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ANFIM: Adaptive Neuro Fuzzy Inference Model For Content Based Image Retrieval

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Abstract

Content based image retrieval, in the last few years has received a wide attention due to the development of multimedia technology. Nevertheless, it remains a challenging task due to the retrieval of images in an efficient time by means of classification process. This paper focuses on the development and validation of a content-based image retrieval system to classify and retrieve images using adaptive neuro fuzzy inference system. The proposed system consist of the following phases (i) Preprocessing of input images using Contrast-Limited Adaptive Histogram Equalization (CLAHE), (ii) Extraction of features using Gray Level Co-Occurrence Matrix (GLCM), (iii) Classification of images are performed using Adaptive neuro fuzzy inference model (ANFIM).The Experimental results show that the proposed retrieval framework is very effective and requires less computation time when compared with the state-of-art retrieval systems, and results in 94.6% of prediction accuracy.

Keywords: Content based image retrieval, Adaptive Neuro-Fuzzy inference Model (ANFIM) , Gray Level Co-occurence Matrix (GLCM), Contrast-Limited Adaptive Histogram Equalization (CLAHE).

Introduction

With the development of technologies such as digital camera, mobiles, image scanner, the number of information systems containing image retrieval functions is increasing rapidly. Efficient image browsing, searching and retrieval tools are required by users from various domains, including remote sensing, fashion, medicine, architecture, crime prevention, publishing, education etc. For this purpose, many image retrieval systems have been developed which includes text based image retrieval and content based image retrieval techniques. Text-Based image retrieval uses traditional database techniques to manage images, where images are manually annotated by the text descriptors. It is widely used by database management system to retrieve images. There are detriments with this methodologies such as significant level of human work is examined for manual annotation and the annotation incorrectness because of the objectivity of human recognition [1,2]. To overcome these disadvantages, content-based image retrieval (CBIR) is introduced. When a query image is given as input, content based image retrieval (CBIR) methods retrieves similar images from a large database [3]. A CBIR system which uses region features to represent images is known as Region Based Image Retrieval systems (RBIR). On the other hand CBIR systems utilizing global features for describing images are classified as Global CBIR systems. Local and Global features of an image largely represent color, texture, shape and spatial relationships of different objects in an image. Color is the most commonly used feature of an image. The perceived color at any pixel of an image is obtained by mixing three preliminary colors in appropriate proportion. Commonly used color spaces for image retrieval application are RGB, CIE L*a*b*, CIE L*u*v*, HSV and opponent color space.

Texture can be defined as the visual pattern that has properties of homogeneity not resulting from the presence of only a single color or intensity. Commonly used methods are Fourier power spectra, Co-occurrence matrices, Shift-invariant principal component analysis (SPCA), Tamura feature, Wold decomposition, Markov random field, Fractal model, and Multi-resolution filtering techniques such as Gabor and wavelet transform. Shape feature provides the most important semantic information about an image. Shape features are usually described using part or region of an image. Some boundary based representative shape description techniques are chain codes, polygonal approximations, Fourier descriptor and finite element model. Research in content-based image retrieval today is a lively discipline, expanding in breadth. Discovering new and innovative processes of locating a desired image from an expanding collection of images has been a major area of interest for many professional fields. In the past decades, many commercial products and experimental prototype systems have been developed, such as QBIC [4], Photobook [5], Virage [6], VisualSEEK [7], Netra [8], SIMPLIcity [9-11].

Related Works

A.D. Doulamis et al. (2000) presented a fuzzy representation of visual content, which is useful for the new emerging multimedia applications, such as content-based image indexing and retrieval, video browsing and summarization [12]. Jun Yu, M.D.Srinath (2001) proposed a novel method to detect scene cuts adaptively using color histogram and entropic threshold.[13]. H.-W. Yoo et al. (2002) represented a method using vector quantization (VQ) on color features (hue, saturation, and value) and texture features (Active Shape Models, contrast, correlation, variance, and entropy) from the gray-level co-occurrence matrices [14]. Steji_cc et al. (2003) proposed a method for optimizing the LSP-based computation, based on genetic algorithm .It incorporates relevance feedback mechanism to automatically specify LSP-based queries [15]. Wei Jiang (2003) proposed a new method to quickly and accurately learn the user's query concept in classifier based CBIR problem [28]. This method is to augment the training set by sample re-weighting method and boosting. It is incorporated into SVM as a new Boost SVM algorithm. To be an adaptive to the CBIR problem, AdaBoost algorithm is modified, by introducing Adaptive neuro fuzzy inference system.

