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Content-based Image Retrieval Using the 2-Dimensional Convolutional Neural Network

Rajath Arakere Narayanaswamy[1,2]* **Vidyalakshmi Krishne Gowda[2]**
Geevagondanahalli Narayanappa Keshava Murthy[3]

[1]*Department of Computer Science & Engineering,*
GSSS Institute of Engineering & Technology for Women, Mysuru, India
[2]*Department of Computer Science & Engineering (Data Science),*
Sri Siddhartha Institute of Technology, SSAHE University Tumakuru, India
[3]*Department of Electronics and Instrumentation Engineering,*
Siddaganga Institute of Technology, Tumakuru, India
* Corresponding author's Email: rajath191985@gmail.com

Abstract: The utilization of content-based image retrieval (CBIR) technologies poses a considerable challenge within research domains because of immense volume of multimedia content accessible on internet. There are billions of images uploaded to internet every tear, it seems like a challenging effort for the research community to identify a relevant image using search engines. To effectively retrieve relevant images, 2-Dimensional Convolutional Neural Network (2DCNN) based CBIR is implemented in this work. The stages involved in this implemented method are data collection, pre-processing, feature extraction, and classification. At first, image data are collected from the Caltech 256, Corel 1.5 K, 5 K, 1.5 K datasets, and Normalization is utilized to eliminate noise in pre-processing phase. After, features like texture, shape, color, etc. are extracted utilizing the Principal Component Analysis (PCA) technique, and finally, relevant images are retrieved utilizing the 2DCNN approach. The existing methods such as Deep Neural Network based on the search and Rescue (DNN-SAR), Discrete cosine transform-based singular value decomposition (DCT-SVD), and low-level features and deep Boltzmann machine with content-based image retrieval (LB-CBIR) method are compared with the implemented method, and this 2DCNN method achieved a better classification value of 99.99% accuracy.

Keywords: Content-based image retrieval, Classification, 2DCNN, Deep learning, Principal component analysis.

1. Introduction

In recent decades, the multi-media and internet have attained rapid growth in this technological world. Web images from various sources such as multimedia, duplicate video detection, storage systems, and medical image diagnosis, have increased as a result of technological advancements. [1, 2]. So, CBIR is a major task in image processing [3], and it was developed by the researchers to retrieve the data obtained from large databases [4]. CBIR has become one of significant research fields that can be effective in the retrieval of medical images [5]. In this sense, the CBIR system processes images directly, assessing image features are essential elements to identify an image and classify groupings of images in a general way based on how similar their virtual representations appear [6]. Texture, color, and form features are the features that are typically employed in CBIR. Since these are low-level features, they can be required not only for image retrieval but also for many other applications, including computer vision, BL, image recognition, and classification [7].

Basic requirement for any image retrieval system is the ability to use a computer to search and sort related images from the archive with the least amount of human interaction [8]. Researchers have recently created a novel technique for retrieving images that automatically indexes images based on visual content/features like color, shape, and texture [9]. To extract texture features during indexing of images, several methods are frequently employed, including Hidden Markov random field, Gray-Level Co-occurrence Matrix (GLCM), CH, HSV Colour Space, HSV, Local binary patterns-based descriptors (LBP), etc [10]. Previous approaches used both locally and globally defined image characteristics to evaluate visual information [11]. Therefore, it is insufficient to construct an efficient CBIR system also based on texture [12]. CBIR is a new DL-based technology that enables pathologies to conduct speed and precise searches on previously identified and treated cases [13]. The majority of image retrieval systems are therefore unable to utilize the advantage of partially identified datasets [14]. Most of the approaches in CBIR utilized one to two feature descriptors which results in poor accuracy values [15]. The main contributions of this proposed model are given below,

- Caltech 256, Corel 1.5 K, 5 K, 1.5 K datasets were employed to analyze performance of proposed 2DCNN model.
- Pre-processing is performed by utilizing normalization process to remove the unwanted noises present in the images which increases method's performance and passed to feature extraction.
- PCA is used to extract the most practical features and minimize dimensionality by removing non-co-related features without affecting much of the image's information.
- 2DCNN is used for the CBIR classification process. Implemented approach's performance is analyzed to recall, accuracy, precision, and f-score.

This paper is arranged as follows: literature survey is explained in Section 2, and methodology is given in Section 3. Results and discussion are explained in Section 4, and Conclusion is in Section 5.

