Time Conserving CBIR System for Fabric Images based on Color and Texture Features

V. Alan Gowri Phivin, A.C. Subhajini

Abstract: Digital images play an inevitable role in human life and hence, the utilization of images grow day-by-day. Though the advanced storage technology helps in massive data storage, efficient retrieval system is the need of this hour and this issue is well-addressed by Content Based Image Retrieval (CBIR) systems. The CBIR systems are widely present for healthcare and remote sensing domain. However, the presence of CBIR systems is found to be limited for fabric images. Taking this as a challenge, this work presents a CBIR system exclusively meant for fabric images by extracting color and texture features. When the user passes the search query image to the CBIR system, the features of the query image is compared with the features of the images in the dataset, which is performed by Extreme Learning Machine (ELM) classifier. The performance of the proposed CBIR system is found to be satisfactory in terms of retrieval accuracy and time consumption.

Keywords: CBIR, Color and Texture Feature, Image Retrieval.

I. INTRODUCTION

Digital images play an integral role in almost all the domains such as healthcare, security systems, remote sensing, entertainment and all other commercial applications. As the utilization of images is skyrocketing, a proper mechanism to organize the images is the need of this hour. The increased utilization of images makes it difficult to locate the required image in a reasonable time span. At this juncture, Content Based Image Retrieval (CBIR) system comes into picture. The central goal of CBIR system is to retrieve the required image from the voluminous dataset by considering the query image passed into the CBIR system [1,2].

The CBIR system deals with the voluminous image dataset for the sake of retrieving similar images in the dataset with respect to the query image. The user can pass a query image to the CBIR system, such that the CBIR system compares the query image with the images in the dataset based on the relevance factor. Hence, the choice of relevance factor plays an important role in achieving better outcome. The features of images are considered as the relevance factor, as the features are observed in all images.

Based on the features, the images can easily be compared and analysed. Basically, all the images are tightly associated with three significant low level features and they are colour, shape and texture. All these features are simple to compute and consume minimal time of retrieval. All the digital images are loaded with rich low-level features, which are capable enough to distinguish between the images in the dataset [3,4].

Now-a-days, the usage of online commercial applications is undergoing huge elevation, as it is more convenient and hassle-free. Though the CBIR systems are common for different domains such as photography, medical systems and security based systems, the CBIR solutions for textile industries are very limited and scarce. The users show great interest in shopping apparels online, however most of the applications differentiate between the colour of the fabric images. Though colour is the most important feature of fabric, texture is also given equal importance.

For instance, the user may be interested in the fabric of velvet material, however the texture is not focussed by most of the applications. In order to address this issue, this article proposes a CBIR system for fabric images that considers both the colour and texture properties of an image. As the texture property is considered, the CBIR system can distinguish between woollen, jean, velvet, lace trim clothes and so on. This idea enhances the shopping experience of the users.

In order to achieve the research goal, this work is segregated into three different phases and they are fabric image pre-processing, feature extraction and relevant image ranking. The fabric image pre-processing technique attempts to enhance the quality of the fabric image, in order to make it suitable for further processing. The feature extraction is the key phase, which is meant for extracting useful features from the fabric images and is attained by Local Directional Pattern (LDP), Contourlet Transform and colour moments.

The feature vector is formed on the basis of the extracted features from the fabric images. The third phase is meant for differentiating the images in the dataset by taking the query image passed by the user into account. This phase is achieved by means of Extreme Learning Machine (ELM). The highlighting points of this article are listed below.

- This work presents a CBIR system for fabric images based on colour and texture features, which is observed to be scarce in the literature.
- The proposed work consumes reasonable time for retrieving the images that are relevant to the query image.
- The performance of the proposed work is better in terms of standard performance measures such as precision, recall and F-measure.

The remainder of this article is systematized in the following way. Section 2 presents the detailed review of literature with respect to CBIR systems operating with different images.

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The proposed CBIR system for fabric images is elaborated in section 3 and the performance of the proposed work is analysed in section 4. Finally, the conclusions of the work are summarized in section 5.

