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Feature Extraction Methods by Various Concepts using SOM

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Abstract—Image retrieval systems gained traction with the increased use of visual and media data. It is critical to understand and manage big data, lot of analysis done in image retrieval applications. Given the considerable difficulty involved in handling big data using a traditional approach, there is a demand for its efficient management, particularly regarding accuracy and robustness. To solve these issues, we employ content-based image retrieval (CBIR) methods within both supervised , unsupervised pictures. Self-Organizing Maps (SOM), a competitive unsupervised learning aggregation technique, are applied in our innovative multilevel fusion methodology to extract features that are categorised. The proposed methodology beat state-of-the-art algorithms with 90.3% precision, approximate retrieval precision (ARP) of 0.91, and approximate retrieval recall (ARR) of 0.82 when tested on several benchmark datasets.

Keywords-Image retrieval; Feature extraction; SOM; DWT; Query analysis.

I. INTRODUCTION

Content-Based Image Retrieval (CBIR) methods recognize and index pictures in large databases by considering colour, texture, shape, or spatial content, as opposed to using tags or metadata keyword descriptions that may be associated with images in the databases.

Image clustering is typically performed using a Self-Organizing Map (SOM), an acknowledged unsupervised learning algorithm with undisputed advantages. Jayanthi et al. (2015) compared the Tamura texture features, the RGB colour histogram, Gabor features, and the Joint Photographic Experts Group (JPEG) coefficients histogram to the features of CBIR systems. Hongkai et al. (2015) proposed using the Hough transform and dynamic adaptative K-means grouping to locate straight planes and closed planes for optimization goals, respectively. Fu et al. (2006) used z-score normalization for CBIR to combine the Gabor filter with Zernike moments and normalize the results.

Gupta et al. (2015) discussed images in terms of colour, texture, shape, and local characteristics in the spatial domain to index the image in question. Agarwal et al. (2014) presented a solution to the problem of image retrieval utilizing just colour features, which frequently yields disappointing results because the majority of photos with identical colours does not share identical content. Their novel colour edge detection and discrete wavelet transform (DWT)- based CBIR algorithm varies from traditional histogram- based approaches. Lai et al. (2012) suggested a novel approach for producing image hash values centered on the Hough transform. A secret key with security properties is introduced to the hash value calculation procedure.

Liu et al. developed an unconventional image feature representation approach called as colour difference histograms (CDH) for efficient retrieval of image. Zhang et al. (2012) computed the HSV colour space colour histogram and evaluated hue and saturation values. Colour histograms applied to the CBIR method do not reflect the spatial arrangement of colour regions and fail to correspond to similar image regions robustly.

A suggested picture retrieval system by Gupta and Dixit (2016) incorporates texture, colour, and shape features.

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Implemented is a revolutionary CBIR technique that combines the Hough transform, the dominant colour descriptor (DCD), and the DWT characteristic using an auxiliary support vector machine(SVM) classifier. GeneralisedBiassed Discriminant Analysis (GBDA), a new method for CBIR, was introduced by Zhang, Wang, and Lin (2012).

The algorithm eliminates problems by employing the differential scatter discriminant criteria (DSDC), which deals with the Gaussian distribution assumption using reconstructing the between-class scatter and employing a closest neighbour technique. Employing the VHSICHDL (Very High-Speed Integrated Circuit Hardware Description Language), the structure of the multi-leveled decomposition discrete wavelet transform (DWT) is described and synthesised. This architecture was discussed by Khamees Khalaf Hasan et al. in their 2013 paper. Das et al. proposed a method for partition selection with sparse autoencoders that is primarily used in content-based image classification.

Our suggested approach effectively extracts and processes multimedia data using the self-organized map (SOM). A system for retrieving relevant photos from the vast amount of image data in the database is developed that uses a variety of attributes and the SOM technique.

The format of this essay is as follows; the suggested methodology is presented by Section 2 , while Section 3 describes the feature extraction methods. Section 4 discusses the SOM approach. The experimental setup and dataset are discussed in Section 5. Performance evaluation is covered in Section 6, whereas the article is summarized in Section 7.

