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Extraction and Representation of Low-Level Image Features for an Improved CBIR System using PCA Algorithm

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Abstract

Fast and efficient picture search in huge image databases has gained widespread acceptance in a variety of applications these days. CBIR (content-based image retrieval) is a method of retrieving pictures that is based on automatically determined image attributes. It uses a variety of unique picture feature extraction approaches to find relevant photos. Even if higher level qualities are used to eliminate semantic gaps in the data that may be obtained from visualised information, there is a disparity in how different people understand graphical information, and these semantic variances are difficult to eliminate. The presented ultra-real-time CBIR system is based on low-level characteristics. Lower level qualities such as colour, texture, and shape are extracted using various approaches in this study, and all of the information is recorded in feature vector representation format, which is then combined to build a unique feature vector. Then, using the Euclidean Distance Similarity Metric, these extracted image characteristics are compared to other image attributes. Using accuracy and recall rates, the performance of the proposed approach is evaluated with three current CBIR approaches. When compared to eighteen other ML algorithms, the proposed methodology has reported a greater precision-recall rate and is more efficient.

Keywords: *CBIR, Neural Network, Machine Learning, PCA algorithm*

1.0 Introduction

This data is now used as images in almost every aspect of social life, including business, government, colleges, hospitals, corruption prevention, surveillance, engineering, and historical study, resulting in a rapid increase in the extent of digital information. These photographs and their data are categorised and stored on machines, and problems arise when retrieving them from collected media. As a result, Content Based Image Retrieval (CBIR) from large resources has grown in relevance in recent years, particularly in the preceding decade. The term "content-aided" refers to the fact that the exploration focuses on the information contained in the image rather than the metadata.In CBIR system, visual features of the image like colour, texture, shape or any content could be autonomously mined from the image and employed to retrieve relevant images from the image data samples. These features are known as low-level features which have certain visual properties of an image. The obtained images are further graded conferring to similarities between the query image and images in the data samples using a similarity matching metric[1]. CBIR technique comprises two significant approaches: feature mining and similarity matching[2].

Since images are high in information and deprived of

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linguistic restricted to assist worldwide interactions, etc., CBIR has a wide range of applications in a variety of sectors, including military operations, medical science, education, architectural design, justice division, and agriculture, among others, because images are rich in information and lack language restrictions to aid international connections, etc. Customer digitalized photographs, digitalized galleries, Moving Picture Experts Group (MPEG-7) content descriptor, common picture pool for approving, and typical gatherings are examples of CBIR's common appliances. CBIR systems have been established in recent years to efficiently process large image data samples. In order to obtain similar pictures from an image dataset, low-level characteristics in the image are used. Various CBIR techniques have been used to execute various approaches Global colour and texture characteristics were used in some techniques, whereas local colour and texture attributes were used in others. Shape is also a property that may be used to recognise objects indefinitely. Colour, texture, and form are the most beneficial features of CBIR in terms of toughness, efficacy, execution ease, and reduced storage requirements[3].

According to the CBIR approaches, characteristics may be divided into two categories: lower level and higher level attributes. Lower-level qualities are used to eliminate sensuous distinctions between the entity in the world and the data in a portrayal created from a cassette of that sight. The higher level characteristics are used to eliminate the semantic gap in the data obtained from the displayed data. Knowledge and the explanation that similar information might provide for a person in a certain situation[4]. These semantic discrepancies are difficult to eliminate since different people have different levels of knowledge of pictorial information. The presented ultra-real-time CBIR system is based on low-level characteristics. In order to address this problem, this work proposes an enhanced CBIR technique that uses colour, texture, and form attributes to effectively compare a query image with a huge image database in order to get comparable images with a greater precision and recall rate[5]. Thus, HSV colour quantization for colour features, threshold technique on Binary image for texture features, and radial Chabysev approach for shape features are used to extract colour, texture, and shape features from an image database. Finally, using the basic Euclidean distance as a similarity measure, the query feature vector is matched with the target feature vector in the picture collection[6].

2.0 Low-Level Feature Extraction and Representation based Improved CBIR System

A novel Content-based Image Retrieval Methodology is described in this part, in which the contents of pictures, such as colour, textual, and form features, are retrieved for accurate image retrieval. The diagrammatic representation for suggested approach is given in Figure 1. Three separate steps are used to elaborate and discuss the suggested solution. For image comparison, they are Feature Extraction, Feature Representation, and Similarity Measure.

2.1 Feature Extraction

Multi-level 3D Colour-texture feature is an integrated feature which contains information from both Colour and texture. Integrated features are far more effective in comparison to individual features of Colour and texture[7]. For the proposed CBIR system along with multi-level 3D Colour-texture feature, other-low level features are also used i.e., Colour moments, and histogram in 10 probability bins. CLCM (Colour Level Co-Occurrence Matrix) or multilevel 3D Colour-texture features are based upon the GLCM (Grey Level Co-Occurrence Matrix). 14 features are defined by Harlick[17], but due tostrong co-relation only four are used to extract the CLCM i.e., contrast, co-relation, energy and homogeneity.

