www.ijecs.in
International Journal Of Engineering And Computer Science ISSN: 2319-7242
Volume 5 Issue 10 Oct. 2016, Page No. 18274-18282

An Efficient and Scalable Technique for Texture Analysis to Obtain in IR Model

Akanxa Mishra, Namrata Sharma

PG SCHOLAR CSE, SDBCE college, RGPV university, INDORE, INDIA
mishraakanxa89@gmail.com

ASSISTANT PROFESSOR CSE, SDBCE college RGPV University, INDORE, INDIA
nsharma@sdbce.ac.in

Abstract: Nowadays the popularity of multimedia contents search is increasing rapidly such as images, videos, and the audio. Among them, the images are much popular for search and data retrieval processes. In literature there are a number of techniques are exist for efficient and precise image retrieval but according to the conclusion of literature the content based techniques are a much promising approach. In content-based image retrieval systems, the image internal descriptors or features are used for representing the image contents. In these descriptors the shape, colour and texture are primary image content descriptors. A number of works are available for different combinations of these features but there is work exist for the texture analysis. In order to recognize the feature based similar objects, the texture feature played an essential role.

In this work the texture analysis is a key area of interest, therefore different texture analysis techniques are studied and LBP is selected for further work. Thus the LBP based texture classification technique is proposed and implemented in this work first. In addition of to demonstrate the effectiveness of the proposed texture analysis technique, the application of the approach in content-based image retrieval is also demonstrated. The implementation of the proposed approach is provided using the visual studio technology. After implementation of the technique, the performance of the system is evaluated in terms of precision, recall, and f-measures. Additionally, for finding the computational complexity the time and space complexity is also computed and compared with the traditional LBP based technique. According to the obtained performance, the proposed technique results from more precise results in less resource consumption.

Keywords: **LBP, texture analysis, texture classification, CBIR, low level features, implementation**

Introduction

In this age of technology, almost everyone knows about the internet and their importance. To find the various kinds of information the users are also dependent on the internet based applications. Among various applications, the search engines are played an important role for finding the user query-relevant data. Not only the search engines are used for finding the documents and web contents, now in these days these applications are also used for searching of multimedia contents such as audio,

video, and images. In this presented work the images are the key area of study.

In literature for finding the user query relevant images from the image databases two kinds of techniques are available namely text-based image retrieval and the content-based image retrieval techniques. But researchers preferred to use the content based image retrieval techniques because in the content-based retrieval techniques the image is evaluated for finding the key features of images. These features are used to find the less amount of data by which the retrieval makes efficient and accurate. In content-based image retrieval the three main features are used in literature namely shape, texture, and the color . Additionally, for finding the valuable features a number of different kinds of methodologies are exist.

In this presented work the texture feature is studied in detail and their impact on the image, a content search is measured. Therefore first the available texture computation technique is modified for accurate texture classification and then the modified technique is used with the image database for performing the search on the image database. Thus the proposed work contribute for the image texture feature classification in the small amount of effort and then utilized with the image retrieval technique to improve the object recognition in a large image database. The main aim of the proposed work is to find the efficient method for image texture classification and then demonstrate the effectiveness of algorithm through the image object recognition. To achieve the desired goal the following objectives are placed in this work.

1. Study of image retrieval techniques and texture computation techniques: in this phase, the different image retrieval techniques are studied, in addition of that the contribution of different features on image object identification is evaluated.
2. Study of the texture analysis application and recent contribution on texture classification: in this phase, the recent studies on texture classification are studied and an efficient technique is concluded for further modifications.
3. Design and implementation of an efficient and accurate texture classification technique: in this phase, a lightweight method for texture feature classification is designed and developed. Additionally, a suitable simulation for providing the efficient feature classification is also demonstrated.
4. Comparative performance study of the proposed technique: in this phase the proposed technique is implemented with the image retrieval technique and the performance analysis with the traditional technique is performed over the precision, recall and f-measure values.

