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Validation of Various Distance based Feature Vectors for SVM based CBIR System

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ABSTRACT
There are many distance measures used as features for achieving the content-based image retrieval, or CBIR task. but it's a challenge to adopt the best suitable features to fit for classification of multi class image dataset. The accuracy of CBIR techniques is heavily dependent on the selection of the derived features. Therefore, this paper aimed to validate the performance of various distance measures-based features including L1 norm, L2 norm, Mahalanobis, and correlation-based features. The paper proposes gabber filter and wavelet decomposition-based approach for feature vector reduction. The relative deviation, mean or RGB and moment are used as feature vectors for CBIR matching task. The support vector machine (SVM) is proposed to classify and implement the CBIR system for Corel 1K imaging data. The classification accuracy and class vie precision are validated for quarry image of African people. It is concluded that performance varied for different quarry images and maximum accuracy of 91.25 is achieved for correlation measure which offer nearly 6% improvement over Mahalanobis Distance measures.
Keywords: CBIR, Image Correlation, Moments, Mean, Deviation, Distance Measures, SVM, Classification.

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I.

II. INTRODUCTION

Owing to the growing demand for effective and efficient techniques to retrieve photos based on their content rather than metadata, content-based image retrieval (CBIR) has attracted considerable interest in the last decade [1]. With an emphasis on machine learning strategies, feature extraction methodologies, and assessment metrics, this study verified the effectiveness of feature vector-based approaches and CBIR developments.

The selection of the correlation and distance metrics is a key factor in CBIR feature extraction. The capacity of the system to precisely recognize and retrieve related photos is significantly affected by these actions. The retrieval accuracy is affected by different distance measures, such as Manhattan, Euclidean, or Mahalanobis, which offer differing degrees of sensitivity to feature variances [2, 3]. In contrast, correlation measurements aid in quantifying the links between traits, allowing for more complex comparisons. The particular image properties and intended retrieval results determine the best measurements. CBIR systems can increase their feature extraction capabilities, which will improve retrieval effectiveness and user satisfaction by carefully evaluating and implementing appropriate distance and correlation measurements.

1.1 CBIR Systems

The basic ML based CBIR system is illustrated in the Figure 1. the System uses a Support vector machine (SVM) based approach, and uses a user-inputted "query image" to be processed by classifiers. The system compares the query image to a large dataset, resulting in a matched set of images based on feature learning algorithms. Template images are used for training. The accuracy and efficiency of CBIR system highly varied based on the quality, quantity and diversity of the training dataset. Feature extraction techniques, such as colour histograms, and correlation measures and distance-based descriptors, play a crucial role in identifying relevant image feature matching ML approach. The paper has tested various such feature vectors for CBIR classification.

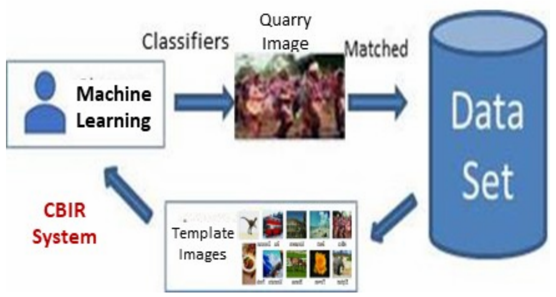

Fig. 1 The CBIR system using learning process

It is clear from Figure. 1 that the selection of suitable ML-based features is essential for determining the accuracy of the CBIR system. among all SVM classifiers is widely used for the relatively small and intermediate sizes of image datasets.The remainder of this paper is organized as follows. First, various distance measures based on the CBIR system are reviewed in section 2. The section also concludes with various advantages of correlation-based methods and tabulates the summary of methods, including their limitations. The CBIR relevant challenges are presented in Section 3, followed by Section 4, which describes the various distance-based feature voter modelling for the CBIR system. The validation of various CBIR systems with feature vectors, including databases, is presented in section 5. This is followed by the conclusions in section 6.

III. RELETED REVIEW

Numerous researchers have already sought to increase the effectiveness of CBIR systems. The Figure. 2 illustrates the classification of feature vectors used in Distance-based CBIR systems.

