressed in Equation (4).

$$DP_{uv} = \begin{cases} \frac{1}{N^2}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} P_{x,y} & if \quad u=0 \quad and \quad v=0 \\ \frac{2}{N^2}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} P_{xy} \cos\left(\frac{(2x+1)u\pi}{2N}\right)\cos\left(\frac{(2y+1)v\pi}{2N}\right) & \end{cases}$$

………(4)

The DCT operation is obtained by the image given as input in the form of N by M. The image function can be represented by f(i,j) which is the intensity of pixel in row i and column j. Most of the energy signal are at low frequencies that are present in the upper left corner of the DCT. The Discrete Cosine Transform inputs have an array of 8 by 8 integers each containing pixel's gray scale level from 0 to 255.

A faster variant of DCT is the FFT. The same computations can be used on FFT also and both possess the same speed. The Fourier transform in continuous and discrete are not exactly suitable for optimal for compression. The Cosine basis functions can afford high energy compaction and The Discrete Cosine Transform provides a higher compression rate, for similar image quality.

In mathematics have never heard about Discrete Cosine Transform (DCT), but computer and image processing applications users interact with Discrete Cosine Transform indirectly with all the computations. Even those who know less about technology are familiar with JPEG and MPEG image files. MPEG image file compression allows a

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DVD to contain a video signal of full-length for home watching with improved picture quality than those played on VHS. Both compression algorithms depend on Discrete Cosine Transform frequency separation.

The size of the training set 'p' can be represented as $T_P = \{(x_1, y_1), \ldots, (x_p, y_p)\}$ where $x_i \in R^n$ is the input vector of dimension n, $y_i \in R^m$ is the output vector of dimension m and R represents the set of real numbers. The function fw represents the weight w of the Neural Network.

After training and testing a Neural Network on new samples, the output so obtained is true up to a particular level. But this generalization of Neural Network does not aid incomplete correctness or partial of the output. In CBIR system, the partial correctness is obtained as the image correctly identified as MRI brain images, however the system fails to further classify the image as MRI brain image with stroke and without stroke. The network checks whether the sample generates the desired output or not. A fuzzy approach is employed to solve partial correctness. The Neural Network using Fuzzy Logic introduced in this work utilizes the standards as given in Table 1.

The Gaussian transfer function represents a local area of the input space and is used for the local functions approximation. The devised bell ψ function is derived from the integral transform with the following properties

$$\psi(x)_{max} = 1$$

The integral of I of ψ (x) over for particular values of 'a'
and 'b' is given by the Equation (5)

$$I = \int_{-\infty}^{\infty} \psi(x)\, dx \qquad \text{----------} \quad (5)$$

In the proposed technique, the state unit vector is fuzzified for faster convergence along with the input vector. The unit delay membership function has 3 linguistic values and the hidden layer containing input vector has 5 linguistic values is shown by Fig. 4(a) and Fig. 4(b).

The fuzzy logic is applied on the outputs with five linguistic values to further generalize the output values of the input layer.

From Fig. 4(a) and 4(b), it is seen that the Gaussian and the sigmoidal functions are used alternatively. The membership function of the output is given shown in Fig. 4(c).

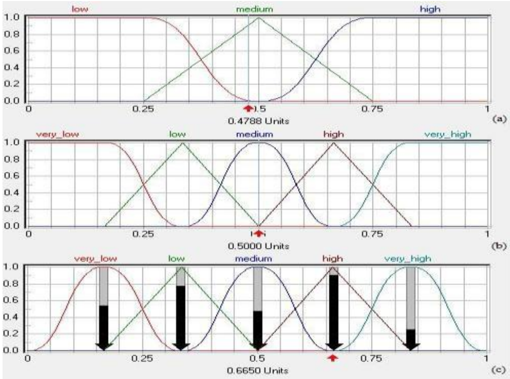

Figure 4(a): Membership function of the unit delay

Figure 4(b): Membership function of the hidden layer input

Figure 4(c): Output membership function

The Degree of Support (DoS) shows the allocated weight of the rule in the system. The situation is described by the 'if' part of the rule and the response of the fuzzy system in this situation is described by the 'then' part. The Degree of Support (DoS) gives the importance of each rule. By applying Mean of Maximum defuzzification, the rules obtained are shown in Table 1.

Table 1 The fuzzy rule table used in this work

If		Then	
X	W	Dos	Out
Very Low	Low	0.34	(V)ery Low
Very Low	Low	0.52	Medium
Low	Low	0.95	Very Low
Low	Low	0.26	Low
Medium	Low	0.86	Very Low
Medium	Low	0.84	Low

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The proposed Neural Network parameters used in architecture are shown in Table 2.