.

Proposed Work

This section provides the system overview for providing the system details and proposed contribution of the proposed domain. In further the proposed model is described using the system diagram and their functional aspects. Finally, an algorithm is presented for demonstration.

A. System Overview

The images are used to define real world objects in a graphical manner. Therefore images are part of information document. Now in these days a number of online image databases exist. In most of the image database search systems, the Content-Based Image Retrieval (CBIR) systems are implemented. The content-based image retrieval is a kind of popular research technique. In this search technique, the images contents are used for making user query. Additionally using the image objects descriptors (i.e. image internal features) such a shape, colour and texture are used to find the similar contents in images database

In this context, the shape features define the object edges and the colour features are used define the colour distribution in the images. Additionally, the texture used to define the objects and patterns of pixel organization. According to the proposed hypothesis, the texture of image can help to find similar pixel organization based object in the same image and/or in the image databases. Therefore the texture feature is studied in detail. In addition of that, a new texture analysis technique by manipulating the LBP (local binary pattern analysis) technique is proposed. The proposed technique helps to classify the similar texture patterns of the image contents. In order to demonstrate the effectiveness of the proposed texture analysis technique, an image retrieval model is also presented in this work. the information retrieval model first utilizes the LBP technique to find the different binary patterns in the query image and using the template matching technique extract the similar region of the image objects. Finally, the concluded features are queried with the KNN classification model to find the similar texture image in the database. This section provides the basic overview of the proposed texture classification technique. In next section the methodology of the proposed technique is provided.

B. Methodology

The proposed work includes two major contributions first the design a texture classification technique and second the implementation of proposed technique for image retrieval process. Therefore the entire description of the proposed methodology is divided in two major modules as:

Texture classification

DOI: 10.18535/ijecs/v5i10.09

The proposed texture classification concept is demonstrated using the figure 2.1. In this diagram the utilized entire components of the system is listed and the description is reported as:

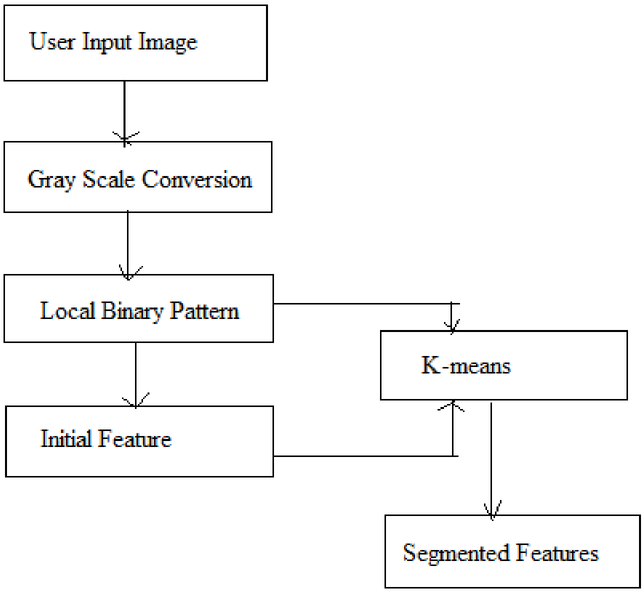

Figure 2.1 **Proposed texture classification**

User input image: That the user provided input for finding the texture feature of the image. The user is free to use any kind of image such as JPEG or PNG or other format of image to compute the features form the image contents.