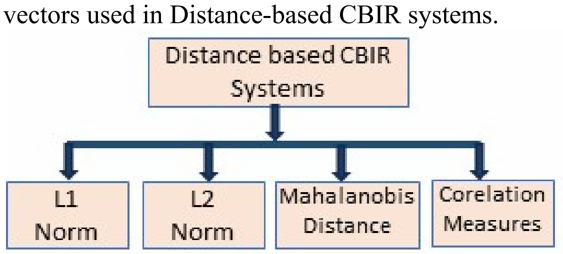

Fig. 2 Classification of feature vectors for CBIR

The CBIR System are classified into four sub-categories representing different distance metrics used to compare feature vectors: L1 Norm, L2 Norm, Mahalanobis Distance, and Correlation Measures. Each subcategory represents a different approach for calculating the distance or similarity between image feature vectors, ultimately influencing the retrieval results in a CBIR system. This section reviews some of the most relevant research in these fields.

A new approach to CBIR using multifeatured SVM classifiers was presented by Rose (2019). To improve the retrieval accuracy, this method places a strong emphasis on integrating several feature sets. This study shows that SVMs can greatly enhance the performance of CBIR systems when used in conjunction with carefully chosen features, underscoring the significance of feature selection in obtaining superior classification outcomes.Tian (2018) provided a thorough analysis of SVM's use of SVM in CBIR. The theoretical underpinnings of the SVM and its versatility across feature spaces were investigated in this study. Tian highlights the robustness of SVM classifiers in handling high-dimensional data and offers insights into how they might be enhanced for image retrieval applications by examining a number of experiments.

An enhanced SVM architecture created, especially for medical image retrieval, is the main emphasis of Chandra and Pinjarkar (2016). They draw attention to the particular difficulties that come with medical images, namely the variety of imaging modalities and the requirement for high retrieval precision because of therapeutic consequences. By utilizing cutting-edge feature extraction approaches, their suggested framework demonstrates the effectiveness of SVM in addressing these issues.

Using L1-norm SVMs, Haq et al. (2019) investigated feature selection and demonstrated how well it could identify Parkinson's illness in speech recordings. Although the primary focus of this study was on audio data, the feature selection concepts presented here can also be used for CBIR, where efficient feature extraction is essential for improving retrieval accuracy. Praveena et al. (2022) presented a hybrid feature-based Independent Condensed Nearest Neighbor model for CBIR, demonstrating the possibility of integrating several feature types to enhance system performance. The results of this study add to the continuing discussion on hybrid approaches in CBIR, despite the fact that it was retracted because of problems with the publication process.For multispectral satellite image retrieval, Joshi and Mukherjee (2017) empirically analyzed a variety of feature extraction techniques, including SIFT and Gabor filters, in combination with SVM. Their results highlight the importance of feature selection for improving retrieval, particularly in specialized applications such as satellite imaging.

The study evaluates distance measures in Convolutional Bayes Image Retrieval (CBIR) systems, establishing benchmarks for future research. Patel et al. (2020) discuss state-of-the-art similarity assessment techniques and hybrid features in CBIR systems. Hameed et al. (2021) review recent trends in CBIR, emphasizing the shift from traditional feature extraction methods to data-driven approaches. Rani et al. (2024) propose an efficient CBIR framework using separable Convolutional Neural Networks. Latha and Raj (2019) introduce a hybrid CBIR method that combines statistical features, DWT-Entropy, and POPMV-based feature sets. Gabriel et al. (2023) discuss a novel CBIR system that integrates feature descriptor techniques with accuracy noise reduction strategies. Koyuncu et al. (2021) analyse the broader context of CBIR research and present a convolutional fine-tuned threshold Adaboost approach.

The literature reviews CBIR research, highlighting various approaches, features, evaluation metrics, and hybrid methodologies. It emphasizes ongoing efforts to improve efficiency and address challenges in diverse image datasets.

Amongst all the correlation-based features are more accurate and widely used and have certain advantages. According to correlation based known CBIR determines the degree of similarity between two feature variation vectors. It performs well at detecting images with consistent contrast and brightness changes, as well as images with similar colour or spatial distributions. Additionally, it is easy to compute and utilize, and it performs well when matching patterns and textures. Database training is not necessary because CBIR operates in unsupervised environments. It may be used for a range of retrieval tasks and is adaptable for huge databases. It is very useful for remote sensing and medical applications. The various advantages of using the correlation based CBIR are illustrated in the Figure 3.