S. Wu et al. (2005) a growing hierarchical self-organizing quadtree map (GHSOQM) is proposed and used for a content-based image retrieval (CBIR) system [16]. The incorporation of GHSOQM in a CBIR system organizes images in a hierarchical structure. The retrieval time by GHSOQM is less than that by using direct image comparison using a flat structure. S. Yan et al.(2009) detailed the development of an in-line method for modifying image quality to improve classification[17]. The final model obtained, termed Adaptive IQMod Classification, which improves the adaptive image quality with adaptive Bayesian Classification.

Zhengmao Ye (2013) proposed a Pattern Classification via Fuzzy C-Means Clustering. It involves the integration of the intensity, color, texture and position of the feature [26]. Poonarin Wongchomphu (2014) presented a new method of the enhance Neuro-fuzzy system for classifications using dynamic clustering. This method shows the impressive high accuracy of classification than the other Neuro-fuzzy methods for linguistic feature selection and rule-based classification [27].

Motivation

From the literature review it is inferred that SVM, the fuzzy c-Means, and the Bayesian classifier retrieves the images based on the training datasets, However when the large datasets are used, these system requires large computational cost, and more number of iterations and execution time. This observation has motivated us to propose a new classification technique called Adaptive neuro fuzzy inference model which reduces number of iterations for training a dataset and obtain the better retrieval accuracy in a less execution time.

The rest of this paper is organized as follows. Section IV Explains about the proposed method Section V begins with preprocessing technique. Section VI details the techniques used for feature extraction. Section VII describes Adaptive neuro fuzzy inference model. Section VIII includes the discussion of Experimental methods and conclusion is given in section IX.

Proposed Method

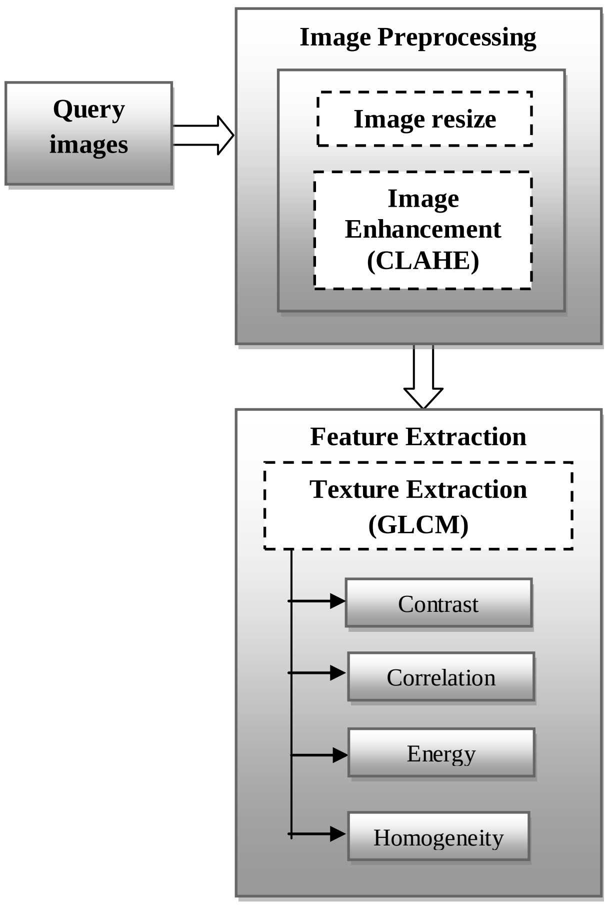
Adaptive neuro fuzzy inference model is known especially for their simplicity in machine learning literature. Figure 1 describes the overall process of the proposed system. This system uses Contrast-Limited Adaptive Histogram Equalization (CLAHE) for enhancement of an image and Gray Level Co-Occurrence Matrix (GLCM) for Feature Extraction and finally Adaptive neuro fuzzy inference model (ANFIM) is used to classify the images. This system would provide better prediction accuracy while compared to the existing methods. The goal of the system is to reduce the time consumption and increases accurate image retrieval. The first step is to pre-process the images from corel dataset using the Contrast-Limited Adaptive Histogram Equalization (CLAHE) method. The second step is towards extracting the features from that images using Gray Level Co-Occurrence Matrix (GLCM).Finally the images are classified using Adaptive neuro fuzzy inference model.