2. Literature survey

Nepoleon Keisham & Arambam Neelima [16] implemented a Deep Neural Network based on search and Rescue (DNN-SAR) approach, used for the effective retrieval of relevant images. This implemented approach was efficient in increasing the CBIR performance and reducing the feature dimension. Caltech 256, Corel 1.5 K, 5 K, 1.5 K were four datasets utilized to evaluated this implemented method. As a result, this approach used decreased the DL technology error and enhanced the categorization accuracy. Due to less amount of image retrieval analysis, this method needs to create faster memories with more processing power to enhance the greater number of image retrieval analyses.

Fatemeh Taheri [17] implemented a low-level features and deep Boltzmann machine (LB-CBIR) model, which was utilized for extracting effective features. This implemented LB-CBIR feature vector method was combined with mid and low-level image features. This method provided more details of image texture employing for analysis multi-criteria fractal geometry. However, the implemented approach fails to detect the image of irregular shapes.

Wenqing Wang [18] implemented a 2-phase CBIR algorithm-based feature fusion and sparse representation for Sparse Feature Learning (SFL), which combined local and global features to retrieve images. The important retrieval phase and the rough retrieval stage were two phases of the architecture of this implemented CBIR system. The sparse feature learning (SFL) model was employed for high numbers and high dimensions of local features and this attained superior retrieval performance. However, this method was not strong to images with complex scenes, hence DL-based CBIR was to develop large-scale image retrieval.

Mukul Majhi & Arup Kumar Pal [19] implemented a hybrid Discrete cosine transform-based singular value decomposition (DCT-SVD) used for an image retrieval scheme. Block-level salient features were extracted in 2 steps: first-phase features were formed followed DCT application, and second-phase features were attained followed SVD process. Olivia, Corel-1K, Caltech-256, GHIM-10K, and Corel-10K were five datasets employed to evaluate this implemented method. Weight factor was applied to fused feature, and implemented work's retrieval outcome provided a satisfactory result. However, the hybrid approach lacks in flexibility while segmenting the image with improper edges.

Niranjana Sampathila [20] have introduced a computational approach for Content-Based Image Retrieval (CBIR) of K-similar images. Suggested approach utilized visual features like shape, texture, and color of images for retrieving similar images from a huge dataset. Image retrieved using the suggested approach with the specified characters was used in the process of diagnosing the disease. In CBIR methodology, Haralick's texture features and the histogram-based Cumulative Distribution Function (CBF) were evaluated. Finally, the K-Nearest Neighbor method was used in the process of retrieving the image that is closest to the query

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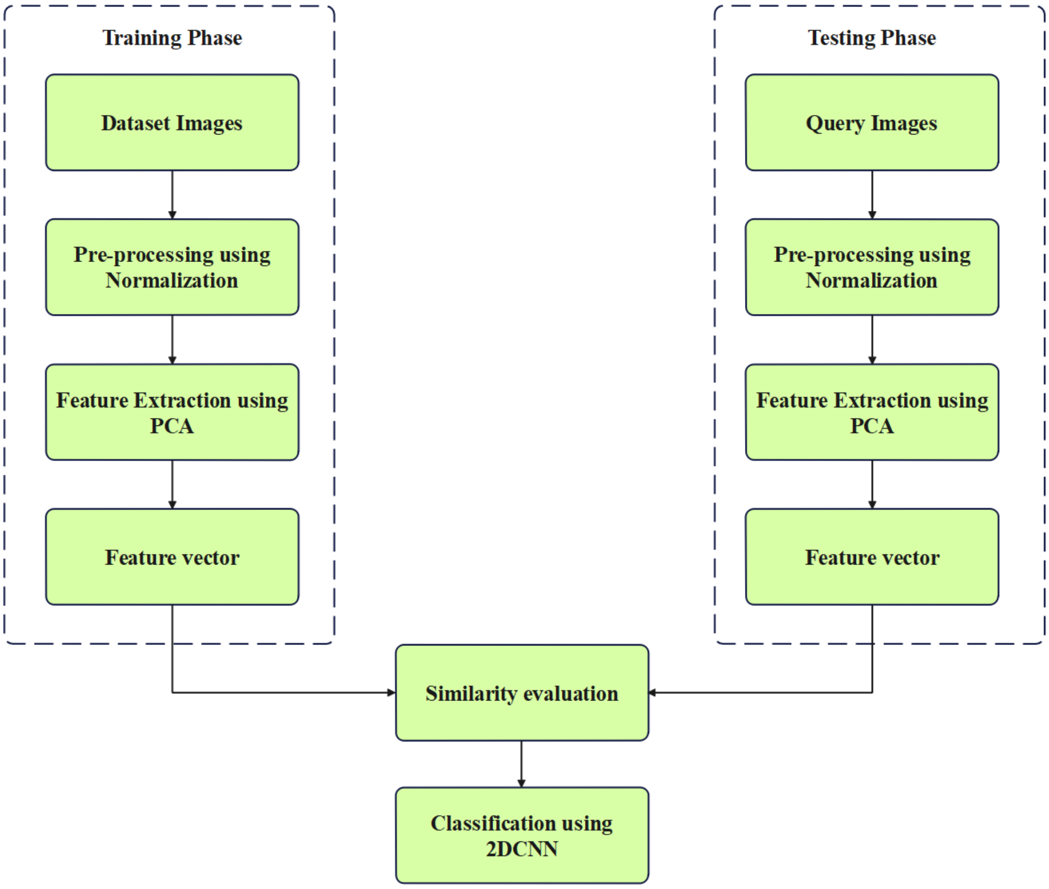