II. REVIEW OF LITERATURE

This section studies and reviews different CBIR systems present in the existing literature, which are meant for different kinds of images. In [5], a CBIR system is presented for single and multi-label high dimensional remote sensing images. Initially, the images are described by means of spatial and spectral descriptors. The spatial descriptors being utilized are pixel values, bag and extended bag of spectral values. In order to describe the spatial aspect, bag of visual words approach is utilized. Both these descriptors are clubbed together for performing image retrieval, which is attained by sparse reconstruction technique. A CBIR system based on fuzzy class membership and rules by classifier confidence is proposed in [6]. This work is based on the class membership based retrieval and the confidence of the classifier. In [7], the CBIR system for Synthetic Aperture Radar (SAR) images is presented on the basis of semantic classification and region based similarity measure. This work classifies between the land cover of the SAR images by patches rather than pixels by performing Semi-Supervised Learning (SSL). The similarity between the patches is found out by Improved Integrated Region Matching (IIRM).In [8], a CBIR system is presented for microscopic images meant for multiple image queries. This CBIR system utilizes a database that contains microscopic images of different diseases. This work presents a multiple image query and slide-level image retrieval. However, this work suffers from computational complexity and cannot attain better accuracy rates. In [9], a CBIR system based on half-toning based block truncation coding. This technique compresses the image block by means of Ordered Dither Block Truncation Coding (ODBTC). This work utilizes Colour Co-occurrence Feature (CCF) and Bit Pattern Features (BPF) for indexing the images using visual codebook. In [10], a Biased Discriminant Euclidean Embedding (BDEE) based technique is proposed for CBIR. This technique processes the samples in the high dimensional space for detecting the image coordinates of low level features. This work considers the intra and interclass geometry of the samples. A visual analytics approach based CBIR is proposed by exploring multidimensional feature space in [11]. This work explores the samples visually by means of a tool called Visual Analytics for Medical Image Retrieval (VAMIR). However, this approach demands prior knowledge about the tool and involves computational overhead.A fast wavelet based image characterization for adaptive image retrieval is proposed in [12]. This work characterizes each query image by different wavelets. The image retrieval process is improved by a regression function and the best wavelet filter is recognized. The image characterization is carried out by wavelet coefficient distributions. Though this work is meant for multiple image kinds, the time complexity of this work is more. In [13], a boosting framework for visuality preserving distance metric is proposed for medical image retrieval. This work presents a distance metric which conserves the resemblance and semantic similarity. The boosting framework is represented in a binary format with respect to label pairs and the distance is computed by weighted hamming distance. However, the efficiency of this work depends on the reliability of the distance metric. A breast histopathological image retrieval scheme based on Latent Dirichlet Allocation (LDA) is proposed in [14]. This work presents an unsupervised technique for retrieving breast histopathological images, which considers the morphological information of nuclei and the gabor filter is employed for extracting the texture property. In [15], a CBIR system based on Error Diffusion Block Truncation Coding features is presented. This work provides two color quantizers with a bitmap image that are processed by Vector Quantization (VQ) for producing the image feature descriptor. The features are extracted by Color Histogram Feature (CHF) and Bit pattern Histogram Feature (BHF). Finally, a distance measure is utilized for distinguishing between the images. A scalable approach for CBIR system is presented for peer-to-peer networks in [16]. This work presents a dynamic codebook by considering the mutual information between the codebook and the relevance information. An indexing pruning method is also presented by this work for improving the image retrieval performance. In [17], a learning based similarity fusion and filtering approach is presented for biomedical image retrieval by utilizing Support Vector Machine (SVM) and Relevance Feedback (RF). This work employs SVM to predict the category of database images with respect to the query image. However, this work is meant for biomedical images. A semi-supervised biased maximum margin analysis for interactive image retrieval is proposed in [18]. This work presents a Biased Maximum Margin Analysis (BMMA) and a semi-supervised (SemiBMMA) for combining the distinct properties of feedback. The BMMA is meant for differentiating between the positive and negative feedbacks and SemiBMMA applies laplacian regularizer to the BMMA. In [19], the deep learning and compressed domain features are fused to present a CBIR system. The high level features are extracted by Convolutional Neural Networks (CNN) and the low level features are extracted by Dot Diffused Block Truncation Coding (DDBTC). Both these features are fused to generate two-layer codebook. A large-scale histopathological image analysis is presented for hashing based image retrieval [20]. A scalable image retrieval technique based on supervised kernel hashing technique is proposed. The binary codes are indexed to the hash table, however the classification accuracy can still be improved. In [21], a CBIR scheme for histopathological images is proposed by means of curvelet and gabor features. Motivated by the existing approaches, this work intends to present a CBIR system for fabric images, which is found to be rare. The main focus of this work is to improve the retrieval rate and accuracy. The following section presents the proposed work in detail.