Grey Scale conversion: For finding the image texture the Gray scaled images are more suitable, therefore in this phase the input image is transformed into the Gray scale image. To convert a color pixel of image in format of [R, G, B] to the Gray scale image the following formula is used.

$$G = \frac{R + G + B}{3}$$

Local binary pattern: The Grey scale converted image is now used with the LBP (local binary pattern) algorithm to locate the texture features of the image. The local binary pattern extraction technique can be defined as:

Given a pixel in the image, an LBP [24] code is computed by comparing it with its neighbours:

$$LBP_{P,R} = \sum_{P=0}^{P=1} s(g_p - g_c) 2^P$$

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

Where g_c is the gray value of the central pixel, g_p is the value of its neighbors, P is the total number of involved neighbors and R is the radius of the neighbourhood. Suppose the coordinate of is (0, 0), then the coordinates of g_p are

$$\left(R\cos\left(\frac{2\pi p}{P}\right), P\sin\left(\frac{2\pi P}{P}\right)\right)$$

The Grey values of neighbours that are not in the image grids can be estimated by interpolation. Suppose the image is of size I*J after the LBP pattern of each pixel is identified, a histogram is built to represent the texture image:

$$H(k) = \sum_{i=1}^{I} \sum_{j=1}^{j} f(LBP_{p,r}(i,j), k), k \in [0, k]$$

$$f(x, y) = \begin{cases} 1 & x = y \\ 0 & otherwise \end{cases}$$

Where, K is the maximal LBP pattern value. The U value of an LBP pattern is defined as the number of spatial transitions (bitwise 0/1 changes) in that pattern

$$U(LBP_{P,R}) = |s(g_{p-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{p-1} |s(g_p - g_c) - s(g_{p-\ldots}$$

The uniform LBP patterns refer to the patterns which have limited transition or discontinuities ($U \leq 2$) in the circular binary presentation. In practice, the mapping from$LBP_{P,R}$ to $LBP_{P,R}^{u2}$ which has P*(P-1) +3 distinct output values, is implemented with a lookup table of 2^P elementsTo achieve rotation invariance, a locally rotation invariant pattern could be defined as:

$$LBP_{P,r}^{riu2} = \begin{cases} \sum_{p=0}^{p-1} s(g_p - g_c) \; if U(LBP_{P,R}) \leq 2 \\ P + 1 \; otherwise \end{cases}$$

The mapping from$LBP_{P,R}$to$LBP_{P,R}^{u2}$which has P+2 distinct output values.

Initial features: Traditionally computed LBP features are termed here as the initial feature sets. Now the each different texture of the image is used to find the mapping of the image objects. Therefore the k-mean based process is used to find the similar image segments in the image contents.

K-means algorithm: Now the computed features and the input Grey scaled image is produced to the k--means for finding the image segments which contains similar compositions of the pixels.

Segmented features: Segmented images of the input image represent the different similar regions of the image objects.

The entire process of the image texture classification can be summarized using the following algorithm steps as given in table 2.1.

Input: User Image I Output: segmented images S_n
Process: 1. $IM = readImage(I)$ 2. $G = ConvertToGray(IM)$ 3. $F_l = LBP.findFeatures(G)$ 4. $TP = FindUniquePatterns(F_l)$ 5. $S_n = kmean.cluster(G, TP)$ 6. Return S_n

Table 2.1 **Proposed algorithm for texture classification**

C. Proposed Image Retrieval

The proposed model of the image retrieval using the proposed texture classification model is demonstrated using figure 2.2. The required components of the proposed model are demonstrated in the same diagram**.**

Input Query image: The proposed image retrieval technique is a content-based image retrieval technique. In this approach, the image-based query is supported for retrieving similar images from the image database. Therefore user provides a query image to the system for finding the relevant image according to the query.

Image database: In order to make the query there are two scenarios are required first the query scenario and the database scenario. The database scenario can be the storage of image which can be a structured database of the image repository on which the system search the similar object based images on the basis of the texture features.