Figure. 1 Block diagram of implemented method

(a) (b)

Figure. 2 Sample original and similar images of the Caltech 256 dataset: (a) Original Image and (b) Similar Image

database. However, the implemented had less performance in image retrieval.

Fatemeh Taheri [21] implemented low-level features and deep Boltzmann machine with content-based image retrieval (LB-CBIR) method. This method was an advanced image description by combined the low-level features and deep Boltzmann machine used for extracted effective features in CBIR. Corel 5 K, Oxford buildings, Caltech-256, Corel 10 K, Corel 1 K-Scale, and Corel 1 K-illumination were dataset. Wavelet transform and multi-criteria fractal geometry evaluates were combined in this method provided the high image texture. Due to high semantic gap in image retrieval, this method needs to use saliency-based images methods to decrease semantic gap in retrieval of image.

3. Methodology

In this study, a 2DCNN model is proposed to categorize Content-Based Image Retrieval (CBIR). Implemented method's block diagram is illustrated in Fig. 1. Caltech 256, Corel 1.5 K, 5 K, 1.5 K datasets are utilized in this paper for gathering the images and the normalization is utilized for pre-processing the image, which improves model performance. PCA is employed to extract features from pre-processed images. At last, 2DCNN is employed for the CBIR categorization process.

3.1 Dataset collection

In this work, Caltech 256, Corel 5 K, 1.5 K, 1 K are four datasets utilized in this implemented method. Caltech 256 dataset has some unique features such as new and larger clutter categories, larger category sizes, and overall increased difficulty. It is also considered one of the greatest datasets which are used to train the models for visual recognition. Sailboats, frogs, cell phones, and many other categories in cluttered images are recognized by this dataset. There are 30,607 images in the Caltech 256 [22] image dataset, which are divided into 256 groups. Of the 30,607 images in total, 60% are chosen at random for training purposes, while the remaining 40% are chosen for testing. Fig. 2 shows the Caltech 256 dataset's sample original and similar images.

3.2 Pre-processing

Following the data collection, the raw data is pre-processed to remove the unwanted noises present in the images. In this study, pre-processing is used to eliminate noises from the image, and normalization is employed to modify the image's pixel intensities. Normalization is pre-processing technique is primarily to prepare data part for DL methods. The purpose of normalization is to use an essential scale to regulate values of numerical data in a database (i.e., values among 0 and 1) without changing losing data or original value ranges. To maintain values on a scale that is adapted to all of the numeric columns utilized in this technique, normalization is applied to developing a unique value is resource data ratios and control basic distribution.

3.3 Feature extraction

After pre-processing, feature extraction is an important step in the CBIR system to extract the features in the dataset. The extraction of the feature is an effective tool to extract the significant informative and discriminative features that improve the performance of image retrieval. In this study, the PCA approach used for the process of feature extraction is given below,

3.3.1 Feature extraction

This PCA is a commonly utilized eigenvector-based method that helps to extract the most practical features and minimize dimensionality by removing non-co-related features without affecting much of the image's information. PCA's primary advantage is its extremely low noise sensitivity, which it employs to discover the internal data structure based on information variances. Additionally, PCA performs computationally faster because it requires less information. By using this method, a decreased number of uncorrelated variables can be generated from the initial collection of correlated variables. The variables that are obtained from the conversion process are known as principal components (PCs). This procedure aims to make it easier for researchers and statisticians to understand complex data by allowing them to find the best balance between decreasing the number of variables and losing original information (variance) as a result of minimizing the original dimensions. Extracted features output is passed as input to classification phase, and this improves classification outcomes.