III. PROPOSED CONTOURLET BASED CBIR SYSTEM FOR FABRIC IMAGES

This section elaborates the proposed CBIR system preceded by the overview of the proposed approach.

3.1 Overview of the proposed approach

The main objective of the CBIR system is to render better access to the images stored in the voluminous dataset, by considering the user search image. This increases the accessibility and helps in decision making for the user. For instance, the CBIR system prompts the user to pass in a search query image to the system, which manipulates the search query and extracts the significant features from it. The features of search query image are compared with the features of the images being stored in the image dataset. Based on the relevance score, the similar images are ranked and returned to the user. The overall flow of the proposed approach is presented in figure 1. In figure 1, the dotted lines denote the training process.

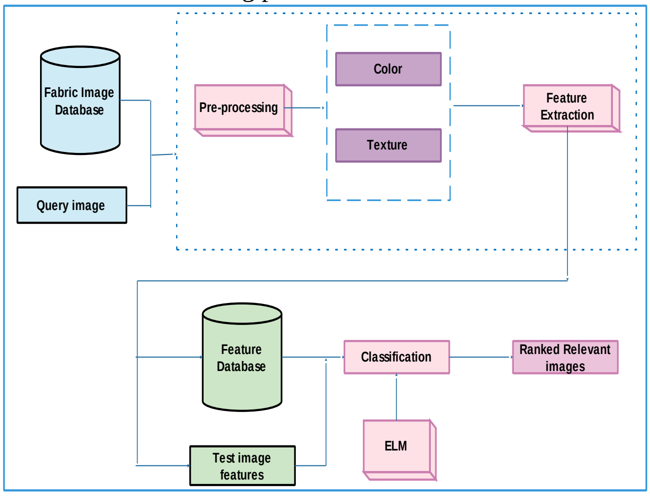

Fig.1: Overall flow of the proposed CBIR system

Though this process seems to be simpler, it involves several challenges such as retrieval time and accuracy rates. An efficient CBIR system handles both the performance issues. A CBIR system has to present better retrieval accuracy rates in a reasonable amount of time. Considering these points, the proposed CBIR system extracts sharp and significant features from the fabric images, which helps in attaining better accuracy in a reasonable amount of time.

In order to achieve the goal, the proposed approach involves two important phases, which are training and testing. The training phase is the knowledge gaining phase that imparts knowledge to the CBIR system and the testing phase is meant for the user. In the training phase, the CBIR system is trained with the features of the train images. In the testing phase, the user is prompted to pass a search query image from which the features are extracted and compared with the train feature set. Finally, the images that share maximal relevance score are ranked and presented to the user. Though there are numerous CBIR systems for medical and remote sensing images, the CBIR systems for fabric images are very scarce. Most of the systems that treat fabric images are for detecting the defects. Taking this as a challenge, this work proposes a CBIR system for fabric images, which is divided into three major phases such as fabric image pre-processing, feature extraction and relevant image ranking. All these phases are described in the forthcoming sections.

3.2 Fabric Image Pre-processing

The fabric image pre-processing is the most fundamental step that aims to standardize the size of the fabric image. The fabric image dataset contains images of varying sizes and hence, this phase makes the size of the images uniform such that the forthcoming processes can be performed without any hassles. The algorithm of this work is presented as follows.

Proposed CBIR for Fabric Images

//Training
Input: Fabric images
Begin
Pre-process the images;
Obtain color and texture features;
Save the feature vector fv;
End;
// Testing
Input: Search Query image
Output: Set of ranked relevant images
Begin
Pre-process the image;
Extract color and texture features;
Match the feature vector with the trained feature vector;
Return the top 5 relevant images;
End;

3.3 Color and Texture Feature Extraction

The fabric images contain rich set of color and texture features. Hence, the proposed CBIR system focuses on color and texture features. The color and texture feature extraction of the proposed CBIR system is presented in this section.