Image Preprocessing

Preprocessing is an improvement of the image that suppresses unwanted distortions. In order to standardize the time complexity, image resizing is utilized and definition of images can be improved by Image Enhancement.

Contrast-Limited Adaptive Histogram Equalization

Contrast limited adaptive histogram equalization (CLAHE) is an adaptive contrast histogram equalization method , where the contrast of an image is enhanced by applying CLAHE on small data regions called tiles rather than the entire image. The resulting neigh-boring tiles are then stitched back seamlessly using bilinear interpolation. The contrast in the homogeneous region can be limited so that noise amplification can be avoided.



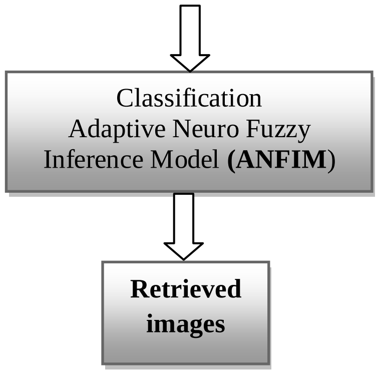


Figure 1: Overall Process of The System

Steps

1. Grayscale image is taken as the input.
2. A grid size is calculated based on the maximum dimension of an image.
3. A grid points are identified from top-left corner and histogram of the region is calculated by Cumulative Distribution Function (CDF) is given in equation (1).

$$h(v) = Round\left(\frac{cdf\,(v) - cdf_{\min}}{(M \times N) - cdf_{\min}} \times (L-1)\right) \quad (1)$$

   Where,
   $cdf\,(v)$ - cumulative distribution function of corresponding pixel
   $cdf_{\min}$ - Minimum non-zero value of the cumulative distribution function
   $M \times N$ - Number of pixels of an image
   L - Number of gray levels used.

4. Repeat step 3 for each pixel in an input image.
5. Finally the intensity of the pixels from the range [min: max] is mapped to the output image.

Feature Extraction

Feature is defined as a function of one or more measurements of images, which specifies quantifiable property of an image. It quantifies some significant characteristics of the image. Texture is the visual tactile quality of a surface. Gray Level Co-Occurrence Matrix (GLCM) has proved to be an accepted statistical method of extracting textural feature from images [18-23]. According to co-occurrence matrix, Haralick defines fourteen textural features measured from the probability matrix to extract the characteristics of texture statistics of remote sensing images. In proposed system, important features such as Contrast, Correlation, Homogenity, Skewness, Kurtosis, Variance and Energy are extracted for implementation. The

GLCMs are stored in a i * j * n matrix, where n is the number of GLCMs calculated usually due to the different orientation and displacements. Usually the values i and j are equal to 'NumLevels' parameter of the GLCM computing function graycomatrix ().

Contrast: It is the difference between the highest and the lowest values of a contiguous set of pixels. It measures the amount of local variations present in the image. A low contrast image presents GLCM concentration term around the principal diagonal and features low spatial frequencies.

$$\sum i,j|i-j|^2 p(i,j) \tag{2}$$

where,

P(i,j) : (i, j)th entry in GLCM

Correlation: It refers to any of a broad class of statistical relationships involving dependence. Measures the joint probability occurrence of the specified pixel pairs.

$$\sum i,j \frac{(i-\mu i(j-\mu j)p(i,j))}{\sigma i \sigma j} \tag{3}$$

where μi, μj, σi and σj are the means and standard deviations of i and j.