3.4 Classification using 2DCNN

The selected features are categorized by utilizing 2DCNN method which produces significant outcomes in different fields include image processing, diagnosis systems, and language processing. In addition to Multi-Layer Perceptron (MLP), CNN uses fewer parameters and neurons, leading to minimal complexity and rapid adaptability. There are numerous uses for the 2D-CNN model in CBIR classification. A type of DL model and Feed-Forward Neural Network (FFNN) is the CNN. The independent position reduces the parameter quantity because of the convolution operation's detention convention constant. The 3 layers' kinds found in CNN are convolution, pooling, and fully connected (FC) layers. Dimensionality reduction, feature extraction, and classification all depend on these layers. Thie filter is slid on the computers through the forward pass of the convolution operation, and the activation is obtained by adding the input capacity of the activation map, which analyses the point-wise result of each score. The sliding filter is defined as a quick distribution of the dot product and is used by the linear and convolution operators. Consider x is input, w is kernel function, $(x \times w)(a)$ on time t is expressed as Eq. (1),

$$(x \times w)(a) = \int x(t)w(a-t)da \tag{1}$$

Where a is R^n for each $n \geq 1$. Parameter t is discrete which is represented in Eq. (2),

$$(x \times w)(a) = \sum_a x(t)w(t-a) \tag{2}$$

K is a 2D kernel, 2D image I as input, and convolution is given as Eq. (3),

$$(I \times K)(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n) \tag{3}$$

To increase non-linearity, two various activation functions are employed like SoftMax and ReLU. ReLU is provided in Eq. (4),

$$ReLU(x) = \max(0, x)\, x \in R \tag{4}$$

The gradient $ReLU(x) = 1$ for $x > 0$ and $ReLU - (x) = 0$ for $x < 0$. Convergence ability of ReLU is best than non-linearity's of sigmoid. Following layer is softmax, preferable when output required to involve classes of 2 or more which expressed in Eq. (5),

$$softmax(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_i)} \tag{5}$$

The pooling layers are used to rescale the output structure without sacrificing any essential information and produce an input statistic. There are different pooling layers kinds, this work employed highest pooling that individually generates large values in individual points (i,j) rectangular neighborhood in 2D information for each input feature accordingly. Final layer is FC layer with m and n illustrated outcome and income. Output layer's parameter is denoted as weight matrix $W \in M_{m,n}$. Rows and columns represented by m and n, and bias vector $b \in R^m$. Eq. (6) represents activation function f with fully connected layer output, where the input vector is $x \in R^n$.

$$FC(x) := f(Wx = b) \in R^m \tag{6}$$

Where Wx is matrix product f function is utilized as component. This layer of FC is used for difficulties in classification. CNN's FC layer is generally included at top level. Production of CNN is compressed and represented as a single vector.

3.4.1 Principle components in 2DCNN

The input layer preparation is comprised of principal components from every pixel, and fed as input layer into the 2DCNN shown in Fig. 4. All N spectral bands of each pixel are analyzed by PCA to obtain the first Q main components. Target pixel's input layer is formed by the Q primary components from every R×R pixel that surrounds the target pixel. PCS utilizes the spatial information present in the hyperspectral data to extract main features in spectral dimension. 2DCNN architecture utilized with a FC layer represented by FC(20R′′ × R′′ × M) and convp-n(1 × 2 × 2) and convp20(20 × 2 × 2) compositions. Because of a cascade of 4 convp-20(1 × 2 × 2), outcome 2DCNN is exceedingly nonlinear and can recognize more extract spatial-spectral patterns stored in data of hyperspectral.