3.3.1 Color feature extraction

The color features of the fabric images are extracted by three different color spaces such as RBG, CIELAB and HSV. The reason for the employment of three color spaces is to capture as much color information as possible. The CIELAB model targets the color and the intensity information of the fabric images. The HSV model distinguishes between the color being present in the fabric image and the intensity information is obtained. Each color space has three color channels, such that the feature set contains rich color information. Initially, the mean and standard deviation are computed for all the three channels of the three color spaces which provide eighteen color features. In addition to this, the mean, standard deviation, skewness, kurtosis, energy, entropy min and max values are computed with respect to gray level intensity image. Totally, twenty six colour and gray features are obtained from three different color spaces from the fabric image. Hence, the color features of the fabric images are extracted and are stored.

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3.3.2 Texture feature extraction

Texture is the most important feature of fabric image, which can differentiate between the fabric images effectively. As the fabric images provide different patterns of texture, it is mandatory to obtain the complete texture information. In order to capture better information about texture, this work employs LDP and contourlet transform as presented below.

3.3.2.1 LDP

LDP is an enhancement of Local Binary Pattern (LBP), which is based on the image gradients and is stable. On the other hand, LBP is unstable as it considers pixel intensity. The reason for the choice of LDP is that it processes the fabric images in multiple directions and the pixel is indicated by an eight bit binary code [22].

Let Im be a fabric image with pixels (a_i, b_i). The eight directional outputs of the process is performed by Kirsch compass edge detector $\left(D_{op_k}\right)$ as presented by eqn.(1).

$$D_{op_k} = \sum_{x=-1}^{1} \sum_{y=-1}^{1} Mi_{dir}(x+1, y+1) \times Im(a+x, b+y) \quad (1)$$

The D_{op_k} $(k = 1,2, \ldots, 8)$ is computed for all the eight directions. All the eight directional outputs are presented by codes, in which the corresponding bit is set to 1 and the remaining bits are fixed as 0. This kind of processing is continued for i count of directional outcomes and the corresponding bit is fixed as 1 and $8 - i$ bits are set to 0. Finally, all the directional outcomes of a pixel are represented as

$$LDP_{a,b}(op_1, op_2, \ldots, op_8) = \sum_{i=1}^{8} s(op_k - op_i) \times 2^k \quad (2)$$

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (3)$$

In equation (3), op_i denotes the i^{th} significant directional outcome. Here, i is changed from 1 to 5 for analysis and is found that better results are produced when the value of i is 3. Finally, the LDP codes are found out for all the image pixels by the following equation.

$$LDP_{his} = \sum_{a=0}^{M-1} \sum_{b=0}^{N-1} P(LDP_{(a,b)}, LDP_{p_k}) \quad (4)$$

In equation 4, LDP_{p_k} denotes the LDP's k^{th} pattern value that differs in line with the $k's$ value. The value of P is assigned to 1 and 0, when $a = 0$ and $a \neq 0$ respectively. The LDP features are extracted by this way and the following section describes the contourlet transformation.

3.3.2.2 Contourlet Transform

The main reasons for the employment of contourlet transform are its multiresolution, localization, directionality and anisotropic features [23]. Contourlets are the improvised version of curvelets and it can operate over discrete domain well. In addition to this, contourlets offer iterated filter bank, which results in efficient transformations. Contourlet clubs both the Laplacian Pyramid (LP) and Directional Filter Bank (DFB) together. The DFB captures the high frequency components and so the low frequency components are expelled before they are processed by DFB. Let $a_0[n]$ be an input image passed through LP, which provides I bandpass images as denoted in eqn.(5).

$$y_i[n]; i = (1,2, \ldots I) and\ x_I[n] \quad (5)$$

In equation (4), $y_i[n]; i = (1,2, \ldots I)$ represents the fabric image in fine to coarse order and $x_I[n]$ is the lowpass image, which makes sense that the i^{th} level of LP decomposes the input image $x_{i-1}[n]$ into a coarse and a fine image as denoted by $x_i[n]$ and $y_i[n]$ respectively. Each and every bandpass image $y_i[n]$ is decomposed again to the degree of d_i to 2^{d_i} bandpass directional images as denoted by

$$a_{i,l}^{(d_i)}[n]; \quad i = (0,1, \ldots, 2^{d_i} - 1) \quad (6)$$

By this way, the contourlet is applied over the fabric images for extracting the texture features. During the process of feature extraction, the LDP is applied first and is followed by the application of bi-level contourlet to form the feature vector. Based on the feature vector, the system is trained with the help of ELM as follows.