Parameters	Values / Function
Neurons (Input)	150
Neurons (Output)	4
Hidden layers	1
Processing elements	4
Step size	0.1
Momentum	0.5
Output layer learning rule	tan h
Output layer	Momentum
Hidden layer transfer function form	Fuzzy Gaussian
Hidden layer learning rule	Momentum
Maximum Epoch	400

Optimization of Momentum and learning rate using Genetic Algorithm:

Gradient search techniques like back propagation in the neural network are meant for remote search, as they produce the accurate solution in the region. Obtaining a global solution depends on initial values. It is inspired by biological evolution in the Genetic Algorithm (GA). The GA process occurs by duplication, mutation and a various probability of each gene set. (Goldberg 2006). The population GA solution is commonly represented by strings of bit. The fitness function is also computed. Population evolved is driven towards better solutions using operators such as Reproduction, Selection ,Crossover and Mutation.

For successful application of GA is to represent the fitness function and solutions in the required form A fixed length alphabet of bit strings of 0 and 1 are used for encoding the solutions. The effectiveness of GA is to be investigated and to calculate the α and values of momentum in the Neural Network Hidden layer. The optimization of alpha and values of momentum of the GA architecture is shown in Table 3.

Table 3.Parameter used in Genetic algorithm Optimization

Epoch	500 Nos.
Maximum generations	20
Size of Population	10
Optimization lower bound and upper bound α value	0, 1
Momentum optimization lower bound and upper bound value	0, 1
Type of Cross Over	One point
Encoder mechanism	Roulette
Probability of Cross over	0.9
Mutation	Uniform
Probability of Mutation	0.01

VI. Experimental Setup

To substantiate the classification algorithm, this method employs 180 MRI images. Fig. 5 shows the original images.

The frequency transformation of DCT is used to extract the DCT coefficient and these coefficients are mapped on to the class. The information gain is also ranked and computed depending on the mapped class label. The calculation uses information gain, which is given by the expression stated after the following explanation:

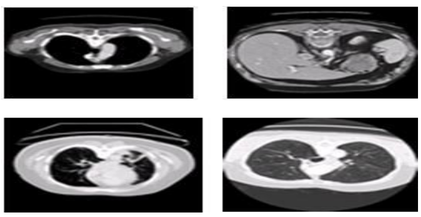

Figure 5: Sample original images

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If, Attr is representing the attributes of all the sets available and Ex is the expected value of all training sets, In the value (x, a), x belongs to Ex defines the expected value of a specific example of x for the attribute. H refers to the entropy of expected value of x and | x | is the number of elements in the set x. The information gain for an attribute is expressed in the Equation (6) as follows:

$$IG(E_X, a) = H(E_X) - \sum_{X \in Value(a)} \frac{|\{X \in E_X \mid value(X,a) = V\}|}{|E_X|} . H\{X \in E_X \mid value(X,a) = V\} \quad \ldots\ldots\ (6)$$

The obtained information gains are ranked and tabulated. Then, the top150 information gain ranks are selected as the attributes for the proposed Neural Network and Genetic Algorithm classification algorithm.

(a) FEATURE SELECTION

The proposed algorithm for feature selection is incremental filtering feature selection (IF^2S) algorithm. It is depends on fuzzy rough set for effective classification. Feature selection algorithm contains 3 phases. In the first phase , to select the suitable subsets by using fuzzy rough set theory . In the second phase, depends on mutual information of the most relevant features are selected. At last, confirm the selected features based on the feature ranking process.

(b) FUZZY ROUGH SETS

S. Ross etal [16], A fuzzy set X contains a set of lower and upper approximation operators, which is based on fuzzy relation (FR). It is defined, for each x ∈ U as in Eqn. 7 and Eqn. 8.

$$\underline{FRX}(x) = \inf_{y \in U} \max \{1 - FR(x,y), X(y)\} \quad \ldots\ldots\ldots(7)$$

$$\overline{FRX(x)} = \sup \{FR(x,y), X(y)\} \quad \ldots\ldots\ldots(8)$$

(c). ALGORITHM: INCREMENTAL FILTERING FEATURE SELECTION (IFFS)

INPUT ALGORITHM

Input: Image

Output: The features in the category of Best, Optimal and Selected.

Step 1: Read the data input

Step 2: Initialization of δ = 0.5,
BFS = {}, OFS

Step 3: For feature subset selection apply fuzzy rough set
Phase I: Subset Selection (Based on Fuzzy Rough Set)
Step 1: Give feature vector from F

Step 2: Compute the FR function for consecutive two features using equation1 and 2.