4. Results and discussion

Python 3.7, and Anaconda Navigator 3.5.2.0 are used to classify the CBIR in this experiment. The system requirements for the implemented research method are as follows: Intel Core i7 7500 processor, 16 GB RAM, and Windows 10 (64-bit). The implemented approach's effectiveness is evaluated in terms of f1-score, accuracy, recall, and precision. The expression of these parameters is represented in Eqs. (7)-(10),

$$Accuracy = \frac{TP+TN}{TN+TP+FN+FP} \tag{7}$$

$$F1 - score = \frac{2 \times TP}{2 \times TP+FP+FN} \tag{8}$$

$$Precision = \frac{TP}{TP+FP} \tag{9}$$

$$Recall = \frac{TP}{TP+FN} \tag{10}$$

where TP denotes true positive, TN represents true negative, FP shows false positive, and FN represents

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Table 1. Various classifiers without PCA for the Caltech 256 dataset

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RNN	89.62	85.34	83.21	84.48
GRU	68.86	67.41	60.78	62.93
CNN	65.41	58.76	55.90	57.82
2DCNN	96.32	95.92	96.53	95.98

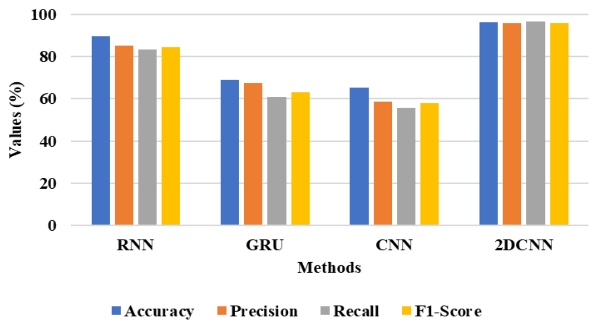

Figure. 3 CBIR classification without PCA for the Caltech 256 dataset

Table 2. Various classifiers with PCA for the Caltech 256 dataset

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RNN	91.45	87.02	85.04	86.01
GRU	70.45	69.06	63.04	65.91
CNN	68.56	61.32	58.05	59.64
2DCNN	99.99	99.99	99.99	99.99

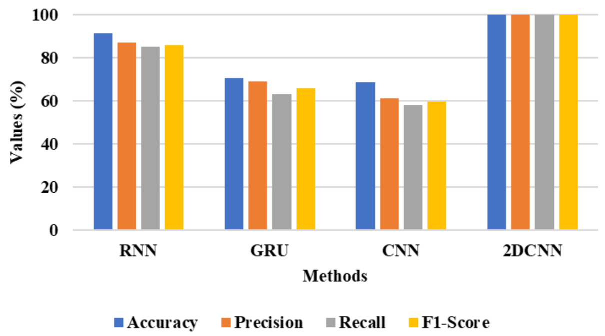

Figure. 4 CBIR classification with PCA for the Caltech 256 dataset

false negative.

4.1 Quantitative analysis

Quantitative analysis of 2DCNN methods is explained in this section in terms of recall, f1-score, precision, and accuracy are representing in Tables 1-8. Implemented 2DCNN model was compared with

Table 3. Various classifiers without PCA for the Corel 1K dataset

Methods	Precision (%)	Accuracy (%)	F1-Score (%)	Recall (%)
RNN	85.53	89.76	86.98	90.68
GRU	91.36	90.53	85.65	91.36
CNN	87.84	88.42	90.32	88.20
2DCNN	**94.20**	**95.50**	**94.36**	**95.41**

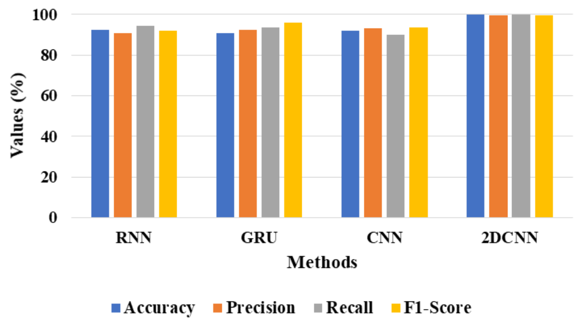

Figure. 5 CBIR classification without PCA for the Corel 1K dataset

state-of-the-art methods like Gated Recurrent Unit (GRU), Recurrent Neural Network (RNN) Convolutional Neural Network (CNN), and Compared to other techniques such as RNN, GRU, and CNN, the 2DCNN is more effective in CBIR. The 2DCNN is able to automatically learn and recognize texture, shapes, and patterns in images because other state-of-the-art methods are unable to capture local patterns and spatial hierarchies.