3.3.3 Fabric image classification by ELM

This phase attempts to find the relevant images in the image database by considering the query image being passed by the user. ELM is one of the fastest and accurate classifiers [24]. The ELM is trained with different training samples and the knowledge is fed to the CBIR system. The acquired knowledge is utilized for classifying between the images.

Let X be the training samples represented by (a_i, b_i), where $a_i = [a_{i1}, a_{i2}, \ldots a_{is}]^q \in Im^s$; where n is the dimension of the training representatives. $b_i = [b_{i1}, b_{i2}, \ldots b_{it}]^q \in Im^t$ denotes the i^{th} class label of dimension t. In this work, t indicates the number of classes. A Single hidden Layer Feed-Forward Neural Network (SLFN) is built by an activation function $act(x)$ and R neurons as denoted by

$$\sum_{i=1}^{R} \beta_i act\left(wt_i . a_j + e_i\right) = b_i; i = 1,2, \ldots, n \quad (7)$$

In equation 6, wt_i is the weight of the feature vector, e_i is the bias of the i^{th} hidden neuron.

Let Hd_l be the ELM's hidden layer output matrix, in which the i^{th} column of Hd_l denotes that the i^{th} hidden neurons output vector by taking the inputs $a_{i1}, a_{i2}, \ldots, a_{in}$.

$$Hd_l = \begin{bmatrix} act(wt_1 . a_1 + e_i) & \ldots & act(wt_v . a_1 + e_G) \\ \vdots & \vdots & \vdots \\ act(wt_1 . a_n + e_i) & \ldots & act(wt_v . a_n + e_G) \end{bmatrix} \quad (8)$$

$$\beta = \begin{bmatrix} \beta_1^q \\ \vdots \\ \beta_G^q \end{bmatrix} \quad (9)$$

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$$B = \begin{bmatrix} b_1^T \\ \vdots \\ b_n^T \end{bmatrix} \quad (10)$$

The matrix form is denoted by

$$Hd_l \beta = B \quad (11)$$

The output samples are computed by norm least-square solution and is represented by

$$\beta = {Hd_l}^{\dagger} B \quad (12)$$

Where $HL^{\dagger}$ is the HL's Moore-Penrose generalized inverse. The ELM training phase is performed by eqn.12. In the testing phase, the output matrices are computed and combined together for finding the the greatest value against the row. The output matrix is computed by the following equation.

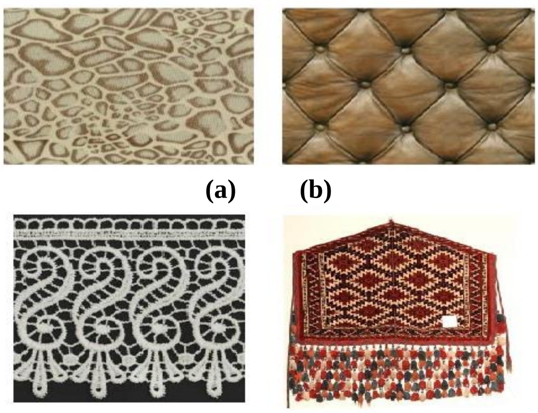
$$b_{testing}(z) = Hd_{l_{testing}}(z) \times \beta_z \quad (13)$$

The proposed approach sets the value of z to 12, because of the attainment of optimal results. The efficiency of classification falls down when the value of z increases. The value 12 is found out by the trial and error method.

The classifier compares the feature vector of the search query image with the feature vectors of the images stored in the dataset. The images with matching feature vectors are recognized by the classifier and are ordered based on the degree of similarity. This work lists out the top five matching fabric images from the image database with respect to the query image. The performance of the proposed approach is evaluated in the following section.

IV. RESULTS AND DISCUSSION

The performance of the proposed approach is analysed and compared with the existing algorithm in terms of precision, recall, F-measure and time consumption analysis. The proposed approach is simulated in MATLAB environment of version 2013a on a computer with 8 GB RAM. The sample fabric images are presented in the following figure 2.