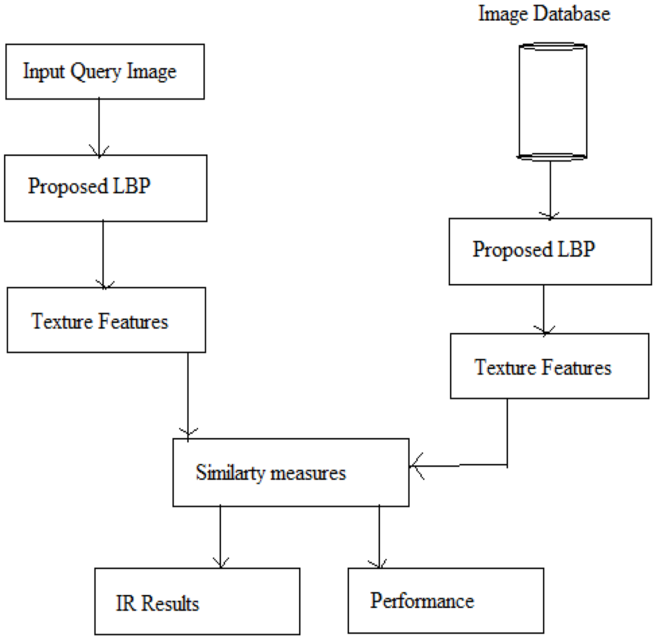

Figure 2.2 **Proposed IR model**

Proposed LBP: After both the input scenarios, the proposed LBP based texture classification is performed for locating the required objects in the queried image. The proposed technique of texture classification is defined in table 2.1.

Thus the query image and the databases images are processed using the texture classification technique and their textures are recovered**.**

Texture features: The extracted features from the query image and database images is computed and listed. In next, the similarity among both the features sets are computed and more likely featured images are selected as the outcome of the proposed image retrieval system.

Similarity measures: In this phase for computing the similar images from the existing image database features the traditional KNN (k-nearest neighbour) classifier is used with the Euclidean distance function. That helps to estimate the most accurate images from the databases.

IR results: For representing the outcomes of the search a results interface is constructed that is used to summit results of the current query.

Performance: Using the obtained search outcomes the performance of the proposed algorithm is computed in terms of precision, recall, and f-measures.

The process of proposed image retrieval technique can be demonstrated using the steps of processes or the algorithm steps. The required process of the proposed IR model is reported using the table 2.2.

Input: query image Q_i, Database images D_n Output: relevant images R_o
Process: 1. $QR = readQueryImage(Q_i)$ 2. 2. $QF_i = ModifiedLBP.Texture(QR)$ 3. $DR_n = readDatabaseImage(D_n)$ 4. $DF_i = ModifiedLBP.Texture(DR_n)$ 5. $for(i = 1; i \leq DF_i.length; i++)$ a. $D = \sqrt{(DF_i - QF_i)^2}$ b. $if(D \leq .25)$ i. $R_i.Add(DF_i.image)$ c. End if 6. End for 7. Return R_0

Table 2.2 proposed IR algorithm

RESULTS ANALYSIS

The implemented enhanced image retrieval technique using modified LBP texture classification is evaluated on the basis of the different experimental scenarios and different sets of data. The evaluated performance of the obtained system is described in this chapter with their outcomes.

A. Precision

In any data retrieval or search applications the precision is a fraction of search results which is most relevant to the input query. The provided precision of the proposed content based image retrieval system are given using figure 3.1. This can be evaluated using the user feedback basis and can be evaluated by the following formula.

$$precision = \frac{relevent\ document\ \cap retrieved\ documets}{retrieved\ documents}$$