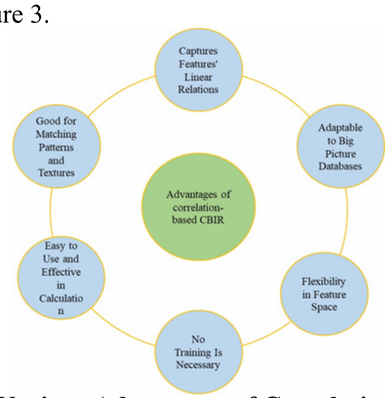

Fig. 3 Various Advantages of Correlation based CBIR

The summary of literature review and limitations are tabulated in the Table 1. The accuracy below 90% is low, 80-90 % ranged as intermediate, else marked high.

TABLE 1. SUMMARY OF LITERATURE REVIEW AND LIMITATIONS

Reference	Methodology	Feature Vectors	Accuracy	Limitations

[1] Rose (2019)	SVM Classifier with Multi Features	Multi-feature extraction techniques	High accuracy reported; specific metrics not detailed	May require extensive feature selection; computationally intensive
[2] Haq et al. (2019)	L1-Norm SVM for feature selection	Voice recordings (not images)	Effective recognition system demonstrated	Limited to audio data; not directly applicable to image retrieval
[3] Tian (2018)	Overview of SVM in CBIR	Various image features	General performance improvements noted	Lacks specific case studies or results; mostly theoretical
[4] Chandra &Pinjarkar (2016)	Improved SVM framework for medical images	Medical image-specific features	Enhanced retrieval performance shown	Limited to medical imaging; may not generalize well to other domains
[5] Praveena et al. (2022)	Hybrid features-based Condensed Nearest Neighbor model	Hybrid feature sets	High performance indicated before retraction	System retracted due to issues; details on accuracy uncertain
[6] Joshi & Mukherjee (2017)	Empirical analysis using SIFT, Gabor, and SVM	SIFT, Gabor features	Improved classification accuracy with fused features	May be sensitive to noise in images; requires careful tuning
[7] Hameed et al. (2021)	Review of recent trends	Texture, shape and distance-based hybrid	N/A	No new results provided; focuses on summarizing existing research
[8] Varma &Choudhary (2019)	Evaluation of distance measures	Various distance metrics applied to features	N/A	Focuses on evaluation rather than new methodologies; lacks direct application results
[9] Patel et al. (2020)	Similarity assessment techniques	Various image features	Intermediate accuracy	Conceptual overview without empirical validation; lacks experimental results
[10] Varma &Mathur (2020)	Survey on similarity measures	Hybrid feature sets	N/A	Theoretical discussion; lacks practical implementation details
[11] Rani et al. (2024)	Framework using separable CNNs	CNN-derived features	High accuracy claimed	Computationally expensive; requires large datasets for training
[12] Latha& Raj (2019)	Hybrid CBIR method	Statistical, DWT-Entropy, POPMV features	Improved retrieval efficiency around 90%	Complexity in feature integration; potential overfitting
[13] Vieira et al. (2023)	Feature descriptor integration with noise reduction	Integrated feature descriptors	Enhanced accuracy reported	May require significant preprocessing; noise handling can be complex
[14] Anand et al. (2024)	Statistical features with ML classifiers	Statistical features L1 norm, Mahalanobis L2 norm, etc.	Intermediate Accuracy	Limited to statistical analysis; potential for overfitting with too many features
[15] Koyuncu et al. (2021)	Analysis of CBIR techniques	Texture based	Intermediate	Review article; no new empirical data presented
[16] Cep et al. (2025)	Fine-Tuned Threshold Adaboost approach	Convolutional features	High retrieval efficiency reported	Complexity of combining multiple approaches; may require fine-tuning

V. OPTICAL RETINAL IMAGE DATA

CBIR is a difficult and complex field of study due to its semantic gap, difficulty in choosing relevant features, lack of understanding of high-level context, difficulty in creating queries, difficulties with feature extraction, constraints on similarity measures, and the handling of large databases. these challenges are illustrated in the Figure 4.