- **Caltech256 dataset:**

Table 1 and Fig. 3 show classifiers performance on Caltech 256 dataset without PCA. The RNN, GRU, and CNN's performance metrics are measured and evaluated with implemented 2DCNN model. Obtained outcome represents that implemented 2DCNN method attained better outcomes by employing performance metrics like recall, precision, F1-score, and accuracy values of about 95.98%, 95.92%, 96.53%, and 96.32%, while comparing other methods of classifiers.

Table 2 and Fig. 4 show classifiers performance on dataset of Caltech 256 with PCA. Performance metrics of CNN, GRU, and RNN are evaluated and matched with implemented 2DCNN method. Obtained outcome shows that implemented 2DCNN method attains better outcomes by utilizing performance metrics like precision, recall, F1-score, and accuracy values of about 99.99%, 99.99%, 99.99%, and 99.99% while comparing other classifiers.

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Table 5. Various classifiers without PCA for the Corel 1.5 K dataset

Methods	Precision (%)	Accuracy (%)	F1-Score (%)	Recall (%)
RNN	**89.54**	**80.69**	**85.60**	**82.71**
GRU	**86.79**	**82.74**	**83.58**	**84.28**
CNN	**84.93**	**85.27**	**88.88**	**87.99**
2DCNN	**92.57**	**92.68**	**92.89**	**91.28**

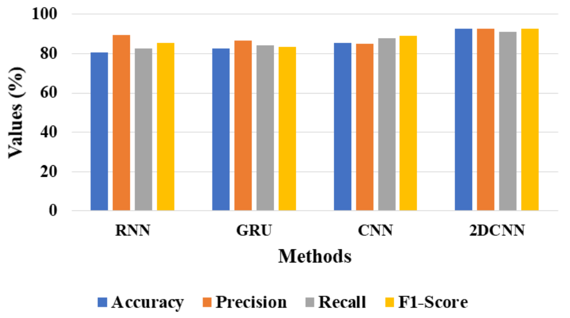

Figure. 7 CBIR classification without PCA for the Corel 1.5K dataset

Table 6. Various classifiers with PCA for the Corel 1.5 K dataset

Methods	Precision (%)	Accuracy (%)	F1-Score (%)	Recall (%)
RNN	90.97	89.45	93.79	91.84
GRU	93.64	92.12	91.46	94.95
CNN	96.31	94.30	95.13	97.20
2DCNN	**99.79**	**99.84**	**99.80**	**99.83**

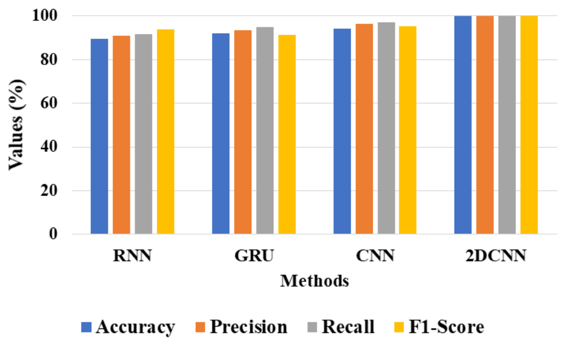

Figure 8. CBIR classification with PCA for the Corel 1.5 K dataset

- **Corel 1 K dataset**

Table 3 and Fig. 5 denotes classifiers performance on dataset of Corel 1K without PCA. Performance metrics of CNN, RNN, and GRU are evaluated and matched with implemented 2DCNN method. Acquires output signifies that implemented

Table 7. Various classifiers without PCA for the Corel 5 K dataset

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RNN	**87.12**	**82.23**	**86.41**	**84.96**
GRU	**89.56**	**85.54**	**81.85**	**88.52**
CNN	**85.78**	**83.89**	**89.63**	**90.74**
2DCNN	**92.70**	**92.48**	**91.78**	**92.50**

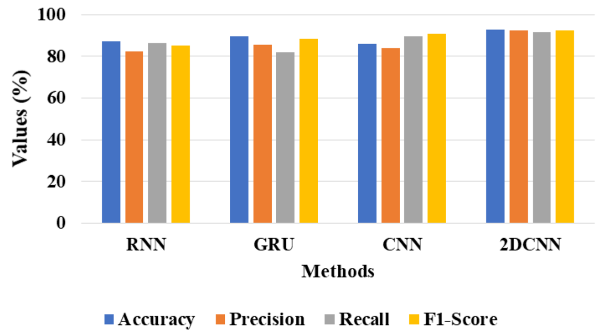

Figure. 9 CBIR classification without PCA for the Corel 5 K dataset

2DCNN method achieves better outcomes by using performance metrics like recall, precision, F1-score, and accuracy values of 95.41%, 94.20%, 94.36%, and 95.50%, while comparing other classifiers.