Energy: It is the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment.

$$\sum i,j\ p(i,j)^2 \tag{4}$$

Homogeneity: It is a substance where all the constituents are of the same nature; consisting of similar parts, or of elements of the like nature. Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$\sum i,j \frac{p(i,j)}{1+|i-j|} \tag{5}$$

Skewness: It is a measure of the asymmetry of the data around the sample mean. If skewness is negative, the data are spread out more to the left of the mean than to the right. If skewness is positive, the data are spread out more to the right. The skewness of the normal distribution (or any perfectly symmetric distribution) is zero. The skewness of a distribution is defined as

$$s=\frac{E(x-\mu)^3}{\sigma^3} \tag{6}$$

where μ is the mean of x, σ is the standard deviation of x, and E(t) represents the expected value of the quantity t.

Kurtosis: It is a measure of how outlier-prone a distribution.

The kurtosis of a distribution is defined as

$$s=\frac{E(x-\mu)^4}{\sigma^4} \tag{7}$$

where μ is the mean of x, σ is the standard deviation of x, and E(t) represents the expected value of the quantity t.

Variance: It computes the variance of input or sequence of inputs. For purely real or purely imaginary inputs, the variance of an M-by-N matrix is the square of the standard deviation.

Classification

Classification is the process of organizing data into categories for its most effective and efficient use. Adaptive neuro fuzzy inference model (ANFIM) is a neuro fuzzy technique where the fusion is made between the neural network and the fuzzy inference system. Using this technique, at first an initial fuzzy model along with its input variables are derived. Next the neural network is used to tune the rules of the initial fuzzy model to produce the final ANFIM of the system. As other fuzzy systems, the ANFIM structure is organized of two introductory and concluding parts which are linked together by a set of rules.

Rule 1 If (x is $A1$) and (y is $B1$) then $Z1=p1x+q1y+r1$

Rule 2 If (x is $A2$) and (y is $B2$) then $Z2=p2x+q2y+r2$

There are five distinct layers used in ANFIM

Layer 1 is the input layer. Neurons in this layer simply pass external crisp signals to *Layer* 2.

Layer 2 is the fuzzification layer. Neurons in this layer perform fuzzification. In Jang's model, fuzzification neurons have a bell activation function.

***Layer* 3** is the **rule layer**. Each neuron in this layer corresponds to a single Sugeno-type fuzzy rule. A rule neuron receives inputs from the respective fuzzification neurons and calculates the firing strength of the rule it represents. In an ANFIM, the conjunction of the rule antecedents is evaluated by the operator **product**. Thus, the output of neuron i in *Layer* 3 is obtained as,

$$y_i^{(3)} = \prod_{j=1}^{k} x_{ji}^{(3)} \qquad y_{\Pi 1}^{(3)} = \mu_{A1} \times \mu_{B1} = \mu_1, \tag{8}$$

***Layer* 4** is the **normalisation layer**. Each neuron in this layer receives inputs from all neurons in the rule layer, and calculates the **normalised firing strength** of a given rule. The normalised firing strength is the ratio of the firing strength of a given rule to the sum of firing strengths of all rules. It represents the contribution of a given rule to the final result. Thus, the output of neuron i in *Layer* 4 is determined as,

$$y_i^{(4)} = \frac{x_{ii}^{(4)}}{\sum_{j=1}^{n} x_{ji}^{(4)}} = \frac{\mu_i}{\sum_{j=1}^{n} \mu_j} = \overline{\mu_i}$$

$$y_{N1}^{(4)} = \frac{\mu 1}{\mu 1+\mu 2+\mu 3+\mu 4} = \overline{\mu 1} \tag{9}$$

***Layer* 5** is the **defuzzification layer**. Each neuron in this layer is connected to the respective normalisation neuron, and also receives initial inputs, x_1 and x_2. A defuzzification neuron calculates the weighted consequent value of a given rule as,

$$y_i^{(5)} = x_i^{(5)}[k_{i0} + k_{i1x1} + k_{i2x2}] = \overline{\mu_i}[k_{i0} + k_{i1x1} + k_{i2x2}] \tag{10}$$

where x_i is the input and y_i is the output of defuzzification neuron i in *Layer* 5, and k_{i0}, k_{i1} and k_{i2} is a set of consequent parameters of rule i.