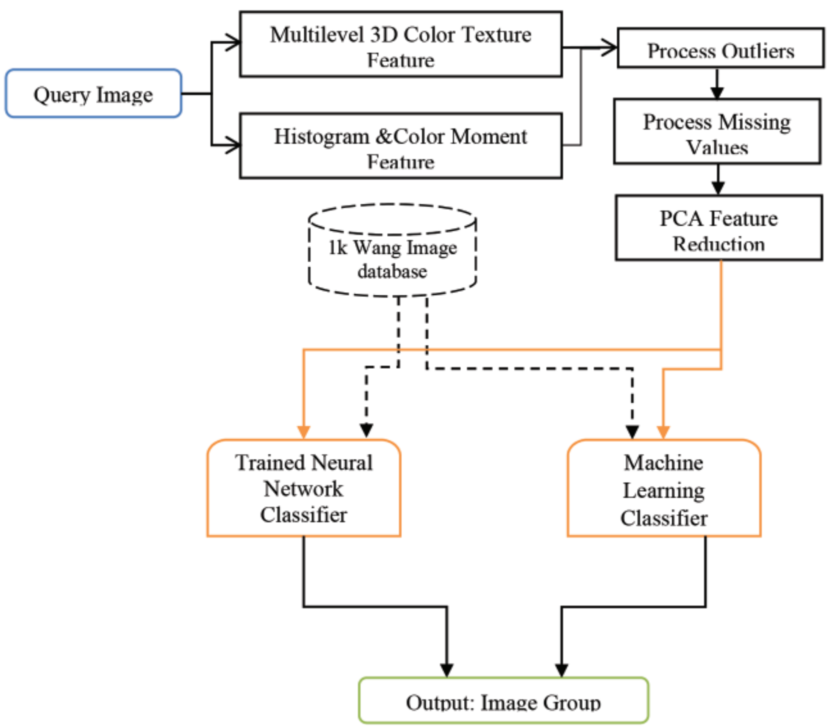


Figure 1: Functional block diagram of Improved CBIR System using Multi-Level 3D Features and PCA

2.2 Feature Selection

PCA Test is one of the best procedures assessed to better optimise the characteristics. These tests are used as feature selection ranking algorithms. Each image is represented by 90 feature points, which are reduced to 80 after applying PCA algorithms and compared. Feature selection techniques aid in reducing the computing complexity of a classifier while simultaneously increasing its speed and accuracy[8].

Figure 2 explains the best regression result with record number of traits and their responses. It shows best model regression result response. Apply PCA to the predictor variables to produce principal components, matching the number of principal components to the number of original features. Keep the first k principal components, where k is selected by cross-validation, that account for the majority of the variance (where k p). Fit these k primary components into a linear regression model using ordinary least squares. According to the theory, the data's greater variability and (presumably) its relevance to the objective variable are best represented by the lesser number of primary components.

PCA tests are a univariate feature ranking approach for classification that assesses predictors and responses, with each predictor variable being independent of the response variable[9]. The strongest correlation with response is shown by the smallest predictor values, which is an important feature. PCA (Principal Component Analysis), enforces a sign convention. It makes each column of coefficients positive who have largest magnitude element. Although changing sign doesn't change its actual meaning. It helps to reduce or select the features to the important ones[18].

2.3 Classifiers

To evaluate and establish the proposed algorithm it is tested with Neural Network Classifier and various machine learning algorithms.

Figure 3, represents the NN classifier that was used to do the evaluation. It takes 80 feature points from each image as input and employs 40 hidden layers. The Levenberg-Marquardt approach is utilised, in which training terminates when generalisation does not improve any more, as shown by the mean square error. Support vector machines, or SVMs, are assessed using six different kernels: linear, quadratic, cubic, fine gaussian, medium gaussian and coarse gaussian. SVM will constantly try to locate the optimum hyperplane to the greatest extent feasible. Only for linear separable problems it can find the hyperplane. However, several binary classifiers can be used to find numerous classes. Different kernels provide it flexibility for non-linear problems as well[18]. Table-I represents different type of kernels used to evaluate the system.