Table 4 and Fig. 6 represent classifiers performance on dataset of Corel 1K with PCA. The performance metrics of CNN, GRU, and RNN are evaluated and matched with implemented 2DCNN method. Attained outcome illustrates that implemented 2DCNN method obtains better outcomes by utilizing performance metrics like recall, precision, F1-score, and accuracy values of about 99.80%, 99.72%, 99.72%, and 99.80% while comparing other classifiers.

- **Corel 1.5 K dataset**

Table 5 and Fig. 7 show the performance of classifiers on the Corel 1.5 K dataset without PCA. Performance metrics of RNN, GRU, and CNN are evaluated and matched with the implemented 2DCNN model. Attained result denotes that the implemented 2DCNN model obtains better results by using performance metrics include recall, precision, accuracy, and F1-score values of about 91.28%, 92.57%, 92.68%, and 92.89% while comparing other classifiers.

Table 6 and Fig. 8 signifies classifiers performance on dataset of Corel 1.5K with PCA. Performance metrics of CNN, GRU, and RNN are evaluated and matched with implemented 2DCNN model. The gained output represents that

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Table 8. Various classifiers with PCA for the Corel 5 K dataset

Methods	Precision (%)	Accuracy (%)	F1-Score (%)	Recall (%)
RNN	89.60	95.31	92.79	92.84
GRU	94.27	93.97	93.46	96.51
CNN	90.38	91.64	95.13	94.30
2DCNN	99.85	99.90	99.86	99.89

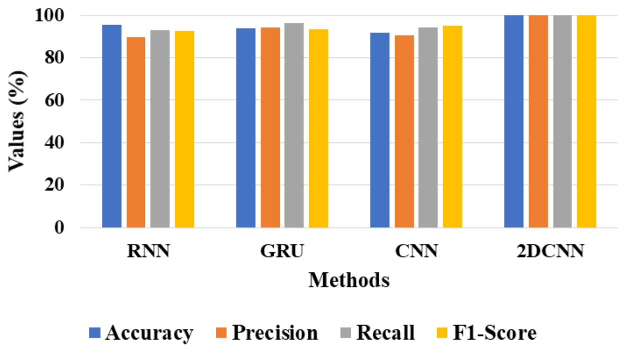

Figure. 10 CBIR classification with PCA for the Corel 5 K dataset

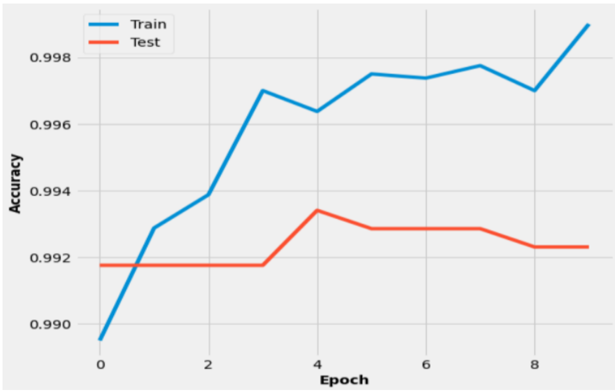

Figure. 11 Accuracy training and testing's graphical representation

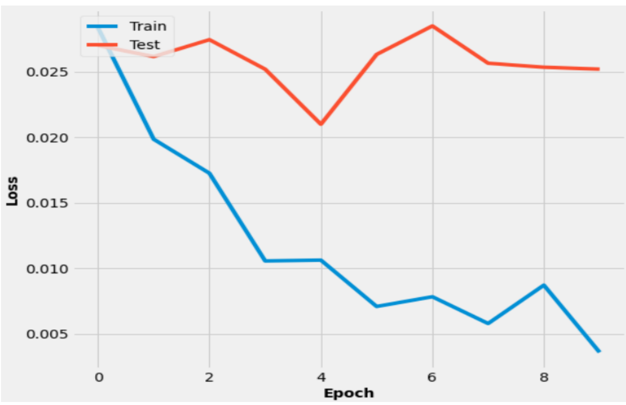

Figure. 12 Loss training and testing's graphical representation

implemented 2DCNN method obtains better results by using performance metrics include recall, precision, accuracy, and F1-score values of about 99.83%, 99.79%, 99.84%, and 99.80% while comparing other classifiers.