***Layer* 6** is represented by a single **summation neuron**. This neuron calculates the sum of outputs of all defuzzification neurons and produces the overall ANFIM output, y,

$$y = \sum_{i=1}^{n} x_i^{(6)} = \sum_{i=1}^{n} \bar{w}_i \left(k_{i0} + k_{i1}\, x1 + k_{i2}\, x2\right) \quad (11)$$

is a type of neural network based on Takagi–Sugeno fuzzy inference system. It integrates both fuzzy logic and neural networks principles. Hence, it has potential to capture the benefits of both the neural network and fuzzy logic in a single framework.

This system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions [24]. Hence, ANFIM is considered to be a universal estimator [25].

Steps

1. The features extracted by GLCM are given as input to the ANFIM.
2. The dataset images are trained using Grid partitioning and sub clustering
3. Sub. Clustering generates an initial model for ANFIM training by first applying subtractive clustering on the data.

$$Di = \sum_{j=1}^{n} e\left[\frac{\|xi-xj\|^2}{ra/2^2}\right] \quad (12)$$

   Where
   n - data points{x_1…………..x_n}in M dimensional space
   D - Density measures for all data points
   r_a - Defines circle where neighboring data points lies and points outside of circle

4. Grid partition- Generates a single-output Sugeno-type FIS on the data.
5. Finally, the retrieved images and their statistical retrieval of image are displayed.

Experimental Method

The experiments are conducted using Matlab (R2012a) on an Intel Pentium 5.0 GHz processor with 2GB memory. The COREL database is used for experimentation. Total size of the database is 10000. It contains different images taken from autumn, aviation, bonsai, castle, cloud, dog, elephant, iceberg, primates, ship, stalactite, steam-engine, tiger, train, and waterfall. The corel dataset images are in different sizes. So, the images are resized to uniform size of 125 x 125. The corel database is shown in Figure 2.

Once a query image is submitted to the system the query image is enhanced using Contrast-Limited Adaptive Histogram Equalization (CLAHE). After that the Features are extracted from the enhanced images using Gray-Level Co-occurrence Matrices (GLCMs). Finally classification is performed by Adaptive neuro fuzzy inference model (ANFIM) to classify the images.

Figure 2: Corel Database

The input to the system is chosen from the corel database shown in Figure 3.

Figure 3: Input Image

Figure 4 and 5 shows the resized image and Contrast-Limited Adaptive Histogram Equalization of an input image respectively. The pre-processing of an image is performed using resize function and Contrast-Limited Adaptive Histogram Equalization of an image is computed using cumulative distributed function (CDF) of an image pixel values.

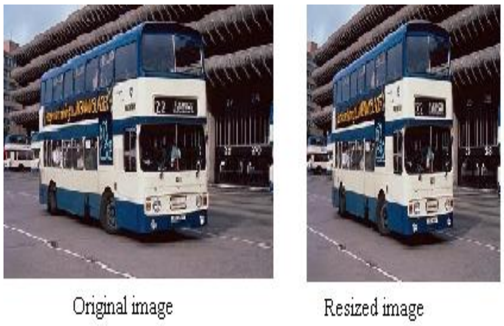


Figure 4: Resized image

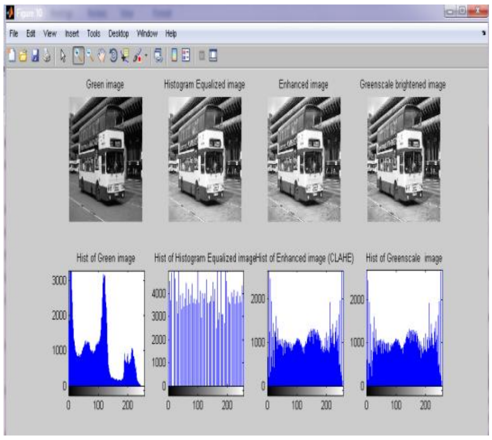
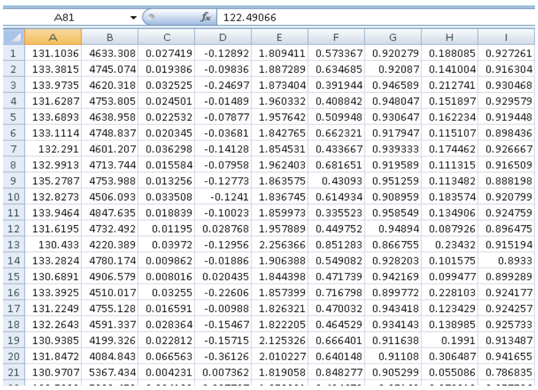


Figure 5: Enhanced images using CLAHE

Figure 6 shows the features of Contrast-Limited Adaptive Histogram Equalization for an input image. Feature extraction is analyzed using Gray Level Co-Occurrence Matrix (GLCM), it is a statistical analysis thus dimensionality is reduced. The enhanced image shown in Figure 5 is the input for the feature extractions process it extracts various features such as Mean, Variance, Energy, Skewness, Contract, Correlation, Homogenity, Kurtosis, and Energy for texture using equation(2-7).