II. PROPOSED METHODOLOGY

Our proposed work presents a range of image features employed to develop an efficient CBIR system. These include colour features, the Speeded-up Robust Feature (SURF), entropy categorization and FD estimation (EFD), the multiwavelet transform (MWT) and a neural network technique that is the self-organizing map.

Figure 1. Sample images of the Wang and corel1k databases

The query image is fed into the CBIR system. To better identify the relevant photographs, the image is preprocessed. Features are then extracted for use in computational approaches to find images that are comparable. With this technique, features like colour, SURF, EFD, along with the multiwavelet transform are retrieved. An evolving non-supervised clustering method called the SOM divides unlabeled information into various clusters, which are frequently displayed in a standard 2D array. The important steps of the suggested work are outlined in the upcoming conclusion. Figure 2 shows the proposed methodology as a block diagram.

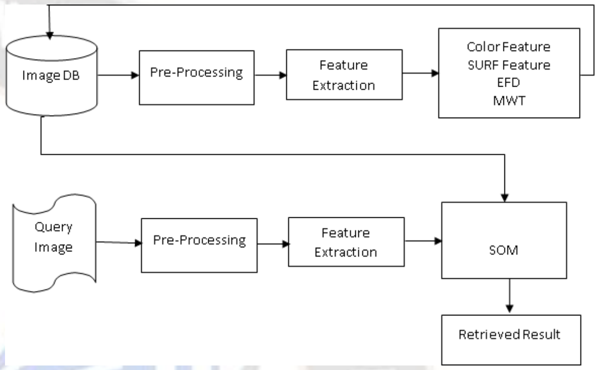

Figure 2. Architecture diagram for the proposed methodology

A. *Preprocessing*

Generally, acquired images cannot be directly used for computational purposes, owing to noise and distortion, and thus require modification. It is essential that the images be transformed into symbolic representations prior to the application of retrieval techniques. Each image may have a different resolution, based on the image acquisition technique used. Before a comparison can be made, therefore, the images are to be normalized using histogram equalization. Furthermore, fine distortions in the images are removed with a filter that least affects their sharpness. Following the query image's preprocessing, its features are extracted. The upcoming section speaks about the feature extraction procedure.

III. FEATURE EXTRACTION

Feature extraction is intrinsic to picture or image processing. Researchers have, in recent times, been working to identify distinct features from an image that describe it precisely so it may be differentiated from other, related images This work extracts the colour feature, Speeded-Up Robust Feature (SURF), entropy categorization and FD estimation (EFD), and MWT features to identify images that are most precise to the query image.

A. *Colour Feature*

The colour features employed in a previous work applied the cubic spline neural network technique. The colour feature,

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which contains key information, it is used on any image with colour. It is, consequently used in image retrieval colour. It is, consequently used in image retrieval systems. The previous sections above have discussed colour features in detail Colour moments, colourcorellograms and colour histograms are different features that carry the colour information in an image. Colour information is generally represented in terms of RGB (red, green and blue), giving colour images a 3D structure. In this work, the RGB coloured images are transformed as the HSV (hue, saturation and value) form of the image for feature extraction. HSV values are recognized as colour features of the given image and are mathematically derived using Equation 1:

$$H = \cos^{-1}\frac{1}{2}\frac{[(R-G)+(R-B)]}{\sqrt{[(R-G)^2+(R-B)(G-B)]}} \qquad (1)$$

$$S = 1 - \frac{3[\min(R,G,B)]}{R+G+B} V = \frac{R+G+B}{3}$$

1) SURF Feature

The SURF algorithm is predominantly employed in object recognition systems. It is a fast feature detector that identifies feature pairs between the query image and target image. It involves four processes that determine how features are picked for object recognition, and include the following:

1. Generating an integral image,
2. Detecting interest points based on the Fast-Hessian detector,
3. Assigning a descriptor orientation, and
4. Generating a descriptor.