- **Corel 5 K dataset**

Table 7 and Fig. 9 illustrate classifiers performance on dataset of Corel 5 K without PCA. Performance metrics of CNN, GRU, and RNN are evaluated and matched with implemented 2DCNN method. Acquired result shows that implemented 2DCNN method obtains better outcomes by employing performance metrics are recall, precision, F1-score, and accuracy values of 91.78%, 92.48%, 92.50%, and 92.70% while comparing other classifiers.

Table 8 and Fig. 10 represent classifiers performance on dataset of Corel 5 K with PCA. Performance metrics of CNN, GRU, and RNN are evaluated and matched with implemented 2DCNN method. Attained outcome shows that implemented 2DCNN method attains better results by using performance metrics are recall, precision, accuracy, and f1-score values of about 99.89%, 99.85%, 99.90%, and99.86% while comparing other classifiers.

Classification of the accuracy training and testing shown in Fig. 11 in that 10 epochs were utilized and accuracy differs from 0.990 to 1. Training accuracy indicates in blue color and testing accuracy indicates in red color. Loss training and testing of the 2DCNN model are shown in Fig. 12. The loss training and testing 10 epochs were utilized and loss varies from 0.005 to 0.030. Training loss is represented in blue color and the testing loss is represented in red color. A training accuracy of 0.999 is attained in Fig. 11.

4.2 Comparative analysis

This section demonstrates comparative analysis of 2DCNN classifier with performance metrics include accuracy, precision, recall, and f1-score as shown in Table 9. Existing research like [16, 19, 21] are employed to estimate classifiers ability. Implemented method is trained, tested, and validated by using the Caltech 256 dataset. Accuracy was increased to 99.99%, and precision of 99.99%, respectively.

4.3 Discussion

Implemented method's advantages and existing models' drawback are discussed in this section. Drawback of existing models are such as DNN-SAR

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Table 9. Implemented method with existing methods comparative analysis

Author	Method	Accuracy (%)	Precision (%)
Nepoleon Keisham &Arambam Neelima [16]	DNN-SAR	90.3	N/A
Mukul Majhi & Arup Kumar Pal [19]	DCT-SVD	N/A	60.35
Fatemeh Taheri [21]	LB-CBIR	75.2	32.12
Proposed	**2DCNN**	**99.99**	**99.99**

[16] method had less image retrieval analysis. So, this method needs to improve image retrieval analysis by expanding faster memories with powerful processing capacity. SFL [18] method was not robust to images with complex scenes, hence DL-based CBIR was to develop large-scale image retrieval. Loc-VAE [20] method during the query time, similar features were extracted which affected the overall performance of the image retrieval. Caltech 256, Corel 1.5 K, 5 K, 1.5 K datasets were employed to analyze proposed 2DCNN method's performance. Extracted different feature vectors from images employing the PCA technique to achieve better classification. The 2DCNN method is employed to increase the capability of the system for CBIR classification. Therefore, 2DCNN approach for CBIR provides increased accuracy and convergence speed by utilizing CNN's memory capabilities, enabling better adaptation to complex spatial content and improving the process of extraction for robust and efficient CBIR.

5. Conclusion

At present, CBIR appears to be a curious research topic, and effective CBIR techniques are explained with the Deep Learning (DL) approach. The 2DCNN technique implemented in this work improves learning process to reduce gap among use and the system of CBIR and helps users retrieve images according to their preference. Here, collecting images from the dataset requires several characteristics, including color, shape, and texture. In this study, feature vectors were extracted from normalized images using a PCA technique. The implemented 2DCNN method is utilized for classification, with extracted optimal features provided as input to the process. When compared to existing methods, Caltech 256, Corel 1.5 K, 5 K, 1.5 K datasets provided best result from the implemented method. Proposed method achieved existing methods for CBIR classification with values of 99.99%, 99.99%, 99.99%, and 99.99% in terms of f-score, recall, accuracy, and precision using Caltech 256 dataset. This method will expand to represent a novel and efficient texture-based image retrieval system built on transfer learning, region networks, and convolutional autoencoders.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, have been done by 1st author. The supervision and project administration, have been done by 2nd and 3rd author.

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