Step 3: If FR X(Xi,Yi) > δ , then these features Xi is added and Yi is applied to BFS $^{\delta} = {}^{\delta}$ + 0.05

Step 4: Continue the above step 3 until δ reaches to 0.9.

Step 5: If BFS (f i) > δ, then the feature fi OFS is added

Step 6: Continue the above step 5 until BFS reaches 0.
Phase II: Joint Mutual Information based feature selection
Step 1: Get the feature of OFS
Step 2: Calculate the JM Information value using the equation 10 and 11.
Step 3:If(JMI (fi ,fj) > δ), then those two features added into the FS.
Step 4: Repeat the steps 4.2 and 4.3 till OFS is 0.
Step 5: Identify the Dynamic Ranking function for ranking the features.

VI. Experimental Investigation

The experimental investigation process is developed in Lab VIEW 8.6 to convert a set of images into their corresponding coefficient of DCT .

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The sampled data is down sampled by selecting alternate pixels. Fig. 6 shows the screen interface of the Lab VIEW GUI.

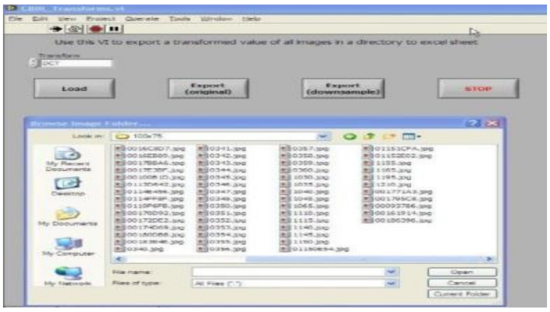

Figure 6: Software developed in LabVIEW

Dynamic Feature Ranking

In the proposed work, based on the time, features has been ranked Then the mutual information value of each feature and the joint mutual information value of a pair of features also ranked. Analyze the uncertainties features' with the help of JM information values between the features. The features mean value are determined for each subset. The mutual information values are varying between 0 and 1 range. Also, the dependency of the features in a subset is characterized based on time. The information gain values between any two features can be calculated. If the value can be increased and normalize the value to the range of [0, 1]. The complete prediction is represented by value 1. If X and Y are independent then the value is represented by 0. The better ranking is described by,

FDS = 2.0 X

$$\frac{[\mathrm{MI}(Si, < t1,t2 >\ + \mathrm{MI}(Sj, < t1,t2 >) - (\mathrm{MI}(Si, < t1,t2 >, (Sj, < t1,t2 >))]}{\mathrm{MI}(Si, < t1,t2 >\ + \mathrm{MI}(Sj, < t1,t2 >)} \quad \ldots\ldots..(9)$$

VII.RESULTS AND DISCUSSION

The proposed approach has been evaluated by experiments on Weka Classifier Database.

Evaluation Metrics

This section deals with the evaluation metric The Classification accuracy is measured and evaluated. In the classification algorithm true positive and negative values are determined in the total number of instances, as given by Eq. 10.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(10)$$

Where TN,TP represent the number of true negatives, true positives FP and FN false positives and false negatives.

The classification accuracy of 96.8 % is predicted from the proposed technology. The proposed model is also compared with the other available models including Naïve Bayes, CART and Multilayer Perceptron Neural Network. The results obtained are shown in Fig. 7.

Figure 7: Comparison between Classification accuracy of our proposed classifier and other classifier

The cross over probability is chosen at 90% of the population for the various convergence. It can be obtained by varying degrees of input statements. In the proposed method the inputs are highly diversified and roulette encoding mechanism was selected.

The plot of MSE (Mean Squared Error) vs. Epoch for various alpha and momentum values is shown in Figure 8.

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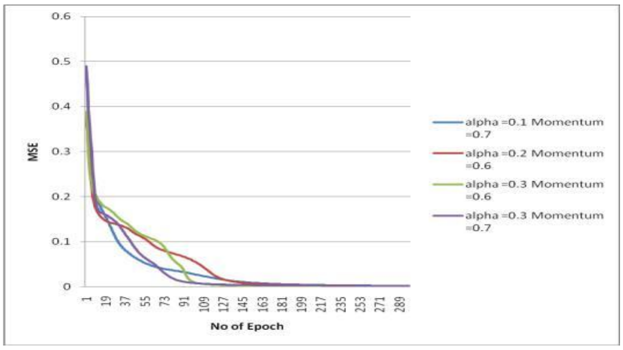

Figure 8. MSE vs. No of Epoch

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