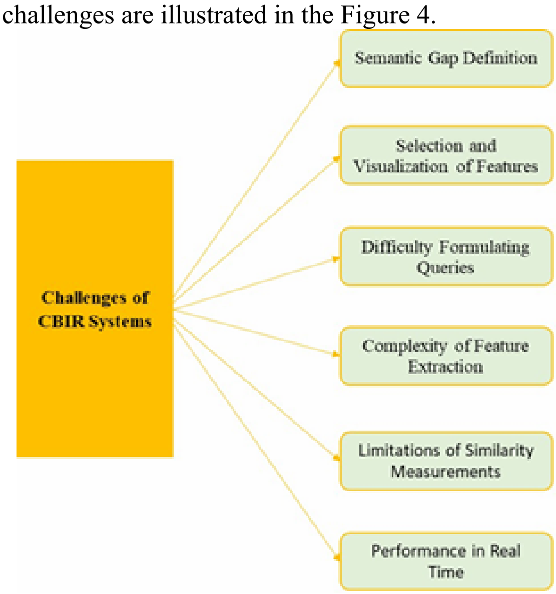

Fig. 4 CBIR system frequent challenges

Assessing the CBIR system's performance in real time and for different image classes is another unresolved issue. Overcoming the language barrier, choosing pertinent features, efficiently managing huge databases, and making sure recovery outcomes satisfy human standards are some of these difficulties. Object, emotion, and scene context recognition, query formulation, large-scale database management, high accuracy and instantaneous temporal retrieval, performance evaluation and comparison, handling various image kinds, and ethical and privacy concerns are all problems that CBIR must overcome.

VI. Various Distance Measures used for CBIR

With strengthening extracting features, closeness assessment, and ultimate investigation effectiveness, algorithmic learning provides an essential function for developing CBIR methods. The following were a few popular feature vectors for predictive modelling techniques for CBIR:

Mahalanobis distance: Distance metric for calculating the separation among a point with a distribution S is the Mahalanobis distance. It is especially helpful in determining how comparable feature vectors taken from images are in the context

IV.

of CBIR based image retrieval systems. The distance is mathematically calculated as in eq (1);

(1)

Distance is calculated between a point x and a mean vector μ, using the covariance matrix of
Where represents the image's feature vector under comparison. The target class or distribution's feature vectors mean is denoted by **μ**.The covariance matrix for the distribution's feature vectors is denoted by . The variable indicates that a vector of matrix has been transposed. The inverse of a covariance matrix being **.**

L1 Norm: The L1 norm has a distance metric that determines the absolute differences among the components of two vectors. It is sometimes referred to as the Manhattan or the taxicab distance. The similarity of feature vectors taken from images can be evaluated using the L1 norm in the context of CBIR systems.
Given two feature vectors dimensional space, the L1 norm distance is defined in eq. (2) as:

where; are features of Quarry image.
y are features of Template image.
is the absolute difference of ith features.
The L1 norm offers a simple method for quantifying the variation in feature values, which facilitates interpretation.also, it is comparatively less sensitive to outliers.
The query image can then be compared to other photos in the collection using this distance to find images that are comparable based on their feature descriptions.
L2 Norm: In CBIR system the L2 norm—also referred to as the Euclidean norm or distance—is a commonly used metric for evaluating how comparable two images are based on their representation of features. In Euclidean space, it measures the separation amongst two points, or feature vectors.Given two feature vectors dimensional space, the L2 norm distance is defined in eq. (3) as:

where is L2 norm distance amongst feature vectors.
Limitations: A single significant deviation in one dimension can have a disproportionate impact on the total distance since the L2 norm can be sensitive to outliers.It makes the assumption that each dimension adds the same amount to the distance, which might not be true in real-world situations where some qualities may be more important than others. Therefore, the performance of L2 norm varies according to the image data and features. for larger

depth or 3D features the L2 norm performance degrades.