A81 122.49066

	A	B	C	D	E	F	G	H	I
1	131.1036	4633.308	0.027419	-0.12892	1.809411	0.573367	0.920279	0.188085	0.927261
2	133.3815	4745.074	0.019386	-0.09836	1.887289	0.634685	0.92087	0.141004	0.916304
3	133.9735	4620.318	0.032525	-0.24697	1.873404	0.391944	0.946589	0.212741	0.930468
4	131.6287	4753.805	0.024501	-0.01489	1.960332	0.408842	0.948047	0.151897	0.929579
5	133.6893	4638.958	0.022532	-0.07877	1.957642	0.509948	0.930647	0.162234	0.919448
6	133.1114	4748.837	0.020345	-0.03681	1.842765	0.662321	0.917947	0.115107	0.898436
7	132.291	4601.207	0.036298	-0.14128	1.854531	0.433667	0.939333	0.174462	0.926667
8	132.9913	4713.744	0.015584	-0.07958	1.962403	0.681651	0.919589	0.111315	0.916509
9	135.2787	4753.988	0.013256	-0.12773	1.863575	0.43093	0.951259	0.113482	0.888198
10	132.8273	4506.093	0.033508	-0.1241	1.836745	0.614934	0.908959	0.183574	0.920799
11	133.9464	4847.635	0.018839	-0.10023	1.859973	0.335523	0.958549	0.134906	0.924759
12	131.6195	4732.492	0.01195	0.028768	1.957889	0.449752	0.94894	0.087926	0.896475
13	130.433	4220.389	0.03972	-0.12956	2.256366	0.851283	0.866755	0.23432	0.915194
14	133.2824	4780.174	0.009862	-0.01886	1.906388	0.549082	0.928203	0.101575	0.8933
15	130.6891	4906.579	0.008016	0.020435	1.844398	0.471739	0.942169	0.099477	0.899289
16	133.3925	4510.017	0.03255	-0.22606	1.857399	0.716798	0.899772	0.228103	0.924177
17	131.2249	4755.128	0.016591	-0.00988	1.826321	0.470032	0.943418	0.123429	0.924257
18	132.2643	4591.337	0.028364	-0.15467	1.822205	0.464529	0.934143	0.138985	0.925733
19	130.9385	4199.326	0.022812	-0.15715	2.125326	0.666401	0.911638	0.1991	0.913487
20	131.8472	4084.843	0.066563	-0.36126	2.010227	0.640148	0.91108	0.306487	0.941655
21	130.9707	5367.434	0.004231	0.007362	1.819058	0.848277	0.905299	0.055086	0.786835

Figure 6: Features Database

Classification is the process of finding similarities between images according to the features found in the datasets. Figure 7 and Figure 8 depict the statistical retrieval of image and retrieved images.

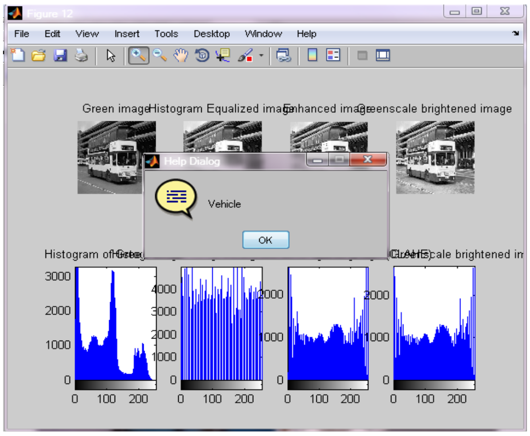


Figure 7: Statistical representation of an input image

Figure 8: Retrieved Images For Input Image

Performance Metrics Based on Precision and Recall

The objective evaluation of the proposed method is carried out based on precision and recall. Precision measures the accuracy of the retrieval. It is the ratio of retrieved images that are relevant to the query image. Precision is calculated using equation (13),

$$P = \frac{Number\ of\ relavant\ images\ retrieved}{Total\ number\ of\ images\ retrieved} \tag{13}$$