SURF extracts the foreground features of the image and is partially suited to the scale-invariant Fourier transform. The standard SURF version is several times faster than SIFT. A matrix representation known as an integral image is capable of supporting the global information that a picture carries. The value I (x, y) at position (x, y) in the integral image speaks for the total number of pixels in the upper left corner of that location in the original image. In order to expedite the feature extraction procedure, the integral picture is first extracted from the source image. Four pixel values can be utilised to do an external integral upon the original image in order to find the integral image. Equation 2 is used to produce the integral image.

$$I\sum(x,y) = \sum_{i=0}^{x}\sum_{j=0}^{y} I(i,j) \qquad (2)$$

Interest points in the image are determined using the determinants of the Hessian matrices in the SURF algorithm. Equation 3 presents the determinant for the second-order partial derivatives in 2D functions, and it can detector.

$$H(x,y) = \det\begin{pmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x\,\partial y} \\ \frac{\partial^2 f}{\partial x\,\partial y} & \frac{\partial^2 f}{\partial y^2} \end{pmatrix} \qquad (3)$$

$$H(\bar{x}) = D_{xx}(\bar{x})D_{yy}(\bar{x}) - \left(0.9D_{xy}(\bar{x})\right)^2$$

$$(\bar{x}) = (x,y,s)$$

One way to build the Fast-Hessian detector is by substituting second-order partial derivatives through a convolution of the image with approximated Gaussian kernels, using box filters. Another way to construct the Fast-Hessian detector is via the parameterization of Gaussian kernels by their size. Equation 4 is used to compensate for the loss of approximation**.**

$$H(X) = H + \frac{\partial H^T}{\partial x}x + \frac{1}{2}x^T\frac{\partial^2 H}{\partial x^2}x (4)$$

$$\hat{x} = \frac{\partial^2 H^{-1}}{\partial x^2}\frac{\partial H}{\partial x}$$

In Equation 3, the S parameter indicates the scaling function.A 3D space of the determinant, referred to as scale space, is obtained using the S parameter However, the scale varies according to the octaves and intervals. Representative points in the image, identified through the SURF algorithm, are considered with equal weights that are dynamically assigned to the interest points in the image. In the training image set, true representative points are presented and false ones are uncommon. The weight for each representative point is calculated, where the number of identified images with respect to point P is denoted as XP along with the number of training images in the object is represented as ‘n’, according to Equation 5 below:

$$W_p = \frac{xP}{n} (5)$$

B. EFD Feature

Entropy categorization and fractional dimension (EFD) is a method involved in image texture feature identification. A multifractal texture analysis is attempted, along with texture complexity-based classification. Local signal complexity is estimated using entropy. If the signal complexity is high, entropy value is found to be correspondingly high. Since entropy values are independent of scale and position features, texture is identified by choosing regions with similar entropy values. With this method, different textures are discovered by recognizing differences in the roughness of homogeneous regions.

Mathematically, the pixel entropy Hx is calculated as in Equation 6:

$$H_X = -\sum p_x M_p \log_2 P_x M_p (6) \text{where } H_X = \text{Entropy}$$

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$P_x M_p$ = Probability of the pixel value

where x is a pixel, s the pixel value range lying between 0and 255, andMpthelocalneighborhood(probabilityof the pixel value). After estimating the entropy value for all pixelsin the image, those with similar values are grouped together to identify textures in the image. If u is considered entropy, then ¡u indicates the set of pixels. Pixels are categorized through this procedure and dim(d) estimated. Further, the FD for each d is calculated using the dimension of box-counting. The dimension of box-counting is the amount of boxes of side length e (Ne) encompassing a non-empty bounded subset S of the Euclidean space Rn,as given in Equation 7:

$$FD_s = \lim_{s \to 0} \frac{\log N_s}{-\log s} \quad (7)$$

In this scenario, the gray-level surface of the ¡u is indicated by subset S. Considering q × q × q cube boxes, Ne represents the number of boxes that overlap with the curved surface of the image to cover d. For each entropy value, one FDd value is estimated. Finally, the texture signature is determined by combining the FDd into a single value, which is considered the feature vector to be used for classification. It is generally believed that a fractal-based feature has higher discriminating power that proves most useful in the effective classification of images.