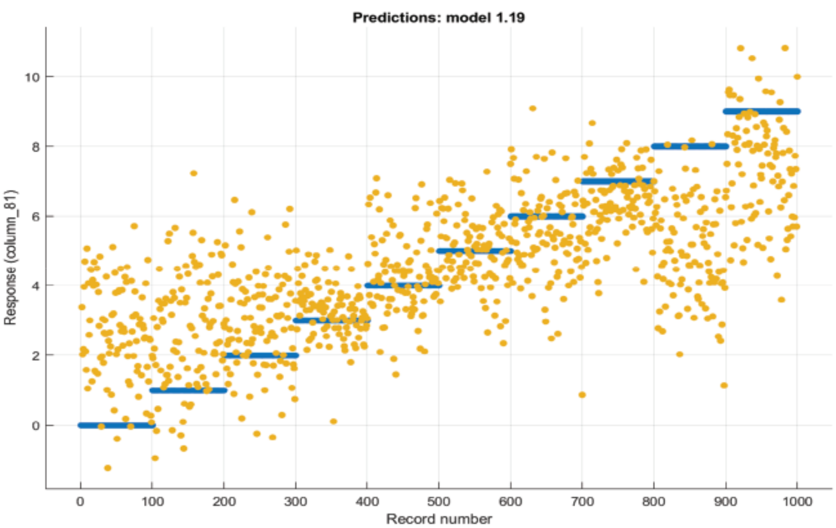


Figure 2: Regression result of PCA model

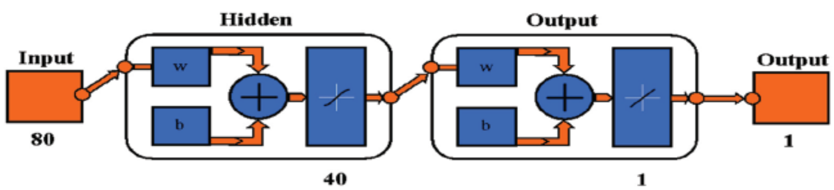


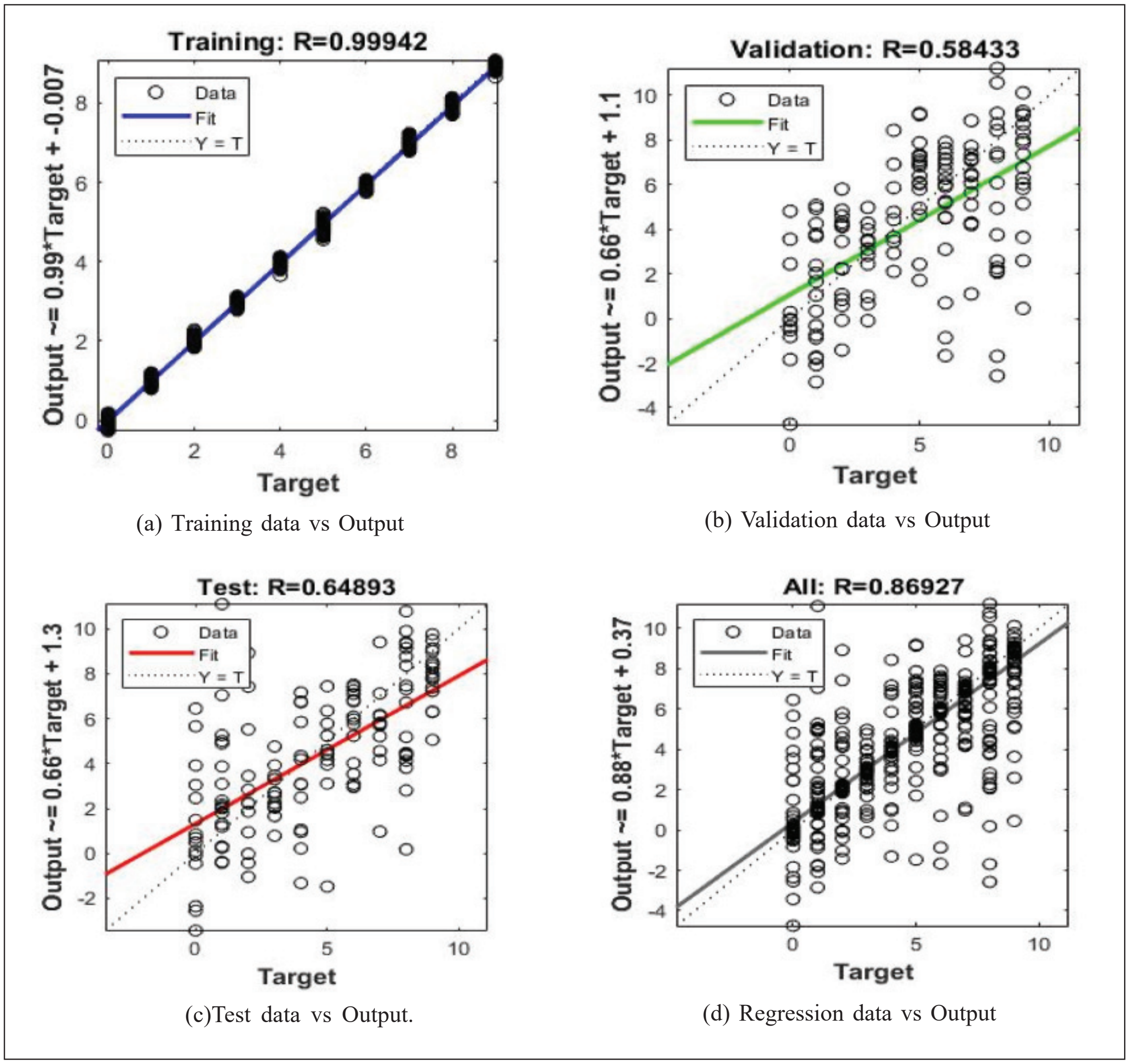
Figure 3: Architecture of Back Propagation Neural Network Classifier