Recall measures the robustness of the retrieval. It is defined as the ratio of relevant images in the database that are retrieved in response to a query image. Recall is calculated using equation (14),

$$P = \frac{Number\ of\ relavant\ \ images\ retrieved}{Total\ number\ of\ relavant\ images\ in\ DB} \tag{14}$$

Table 1: Image categories

Category ID	Image Category
1	Dinosaur
2	Flower
3	Elephant
4	Horse
5	Vehicle

Table 2: Precision and Recall for Datasets

ID	No of relavant images retrieved	Precision	Recall
1	19	95	87
2	16	80	65
3	18	90	67
4	18	90	81
5	19	95	85

Table 2 depicts the calculated values of precision and recall for the images categorized above

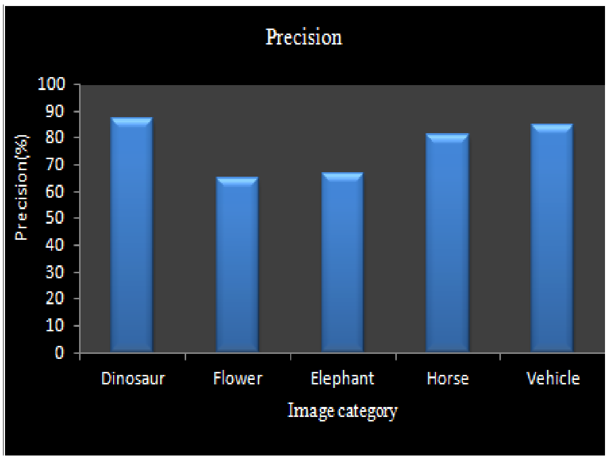


Figure 9: Precision values for image categories

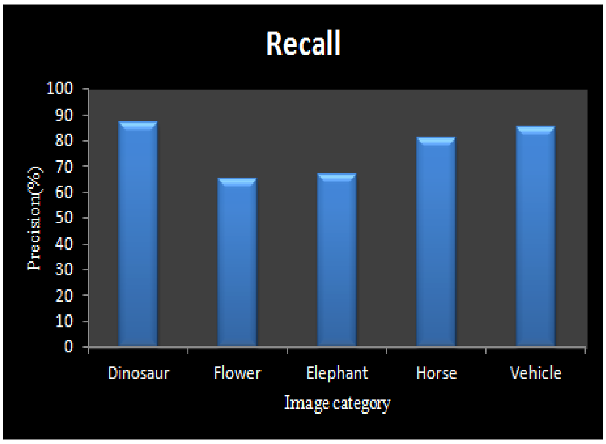


Figure 10: Recall Values For Image Categories

Table 3 depicts the calculated values of precision by different classifiers such as Decision tree, Naïve Bayes, K-NN and ANFIM. From the result, the precision measure of the ANFIM classifier method is 91.5%, 78%, 89.5%, 70.5%,80.2% respectively. Thus ANFIM method is to be considered as the suitable method for the classification. Figure 11 shows comparison of classification methods based on precision.

Table 3: Comparison of average precision of ANFIM with existing methods

ID	Decision tree	Naïve Bayes	K-NN	ANFIM
1	95.9	87.6	98.5	91.5
2	74.6	55.9	76.2	78
3	93.1	84.3	91.5	89.5
4	72.1	74	78.3	70.5
5	41.8	57.9	67.4	80.2