C. *Multiwavelet Transform*

Themost effective picture transform is thought to be the wavelet transform. The wavelet function ψ(t) and scaling function φ(t). define wavelets, which are functions made up of two resultant coefficients.

The wavelet function is a band-pass filter that is scaled for each level, resulting in a bandwidth reduction. For better performance, scalar wavelets, which are used in image compression, segmentation, and denoising, need filters with the characteristics of orthogonality, symmetry, and regularity. To obtain these combined properties in a single transform, therefore, multiwavelets with different scaling filters are used. There are significant differences between multiwavelets. In general, each wavelet has a wavelet function and a scaling function of the form (t), but multiwavelets have over two scaling and wavelet functions. In order to represent multiple scaling functions, vector notation is utilized for the set of functions ϕ(t)=[ϕ1(t), ϕ2(t), ϕ3(t), ϕr(t)], where ϕ(t) indicates the multiscaling function. Identicaly, a multiwavelet function consisting of a set of wavelet functions is notated as ψ(t)=[ψ1(t), ψ2(t), ψ3(t),..ψr(t)]. If r=1, the multiwavelet function is known to be a scalar wavelet function. Though r can hold any value, in the present scenario, r=2 is generally used to define the multiwavelet function. Mathematically, the two-scale multiwavelet function works like the scalar wavelet function, as shown in Equation 8.

$$\emptyset(t) = \sqrt{2} \sum_{k=\infty}^{-\infty} H_k \emptyset(2t - k) \quad (8)$$

$$\psi(t) = \sqrt{2} \sum_{k=\infty}^{-\infty} H_k \emptyset(2t - k)$$

The matrices Hk and Gk, which stand for matrix filters, haver r dimensions with each integer, k. The matrix elements of the mentioned filters offer wider degree of privilege than the conventional scalar wavelet. Multiwavelet filters benefit from notable qualities including orthogonality symmetry and a high level of approximation thanks to the degree of freedom. Finding better ways to use this freedom in the creation of multiwavelet filters is the difficult part.Typically, a discrete wavelet transform is used to decompose 2D picture data into four blocks via a single-level decomposition. The multiwavelet transformation comprises of two channels and consequently two sets of scaling and wavelet coefficients, whereas the four blocks obtained identify the sub-bands signifying either low-pass or high-pass screening in each direction. Figure 2 displays the decomposition of a 2D image.

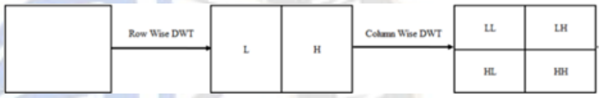

Figure 3. 2D Discrete Wavelet Transform

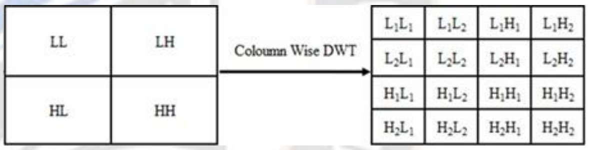

Figure 4. MultiwaveletTransform

Figure 3 depicts the multiwavelet decomposition process. Briefly, the multiwavelet transform acts as a good distinguishing feature with a wide variety of applications, in that it

1. Converts all database images into gray images
2. Decomposes each image into the multiwavelet domain
3. Computes the mean to determine the level with the leastnoise Given that the LL (low-low) method has the least noise, its mean is taken and given to the SOM. In the proposed method, the four different colour, SURF, EFD and multiwavelet transform features are fed into the unsupervised clustering method to identify database images similar to user- specified images.

IV. SELF-ORGANIZING MAP (SOM)

There are 'n' number of methods described in the literature to discover images identical to the query image in content-based retrieval of image systems. Supervised, unsupervised are two methodologies used to classify data into groups. In the supervised technique, the clusters are well known ahead of

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time and it works on labelled data. In the unsupervised technique, the clusters are unknown ahead of time and it works on unlabelled data. Of the many unsupervised methods around, clustering is found to be the most effective way of grouping data. Clustering methods include the k-means, farthest-first, and self-organizing map.