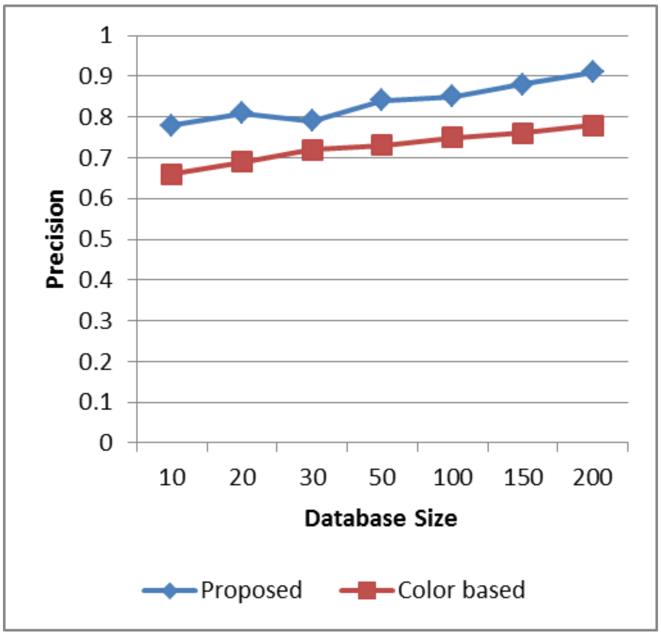

Figure 3.1 **Precision rate**

The precision rate of the implemented system is described in figure 3.1 and table 3.1. the computed precision values are demonstrated using the Y axis of the given figure and the X-axis of the figure. It shows the amount of training images in the database. According to the obtained results, the performance of the proposed system and traditional system is increases as the amount of data in the database is increased. In addition to the precision, rate is growing continuously as the similar kinds of images are also increases in database.

Amount of image in database	Proposed technique	Traditional technique
10	0.78	0.66
20	0.81	0.69
30	0.79	0.72
50	0.84	0.73
100	0.85	0.75
150	0.88	0.76
200	0.91	0.78

Table 3.1 **Precision rate**

B. Recall

In data retrieval application or the search application recall values are measured for accuracy measurement in terms of relevant document retrieved or relevant data obtained according to the input user query. This can be evaluated using the following formula.

$$recall = \frac{relevant\ doucment \cap retrieved\ documents}{relevant\ documents}$$

The figure 3.2 and the table 3.2 show the recall values of the proposed and traditional image retrieval application. In order to represent the performance of the both image retrieval system the X axis contains the amount of images in database and the Y axis reports the obtained recall rate of the implemented system. According to the obtained results the performance of the proposed system is enhances as the amount of data is increases in the database. The retrieval accuracy with the increasing amount of data is also increases thus the proposed concept is adoptable for the image search applications. Therefore the performance of the proposed system is much efficient as compared to the traditional method of image retrieval.

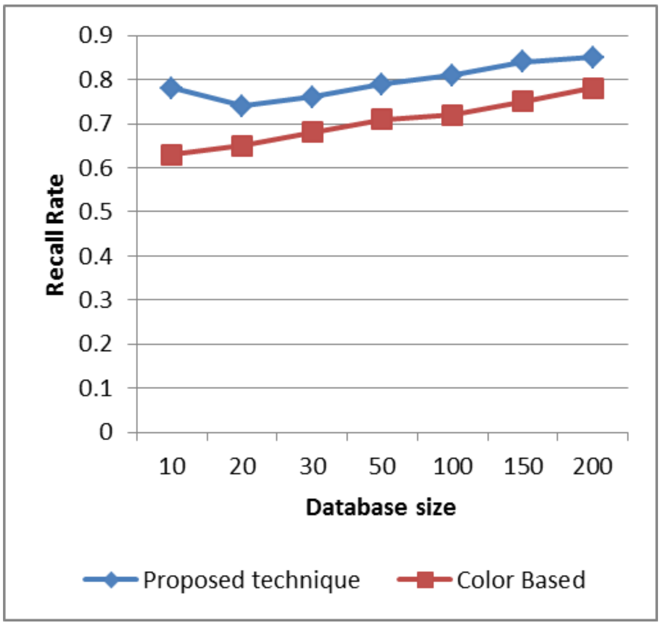

Figure 3.2 **Recall rate**

Amount of image in database	Proposed technique	Color technique
10	0.78	0.63
20	0.74	0.65
30	0.76	0.68
50	0.79	0.71
100	0.81	0.72
150	0.84	0.75
200	0.85	0.78

Table 3.2 **Recall rate**

C. f-measures

The f-measures of the system demonstrate the fluctuation in the computed performance in terms of precision and recall rates. The f-measures of the system can be approximated using the following formula.