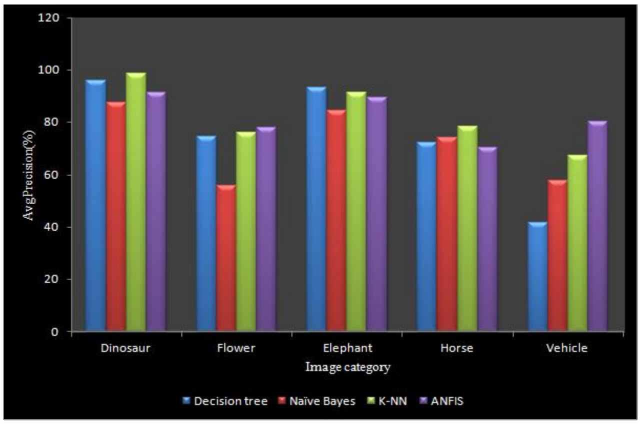


Figure 11: Comparison of Classification Methods Based on Precision

Table 4 depicts the calculated values of recall by different classifiers such as Decision tree, Naïve Bayes, KNN andnd ANFIM. From the result, the precision measure of the ANFIM classifier method is 84.7%, 43.7%, 55.6%, 54.7%, 81.9% respectively. Thus ANFIM method is to be considered as the suitable method for the classification. Figure 12 shows comparison of classification methods based on recall.

Table 4: Comparison of average recall ANFIM with existing methods

ID	Decision tree	Naïve Bayes	K-NN	ANFIM
1	75.9	38.9	47.2	84.7
2	27.3	41.7	36.7	43.7
3	67.0	64.7	74.7	55.6
4	46.3	39.9	61.7	54.7
5	34.9	67.9	78.4	81.9

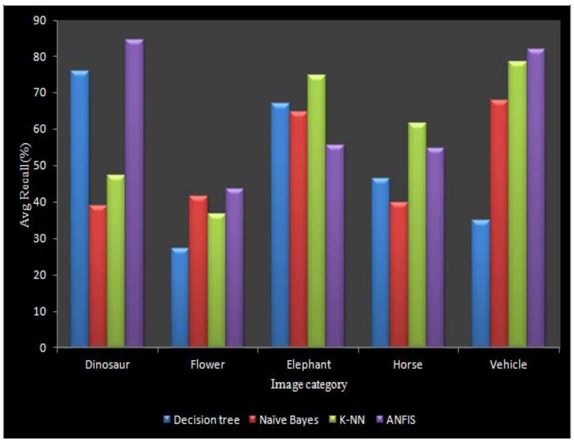


Figure 12: Comparison of classification methods based on recall

Execution Time Comparison of Classification Methods

Table 5 represents the execution time comparison of classifiers, such as Decision tree, Naive Bayes, K-nearest neighbourhood (KNN), Adaptive neuro fuzzy inference model (ANFIM).

Table 5: The Execution Time Comparison of Classifiers

S.No	Classification methods	Execution Time(Sec)
1	Decision tree	1.34
2	Naive Bayes	1.12
3	K-nearest neighbourhood	1.09
4	ANFIM	0.7

The graph depicts that the ANFIM provides less time execution than other classification methods.

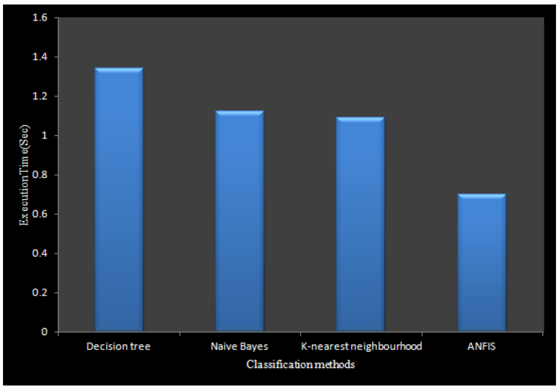


Figure 13: Comparison of Execution Time

Conclusions

Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR).It is the application of computer vision techniques to solve image retrieval problem, that is, the problem of searching for images in large databases. The system based on Adaptive neuro fuzzy inference model is proposed which provides higher prediction and accuracy. It uses Contrast-Limited Adaptive Histogram Equalization (CLAHE) for efficient image enhancement. GLCM is used for the feature extraction. GLCM is Robust against rotation and scale. From the extracted Features Classification is performed using ANFIM classifier. By using this system, the time consumption for executing this system gradually reduced. Thus the proposed system provides better retrieval rate and high accuracy than existing methods. Further, the optimization techniques such as firefly algorithm, particle swarm optimization (PSO) can be implemented for best retrieval rate.

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