In our research, we employ a self-organizing map, a neural network technique that identifies clusters from unlabeled user-provided data. For the categorization of unlabeled data into a group of clusters using this approach, information is provided as a 2D array. Each cluster is thought of as a neuron in the SOM, and each of these neurons has a parametric reference vector attached to it. The vector's dimension matches that of the data that needs to be categorised. The SOM contains input and output layers, identical to any other neural network. Each input layer has a weighted connection to the output layer.

The external layer may take the form of a 3D structure, a lattice (2D), or a raw (1D) form. The initial value of the output neuron (W) vector elements (W = w1, w2,,wn) represents the input space's density function and is random. Additionally, similar input vectors of the same dimension as the output neurons are drawn to the neurons. The resemblance measure function establishes how similar the vectors are to one another.. The Euclidean distance, which commonly acts as a similarity measure, is used in Equation6.9 below

$$D(w,d) = \left(\sum_{v=1}^{n}(w_v - d_v)^2\right)^{1/2} \quad (9)$$

where The distance function is represented as D (w, d), where wv is the n-feature output neuron vector and dv is the n-feature training input vector. Training and testing are the two phases of learning methodologies. Each input vector (dv), during the training phase, is drawn to the output neuron with the smallest Euclidean distance, identifed as the best machine unit (BMU). In accordance with the rule given in Equation 6.10, the BMU (weight) with the vectors of its topological neighbour are drawn to the training vector based on the current training input vector.

$$\mathrm{W_n(e+1) = W_n(e) + (e).h_n + \cdots \alpha(e)[d(e) - W_n(e)]} \quad (10)$$

wn is the weight of the neuron (n) of the current epoch, € is the rate of learning in the current epoch, wn (e + 1) is theneuron weight in the next epoch,hn is the neighbouring kernel surrounding the BMU, pointing to the area of influence a training vector is having on the SOM, and α€ is the weight of the chosen input vector at the current epoch. Each output neuron carries an amount of mass that is calculated employing the input space at the end of the phase. The map that self-organizes is shown in Figure4.

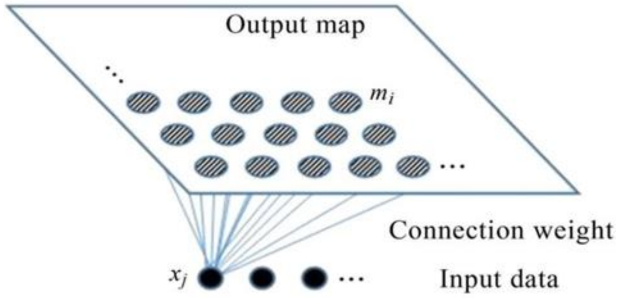

Figure 5. Self-Organizing Map Structure

The alleged image retrieval based on content system takes the database picture and the query image and extracts various feature values from both. These values for features are used to assess pictures that are identical to the query image employing SOM clustering method,

- the input layer size in our suggested neural network structure depends on the feature values, and
- the size of the layer that produces the result is based on the number of picture groups.

A. Clustering

Clustering is the job of partitioning groups into a set of clusters where Qi , Let I=1,2,...n be the number of data samples that correspond to exactly one cluster, where the images from the dataset are clustered using the SOM. Major benefits of the SOM include the considerable decrease in the computational load, the possibility of clustering large numbers of dataset images, and the types of preprocessing structures that may be considered within a limited timeframe. Key SOM features include the following:

1. Clustering high-dimensional data
2. Arranging the resultant clusters in a grid

B. Training Iterations

A comparable layer makes up the SOM, and it divides an array of vectors having any amount of dimensions into many units just as the layer's neurons. The layer can create a visualisation of the spacing of neurons and a 2D approximation of the data collection's topology thanks to the neurons' 2D topological configuration.

Each neuron's weight vector moves towards the centreof cluster containing input vectors throughout SOM training. Furthermore, neurons that move close to other neurons within the input space are neighbours in the topology. As a consequence, an extremely complex input space is able to be seen in each of the two dimensions of the network topology.