$$f - measures = 2.\frac{precision\ X\ recall}{Precision + recall}$$

DOI: 10.18535/ijecs/v5i10.09

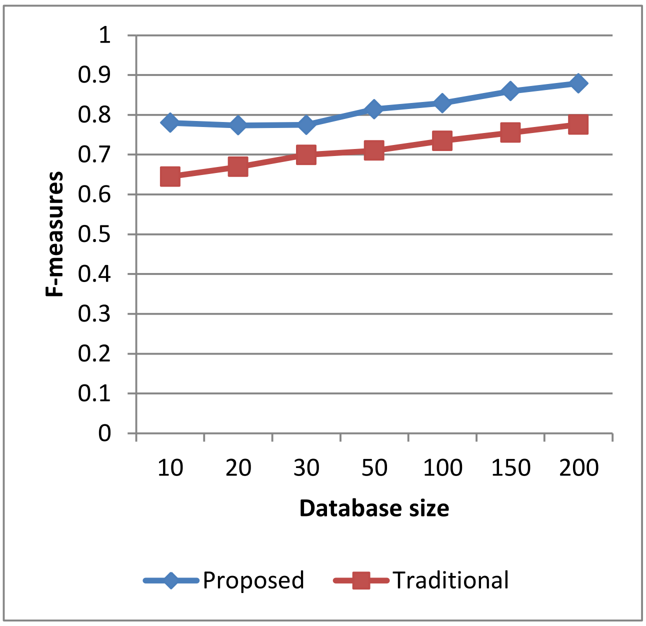

Figure 3.3 **f-measures**

Amount of image in database	Proposed technique	Traditional technique
10	0.78	0.6446
20	0.7734	0.6694
30	0.7747	0.6994
50	0.8142	0.71
100	0.8295	0.7346
150	0.8595	0.7549
200	0.8789	0.7756

Table 3.3 **f-measures**

The figure 3.3 and the table 3.3 show the performance of both the systems in terms of f-measures. To demonstrate the performance of the system the X axis shows the amount of data is placed in storage during experiments and the Y axis shows the obtained performance in terms of f-measures. According to the obtained results the performance of the proposed system is much stable and enhancing as compared to traditional method. In addition of that the results are more progressive manner as the amount of data base is increases. Thus the obtained results are adoptable and efficient for the image retrieval applications.

D. Memory used

The memory used sometimes also called the memory consumption or the space complexity. That amount of main memory required to execute a given algorithm with the amount of data is known as the memory consumption or space complexity of algorithm. The figure 3.4 and the table 3.4 show the performance of the system in terms of space complexity, in this diagram the X axis shows the amount of data available in data base and the Y axis shows the amount of memory consumed in terms of KB (kilo bytes). According to the obtained results the performance of the system becomes consistent and not consuming more memory even when the amount of data to be process is increases in the database but that produces a small amount of effect in memory consumption.

Amount of image in database	Proposed technique	Traditional technique
10	28498	27918
20	29347	28829
30	29854	29173
50	30148	30542
100	30852	31847
150	31104	31382
200	31859	31182