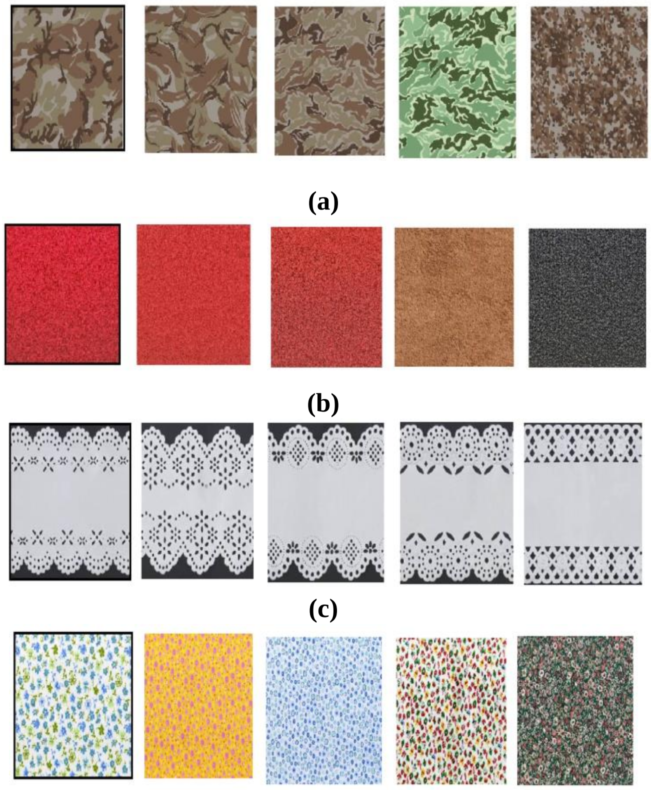


(a) (b)

(c) (d)

Fig.2: Sample fabric images with different textures

The proposed CBIR system is compared against fuzzy based approach [6] and compressed domain features [19]. The dataset being used for fabric image analysis is publicly available in [25]. This work utilized 150 images from the dataset, out of which 60 images are used for training and the remaining images are meant for testing. The sample visual results of the proposed work are as follows.



(a)

(b)

(c)

(d)

Fig.3: (a-d) Sample image retrieval results

In figure 3, the image that is enclosed in black outline is the search query image and the rest of the images are the ranked relevant images retrieved from the image dataset. Precision and recall are the most important performance measures of CBIR that measure the correctness of the image retrieval system. Precision rate of the CBIR system is computed by the ratio of the similar images being retrieved from the image dataset with respect to the search query image (SI_r) and the count of images returned to the user (R_i).

$$P = \frac{SI_r}{R_i} \quad (14)$$

Recall rate is the total number of images that are relevantly extracted from the image dataset by the CBIR system to the total number of actual relevant images present in the dataset. The recall rate is computed by

$$R = \frac{SI_r}{AR_i} \quad (15)$$

The F-measure strongly depends on the precision and recall rates of the approach and the formula for computing F-measure is as follows.

$$F_m = \frac{2(P \times R)}{P + R} \quad (16)$$

The experimental results of the proposed approach are presented as follows. The performance of the proposed approach is justified by three rounds of comparisons. Initially, the performance of color and texture features is justified. The choice of contourlet and LDP is then justified with the other techniques.

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Finally, the performance of ELM is justified by comparing it with the analogous classifiers such as Relevance Vector Machine (RVM) and Support Vector Machine (SVM).

4.1 Performance comparison of color and texture features

Initially, the power of the combination of colour and texture features is proven by incorporating the colour and texture features independently. The fabric images are dominated by two main features, which are colour and texture features. The CBIR system based on colour and texture features yields better results and the experimental results are presented as follows.

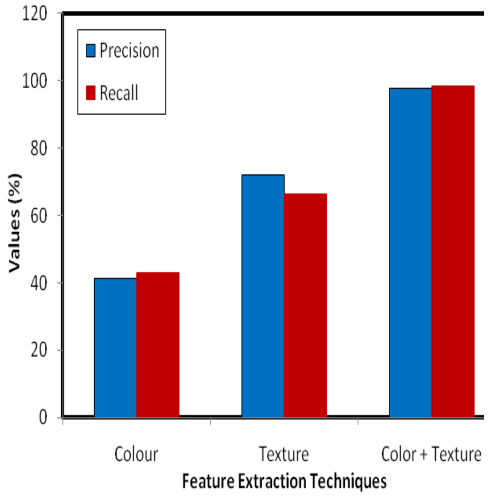

Fig. 4: Performance analysis w.r.t feature kinds

This section performs the analysis by utilising the color features extracted by the proposed approach and the texture extracted by LDP+contourlet independently. From the experimental results, the performance of the combination of color and texture features proves better performance.