The SOM neural network is developed and trained with the best matching unit (BMU). The following example consists of a 5×6 two-dimensional map of 30 neurons. A cluster is formed during training by 1000 iterations of the batch algorithm. The

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SOM neural network expands across all image feature spaces in the 30 neurons. Figure 6 depicts the highest number of hits connected with the neurons.

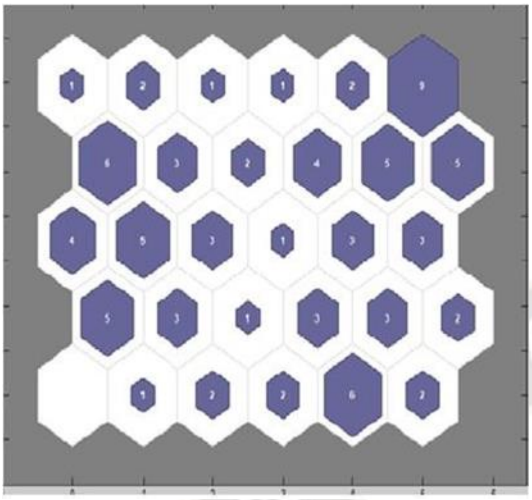

Figure 6. Sample plot hits

1. Create a grayscale version of the questioned image.
2. Equalise the histogram of the grayscale image.
3. Use empirical mode decomposition to extract edges.
4. The 3x3 histogram-equalized gray-scale picture block should be processed by employing the median method.
5. Using the edge values found by the BEMD, adjust the edge placement value of the median processed image.
6. Extraction of a 64-bin vector and stock database storage.

C. Training via Batch Algorithm

Upon creating the SOM neural network, we propose utilizing a batch training algorithm to train it. The neural network is made up of 9 neurons that are arranged in a 3-by-3 2D map. The batch algorithm will be executing 200 iterations during training to form a cluster, and the SOM neural network will expand to encompass all of the image feature spaces of the 9 neurons.

The suggested content-based image retrieval system locates different feature vectors from the user-specified image and database images. These features are utilized to evaluate images that have a distinct similarity to the query image and involve the SOM clustering technique. The suggested system is analyzed using the Corel database. To start with, the weights and learning layers are initialized, following which preprocessing and feature extraction are carried out. In total, seven feature values, that is, one SURF value, two EFD values, three colour feature values as well as MWT features are extracted for each image and given as inputs to the SOM. Before the application of the input images, the SOM network is trained with no target value. The winner unit is calculated using the Euclidean distance method and all related images are retrieved. The proposed system is evaluated on different databases, and the findings are explored in the next section.

V. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed system is experimented with on the Corel10K and Wang image datasets. Of the around 10,000 images considered, 500 are used for training and 1000 for testing. The system proposed involves no image compression technique, and the three extracted features are the SURF, EFD and MWT.

The retrieved characteristics values are fed into the SOM neural network as input, and it then groups the characteristic values into multiple groups. The query image feature values are then provided to the neural network in order to identify which group of clusters the query image belongs to. After comparing the detected clustered features to the feature values of the query image, distance measures are applied, and an analogous distance measure is applied to present a similar image. Results are displayed when similarity values are saved in ascending order. The system's efficiency is also calculated based on precision and recall. The next subsection offers additional data on the comparison of the features.

VI. PERFORMANCE MEASUREMENT

The overall precision rate (APR) and average recall value (ARR), which measure how well the suggested system performs in identifying relevant images, are used to analyse the effectiveness of the retrieval of image based on content system. APR and ARR are calculated mathematically using Equations 11 and 12, respectively.

$$APR = \frac{1}{N_{tL}} \sum_{q=1}^{N_t} n_q(L) \qquad (11)$$

$$ARR = \frac{1}{N_{tN_R}} \sum_{q=1}^{N_t} n_q(N_R) \qquad (12)$$

where n_q denotes the total number of images.