Table 3.4 Space complexity

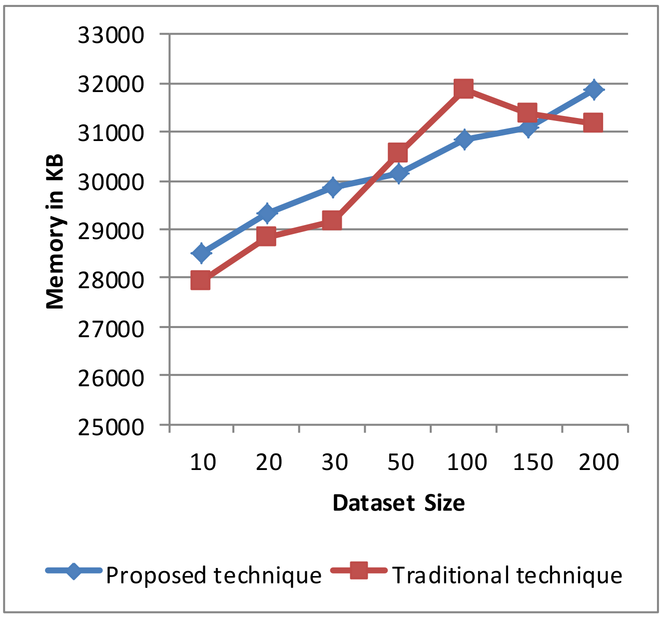

Figure 3.4 Space complexity

E. Time consumption

The amount of time required to complete the retrieval task after providing input to the system is termed as time consumption of the algorithm. The time consumption of the proposed technique is given using figure 3.5 and table 3.5. According to the demonstrated results the X axis contains the amount of images available in the database and the Y axis shows the amount of time consumed during the retrieval process in terms of milliseconds. According to the obtained results the performance of the system is fluctuating with the amount of data produced in the data base thus as the amount of data is increases the amount of comparison time is increases. Therefore the outcomes of the retrieval system take long time as the amount of data in database is increases.

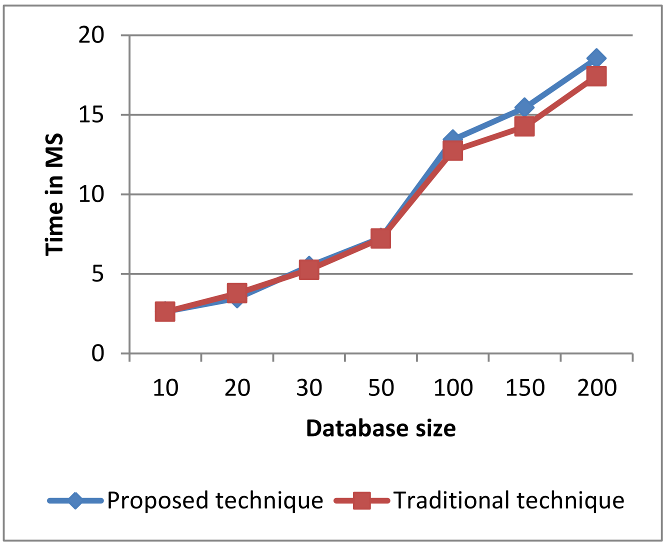

Figure 3.5 **Time complexity**

Amount of image in database	Proposed technique	Traditional technique
10	2.63	2.61
20	3.46	3.78
30	5.48	5.25
50	7.26	7.22
100	13.43	12.73
150	15.44	14.25
200	18.53	17.42

Table 3.5 **Time complexity**

I. CONCLUSIONS

The main aim of the proposed work is to optimize the texture analysis technique and their classification and application simulation. This chapter provides the summary of the entire work performed and the future extension of the work is also included.

The object recognition is one of the most popular domains now in these days of computation. In this technique the image based or visual features based images are used to recognize the images and their objects. In the study that is also found the number of techniques exists which claims to find the most accurate objects in the images or for image retrieval processes. In this presented work, the main aim is to optimize the technique of feature computation. Therefore the texture feature is explored in detail in this work. To study the impact of texture features in content-based image retrieval the traditional technique namely LBP (local binary pattern) is used.

During the LBP study, the method is explored and that is recognized through the available literature that technique helps to distinguish the similar objects in the given image. Therefore the LBP need to be modified for texture classification. To obtain accurate and efficient text classification technique the traditional LBP technique modified using the template matching concept. The template matching enables the method to classify the similar text objects in the given image. In addition of that to compare the proposed modified texture analysis technique, the traditional LBP technique is also implemented. In further, both the techniques are implemented for content based image retrieval process.