4.2 Performance comparison w.r.t. feature extraction techniques

This section justifies the choice of LDP and contourlet by comparing the performance of the combination with the Local Binary Pattern (LBP) and curvelet in varying combinations. The reasons for comparing LBP and curvelet are that both LDP and contourlet are the enhanced versions of LBP and curvelet. The experimental results of this comparison are presented in the following table.

Table 1: Performance comparison w.r.t feature extractors

Texture feature extractors/Perf	LBP+Curvelet	LBP+Contourlet	LDP+Curvelet	LDP+Contourlet
Precision	81.2	86.8	88.1	**98.2**
Recall	82.3	84.9	86.7	**97.6**
F-measure	81.7	85.8	87.3	**97.8**

From the experimental analysis, it is clearly evident that the combination of LDP and contourlet serves well than the other combination of feature extractors. The combination of LDP and contourlet proves the greatest precision and recall measures, which in turn improves the F-measure of the feature extractors. Hence, the power of the feature extractor combination is justified and the following section presents the performance analysis of the classifier.

4.3 Performance analysis w.r.t classifier

The proposed CBIR system employs ELM for classification and the performance of the ELM is compared against the analogous classifiers such as RVM and SVM. The experimental results are presented as follows.

Table 2: Performance comparison w.r.t classifiers

Texture feature extractors / Perf	RVM	SVM	ELM
Precision	84.9	87.9	**98.2**
Recall	81.7	85.5	**97.6**
F-measure	83.2	86.6	**97.8**

ELM is a faster learning classifier that proves better classification precision and recall values. Considering this point, the proposed approach employs ELM as classifier for differentiating between the fabric images. The following section presents the comparative analysis of the proposed approach against the state-of-the-art CBIR systems.

4.4 Performance analysis against existing CBIR systems

This section compares the performance of the CBIR systems with the analogous CBIR systems in the existing literature found in fuzzy based approach [6] and compressed domain features [19].

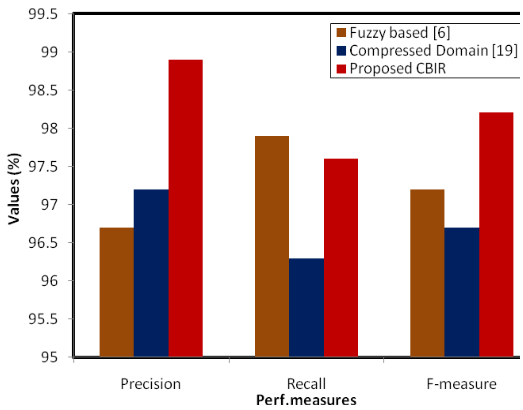

Fig.5: Performance comparison with the existing approaches

The experimental analysis proves that the proposed CBIR system performs well in retrieving relevant images from the image dataset with respect to the search query. The main reason for the better performance of the proposed approach is the utilization of colour and texture features extracted by efficient feature extractors. In addition to this, the image differentiation is carried out by ELM classifier, which further boosts up the performance of the proposed CBIR approach.

The time consumption analysis of the proposed approach is presented as follows. The average time consumption of the proposed work is tabulated as follows.

Table 3: Time consumption analysis (ms)

Technique	Time consumption (ms)

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Fuzzy based [6]	2967
Compression domain based [19]	2138
Proposed CBIR	2112

The time consumption of the proposed CBIR is minimal, yet is comparable with the compression domain based CBIR in [19]. However, the proposed approach achieves reasonable precision and recall rates in reasonable amount of time. Hence, the objective of the work is attained and the conclusions of this work are summarized in the following section.

V. CONCLUSION

This article presents a CBIR system for fabric images based on colour and texture features. The colour features of the fabric images are extracted by employing three different colour spaces and the texture features are extracted by LDP and contourlet. The ELM classifier is trained with the extracted features and the fabric images are differentiated for effective retrieval. The relevant images with respect to the search query image are listed in order and returned to the user. The performance of the proposed approach is tested in terms of retrieval accuracy and time consumption. The proposed CBIR system surpasses all the performance analysis methods and outperforms the existing techniques. In future, this work is planned to be extended to images of different domains. Additionally, the optimal features can be selected from the feature set, for reducing the time and computational complexity further.

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