3.0 Experimental Results and its Analysis

Best result is obtained by using (CLCM) 3D multi-level Colour-texture feature, which are further optimized by PCA ranking and

Table 1: Neural Network Classification Results

	Method	Feature points	Reduced feature point	NN layers	Regression result
1	PCA	90	80	40	0.87



(a) Training data vs Output

(b) Validation data vs Output

(c)Test data vs Output.

(d) Regression data vs Output

Figure 4: Regression Results of NN Classifier

multilayer back propagation neural network. In terms of classification accuracy, 87% is achieved. Figure 4 represents the regression results of training, validation and testing of NN classifier with PCA optimization whichare 0.994, 0.584 and 0.648 respectively.

By carefully comparing machine-learning models with parallel experiments, we looked into the results and found the PCA algorithm yields best classification accuracy among all other tested algorithms. More crucially, in several fields, including cyber security, natural language processing, bioinformatics, robotics and control, and the analysis of medical data, PCA has surpassed well-known ML techniques.

Table 2 shows the result comparison of NN classifier in terms of classification accuracy.

Figure 5 compares the present results, which are shown to be the most accurate, to other unique work carried out by

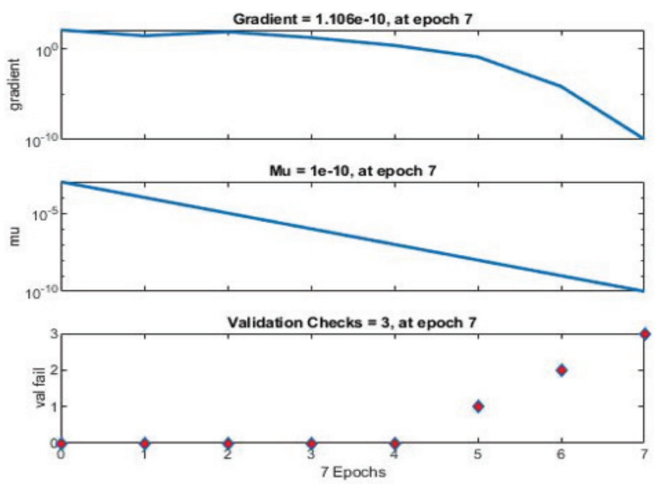


Figure 5: Result Comparison with above machine learning algorithm

Table 2: Machine Learning Algorithm Results

	Model Name	Type	RMSE	R-Squared
1	Linear Regression	Linear	2.92	-0.04
2	Linear Regression	Interactions Linear	19.07	-49.07
3	Linear Regression	Robust Linear	3.12	-0.19
4	Tree	Fine Tree	3.11	-0.17
5	Tree	Medium Tree	2.87	0.00
6	Tree	Coarse Tree	2.68	0.13
7	SVM	Linear	2.19	0.41
8	SVM	Quadratic	2.22	0.40
9	SVM	Cubic	2.28	0.37
10	SVM	Fine Gaussian	2.87	0.00
11	SVM	Medium Gaussian	2.01	0.51
12	SVM	Coarse Gaussian	2.18	0.42
13	Ensemble	Boosted Trees	2.28	0.37
14	Ensemble	Bagged Trees	2.28	0.37
15	Gaussian Process Regression	Squared	2.00	0.51
16	Gaussian Process Regression	Matern	2.00	0.51
17	Gaussian Process Regression	Exponential	1.98	0.52
18	Gaussian Process Regression	Rational Quadratic	1.99	0.52

nineteen machine learning algorithm in terms of outcomes precision.

4.0 Conclusion

Nineteen different artificial intelligence and machine learning algorithms are used to represent and evaluate a new type of feature and its further optimization technique. PCA is one form of feature optimization approach that has been investigated. Feature optimization approaches minimise the amount of features, which reduces computing complexity and improves the overall system's accuracy and speed. The proposed approach is highly suited and produces the best results for CBIR, as evidenced by comparisons to other innovative research. Wang-1K or Corel-1K databases are used to test the system. Integrating other essential elements such as form and textual inquiry, as well as establishing the method with other databases, are other areas where improvements may be made.

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