N_q = the number of relevant images for a query image ‘q’ in a database. Generally, if the APR and ARR values are higher, then it is believed to be performance of the system is efficient. In other words, the higher values indicate the retrieval of higher number of relevant images. The performance of the proposed system can be measured using the recall and precision value. The precision P(q) and recall R(q) is determined as in Equation (13).

$$P(q) = \frac{n_q}{L}, R(q) = \frac{n_q}{N_q} \qquad (13)$$

Similar to APR and ARR value, precision and recall should have higher values as they indicate the improved performance of the proposed image retrieval system. The next subsection deals with the sample outcomes obtained during the extensive experiments carried out for testing of the

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system. Experiments performed on different images of Corel 10K database and the outcomes of the system are presented. For experimental purpose, an image with cluster of ladies finger is given as query image to the system. This brings out all similar images.

$$\text{Precision} = \frac{\text{Number of relevant images retrieved from each group}}{\text{Number of relevant image}} \quad (14)$$

$$\text{Recall} = \frac{\text{Number of relevant images retrieved from each group}}{\text{Total Number of relevant image}} \quad (15)$$

Total Number of Images = 300
Total Number of retrieved Images = 272
Number of relevant images retrieved = Number of images retrieved from each group

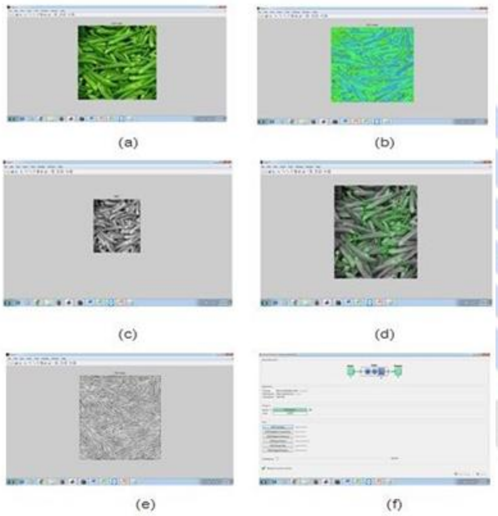

Figure 7. (a) Query image (b) HSV (c) MWT (d) SURF (e) EFD (f) SOM

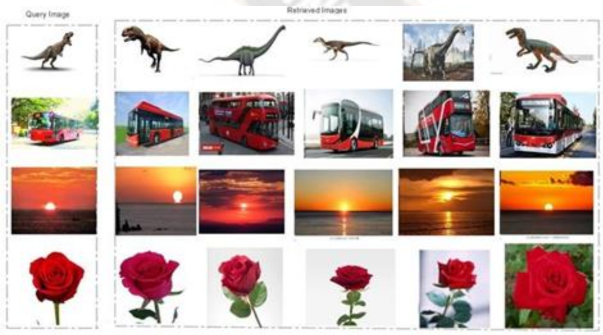

Figure 8. Output of the proposed system

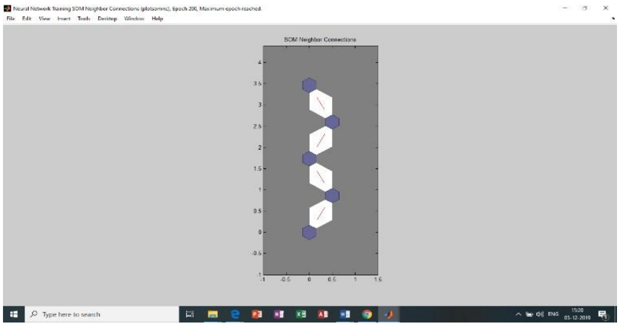

Figure 9. Neighbour Connections SOM

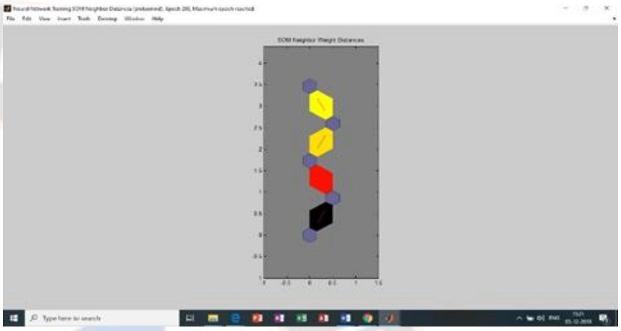

Figure 10. Neighbour weight distances SOM

TABLE I. PRECISION AND RECALL RATES FOR DIFFERENT GROUPS OF IMAGES

Category	Precision	Recall
Flowers	0.93	0.1029
Horses	0.96	0.1066
Lions	0.93	0.1029
Apples	0.90	0.099
Ladies' fingers	0.86	0.095
Balls	0.86	0.093
Boats	0.86	0.095
Birds	0.93	0.1029
Carrots	0.90	0.099
People	0.90	0.099
Average precision rate & recall rate	0.903	0.1094

TABLE II. FOR THE PROPOSED AND EXISTING METHODS, PRECISION AND RECALL