Correlation Measure: In order to evaluate the relationship among features that are taken from images, correlation measurements are crucial in CBIR. They offer a means of measuring the degree of similarity or relatedness between two feature sets, which is very helpful when matching query images to databases template images.
The Pearson correlation coefficient, represented by the letter r, is one of the most widely used correlation metrics. It evaluates how well two variables or data sets correlate linearly. The method first calculated the standard deviations (SD) of x and for y feature vectors eq. (4) as;

Then the covariance matrix is determined as given in eq. (5);

(5)

Where, m is the number of feature vectors.
and*y* are the ithvectors of xand y features.
and is the mean vectors of xand y features
Finally, the Pearson correlation coefficient is determined and defined in eq. (6) as;

(6)

Thus overall, it can be observed that correlation-based approach is relatively more accurate and less sensitive to outliers. But method assumes strong cocreation in image contents for quarry and template images. The steps of CBIR are illustrated in Figure 5. As illustrated that each of the steps are sequentially discussed here.

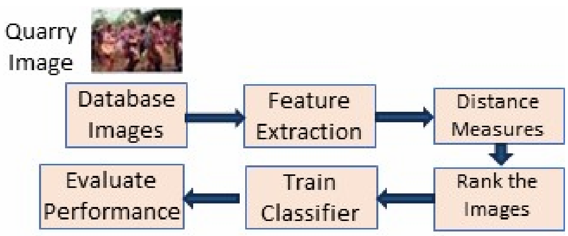

Fig. 5 Sequential CBIR proposed system diagram

Feature Extraction: Utilize techniques like colour histograms, based feature-based learning approaches to extract feature vectors using quarry and template images.
Distance Calculation: Determine the selected distance between each picture's feature vector y in the database and the query image represented by its colour feature vector x.
Sort the images according to their measured distances to the query image; closer distances signify a higher degree of resemblance.Retrieve the top-ranked images-based classifier as SVM as the result of the CBIR process.

VII. Validation and database Results

The CBIR system is validated and SVM performance is tested using the Corel1K image dataset. There are total of 10 classes with 100 images each within every class of data. The dataset image sample are shown in the Figure 6.

The quarry image of 5th African people class is used for validation in this paper. The performance of four feature vector is evaluatedas by reference in Abdivokhidov et al [17].

Fig 6 Corel 1K Image database and class representation

5.1 Results of Image Classification.

In this section the validation results for the African image data class under quarry is presented. The quarry image is initially selected and then feature vectors for quarry and template database images are matched based on the minimum distance and 6 best fit images are selected for the validation. The first experiment is performed by selecting the feature vector as L1 norm. the Confusion matrix for reduced features using SVM is presented for L1 Norm distance in Figure 7. the 5th African people quarry image is selected. it can be observed that relatively low accuracy is noted per class.

	Africa	Beach	Monum	Buses	Dinosa	Elephar	Flowers	Horses	Mounta	Food
Africa	82.00% (41)	4.00% (2)	10.00% (5)	0	0	0	0	0	0	4.00% (2)
Beach	8.00% (4)	62.00% (31)	14.00% (7)	4.00% (2)	0	0	0	0	10.00% (5)	2.00% (1)
Monuments	8.00% (4)	6.00% (3)	72.00% (36)	0	0	4.00% (2)	0	2.00% (1)	4.00% (2)	4.00% (2)
Buses	6.00% (3)	0	6.00% (3)	88.00% (44)	0	0	0	0	0	0
Dinosaurs	0	0	2.00% (1)	0	98.00% (49)	0	0	0	0	0
Elephants	0	2.00% (1)	10.00% (5)	0	0	84.00% (42)	0	4.00% (2)	0	0
Flowers	0	0	0	0	0	0	100.00% (50)	0	0	0
Horses	2.00% (1)	0	4.00% (2)	0	0	0	0	88.00% (44)	0	6.00% (3)
Mountains	0	16.00% (8)	14.00% (7)	4.00% (2)	0	4.00% (2)	0	0	58.00% (29)	4.00% (2)
Food	6.00% (3)	2.00% (1)	2.00% (1)	0	0	2.00% (1)	0	0	0	88.00% (44)

Fig. 7 Confusion matrix for L1 Norm for m=6

The second case of experiment is performed by selecting the feature vector as Mahalanobis distance. The Confusion matrix based on feature matching and classification using SVM for Mahalanobis distance is given in Figure 8. It can be seen that Mahalanobisdistance improves the class representation accuracy by 6 % compared to