The implementation of both the techniques is performed using the visual studio technology and their performance is also compared with different performance parameters. Here for comparative performance study the precision, recall, f-measures are computed which demonstrate the accurate image retrieval according to the given image query. In addition of that, the time and space complexity is also evaluated from both the techniques. The entire obtained performance summary is demonstrated using the table 4.1

S.	Parameters	Proposed	Traditional

No.		technique	technique
1	Precision	High	Low
2	Recall	High	Low
3	f-measure	High	Low
4	Memory consumption	High	Low
5	Time consumption	High	Low

Table 4.1 **Performance summary**

The obtained results demonstrate the efficiency and accuracy of the obtained technique. Thus the proposed model is effective for object recognition task for different machine learning applications.

B. Future Extension

The main aim of the texture analysis of the images are performed successfully additionally the experimental results demonstrate the high accurate outcomes from the proposed algorithm. Thus the given work can be extendable for near future using the following concepts.

1. Extension for three dimensions object recognition

2. Extension with the similar object recognition in real world video based techniques.

REFERENCES

[1] Li Liu, Yunli Long, Paul Fieguth, Songyang Lao, and Guoying Zhao, "BRINT: Binary Rotation Invariant and Noise Tolerant Texture Classification", IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. X, NO. X, 2014.

[2] Sowmya Rani , Rajani N., and Swathi Reddy, "Comparative Study on Content Based Image Retrieval", International Journal of Future Computer and Communication, Vol. 1, No. 4, December 2012.

[3] Zhenhua Guo,Lei Zhang,David Zhang, "A Completed Modeling of Local Binary Pattern Operator for Texture Classification", IEEE transaction on image processing, 2010.

[4] Ritika, "Research on Data Mining Classification", International Journal of Advanced Research in Computer Science and Software Engineering, Volume 4, Issue 4, April 2014.

[5] David Filliat, Emmanuel Battesti, Stephane Bazeille, Guillaume Duceux, Alexander Gepperth, Lotfi Harrath, Islem Jebari, Rafael Pereira, Adriana Tapus, Cedric Meyer, Sio-Hoi Ieng, Ryad Benosman, "RGBD object recognition and visual texture classification for indoor semantic mapping", IEEE International Conference on, Apr 2012.

[6] Gustaf Kylberg and Ida-Maria Sintorn, "Evaluation of noise robustness for local binary pattern descriptors in texture classification", EURASIP Journal on Image and Video Processing 2013.

[7] Lin Zhang, Zhiqiang Zhou, and Hongyu Li,"BINARY GABOR PATTERN: AN EFFICIENT AND ROBUST DESCRIPTOR FOR TEXTURE CLASSIFICATION", IEEE 2012.

[8] Li Liu, Paul Fieguth, David Clausi, Gangyao Kuang, "Sorted random projections for robust rotation-invariant texture classification", Pattern Recognition, & Elsevier Ltd 2011.

[9] Li Liu, Lingjun Zhao, Yunli Long, Gangyao Kuang, Paul Fieguth, "Extended local binary patterns for texture classification", Image and Vision Computing Elsevier B.V. 2012.

[10] Li Liu, Yunli Long, Paul Fieguth, Songyang Lao, and Guoying Zhao, "BRINT: Binary Rotation Invariant and Noise Tolerant Texture Classification", IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. X, NO. X, 2014.

[11] Francesco Bianconi, Elena González, Antonio Fernández, Stefano A. Saetta, "Automatic classification of granite tiles through colour and texture features", Expert Systems with Applications, Elsevier Ltd. 2012.

[12] Chathurika Dharmagunawardhana, Sasan Mahmoodi, Michael Bennett, Mahesan Niranjan, "Rotation Invariant Texture Descriptors based on Gaussian Markov Random Fields for Classification", Elsevier Ltd 2015.

[13] Zhenhua Guo,Lei Zhang,David Zhang, "A Completed Modeling of Local Binary Pattern Operator for Texture Classification", IEEE transaction on image processing, 2010.