Methods	Corel10k dataset		Wang dataset	
	Precision	*Recall*	*Precision*	*Recall*
Ravaetal.	0.422	0.183	0.463	0.175
Luietal.	0.76	0.89	0.645	0.678
Fadaeietal.	0.84	0.332	0.842	0.321
Dubey et al.	0.337	0.691	0.345	0.682
Zhouet al.	0.64	0.213	0.652	0.31
Proposedmethod	0.904	0.18	0.902	0.16

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TABLE III. CORRELATION OF THE COREL10K WITH WANG DATASETS PERFORMANCE

S.No	Category	Existing precision	Existingr ecall	Proposedp recision	Proposed recall
1	Buildings	49.25	22.14	86.25	52.14
2	Africans	74.33	44.23	86.32	50.21
3	Buses	55.00	30.10	78.23	55.32
4	Dinosaurs	93.00	90.00	96.21	93.00
5	Elephants	63.70	35.66	85.24	55.66
6	Food	62.00	31.30	92.34	51.30
7	Flowers	75.60	51.00	93.41	63.10
8	Horses	87.10	44.20	96.52	64.25
9	Mountains	38.00	21.00	80.00	53.62
10	Sunsets	55.50	28.56	85.23	58.26

TABLE IV. A PERFORMANCE COMPARISON OF VARIOUS IMAGE RETRIEVAL SYSTEMS

Performance metric	SIFT	Markov	PCA	Hough	Decision Tree Learning	Feed forward Neural Network	SOM
Mean Average Accuracy in %	78.5	70.6	60.6	70.6	85.5	84.3	90.3
Mean Average Precision in %	0.734	0.764	0.604	0.706	0.85	0.84	0.903
Mean Average Recall in %	0.084	0.075	0.053	0.086	0.075	0.079	0.1094

Table 4 shows a performance comparison of several image retrieval systems, including the scale-invariant Fourier transform and Markov random field, the principal component analysis and Hough transform, and the decision tree and feed-forward neural network.

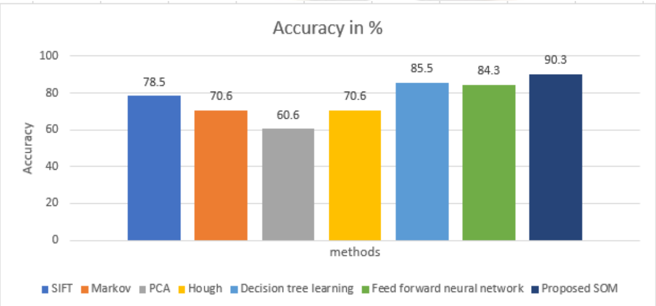

Figure 11. Accuracy comparison with existing method

VII. CONCLUSION

In our work to developed a multi-level fusion technique that extracts new features for CBIR and classifies them under their own names using SOM images. The proposed system uses the unsupervised learning SOM-based approach to deal with queries from a user's perspective. In our research, different feature vectors are determined employing the user-specified image and the database photos. The SOM generates pictures that are closest to the query picture. The proposed methodology is contrasted using a number of other established techniques. The findings show that the unique multi-level fusion-based SOM outperforms previous techniques in terms of precision rate.

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