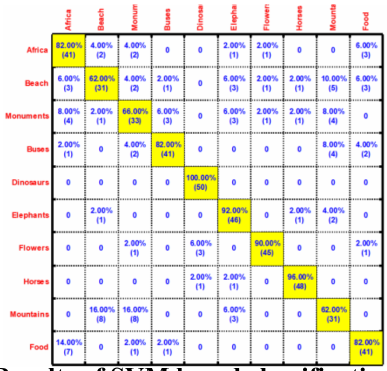

Fig. 8 Results of SVM based classification using the Mahalanobis distance matric for Africa images as quarry

Finally, the classification result of Confusion matrix for Correlation measures based on feature matching and is given in the Figure 9. Method offers relatively higher prediction accuracy for each class.

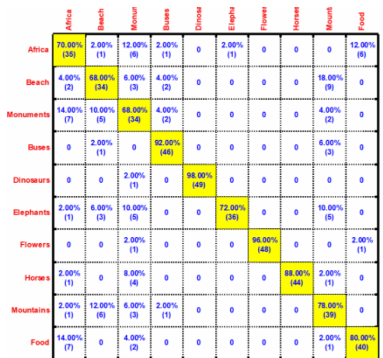

Fig. 9 Results of SVM based classification using the Mahalanobis distance matric for Africa images as quarry

The relative performance of comparison of the classification accuracy is presented in the Table 2. The Table 2 displaying the accuracy of SVM-based classifications using different distance measures and reported accuracy of 79%, 85.8%, and 91.25% respectively for L1 norm, Mahalanobisand Correlation measures.

TABLE 2. OVERALL ACCURACY FOR SVM BASED CLASSIFICATIONS FOR DIFFERENT DISTANCE MEASURES

Feature	Accuracy
L1 norm	79%
Mahalanobis Distance	85.8%
Correlation Measures	91.25 %

The maximum accuracy of 91.25% for quarry image is reported for correlation based CBIR system. although the performance highly depends on the image contents.

Fig 10 Retrieved images with four different distance measures for m=6

The retired image results as an example validation for four different distance measures are presented in the Figure 10. it can be observed that each feature vector retrieves the different set of images for the same Quarry. image which is the 5th image. although every measure accurately retrieves the input Quarry image.
The Table 3 have compared the state of art performance for correlation-based methods. it is concluded that our approach offers better accuracy for similar dataset.

TABLE 2. OVERALL ACCURACY FOR SVM BASED CLASSIFICATIONS FOR DIFFERENT DISTANCE MEASURES

Methods	Accuracy
PunitSoni, et al [18] for HOG	80.02%
PunitSoni, et al [18] for SURF	79. 8%
Proposed Correlation Measures	91.25 %

VIII. CONCLUSIONS AND FUTURE SCOPES

This paper validates the performance of various distance measures-based features, including L1 norm, L2 norm, Mahalanobis, and correlation-based features, for content-based image retrieval (CBIR) using a support vector machine (SVM) classifier on the Corel 1K image dataset. The paper proposes a gabor filter and wavelet decomposition-based approach for feature vector reduction, and uses relative deviation, mean of RGB, and moments as feature vectors for CBIR matching. The classification accuracy and class-wise precision are validated for a query image of African people.

The paper concludes that performance varies for different query images, with a maximum accuracy of 91.25% achieved for correlation measures.

The paper also discusses the challenges of CBIR systems, such as the semantic gap, difficulty in selecting relevant features, and handling large databases. The sequential steps of the proposed CBIR system are illustrated, including feature extraction, distance calculation, sorting, and retrieval of top-ranked images using an SVM classifier.

The validation results for the African image data class are presented, with confusion matrices and retrieved images for different distance measures. The overall accuracy for SVM-based classifications is reported as 79%, 85.8%, and 91.25% for L1 norm, Mahalanobis, and correlation measures, respectively. To evaluate the approach's scalability and generalizability, the evaluation must be extended in the future to larger and more varied image datasets than Corel 1K.In order to determine the approach's suitability for particular CBIR tasks, it will also be evaluated in the future on domain-specific image sets (such as satellite imagery and medical imaging). Additionally, it is beneficial to incorporate various distance measurements and feature kinds into hybrid models in order to possibly increase retrieval accuracy even more.

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