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ARTICLE

AN ENSEMBLE OF OPTIMAL DEEP LEARNING ARCHITECTURE WITH RANDOM FOREST CLASSIFIER FOR CONTENT BASED IMAGE RETRIEVAL SYSTEM

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ABSTRACT

Content based image retrieval (CBIR) extract the details from the images depending upon the content exist in the image as feature descriptors. It intends to the process of retrieving images with maximum resemblance among the visual content exist in the massive databases. Feature extraction and similarity measurement are the two essential steps involved in CBIR. This paper presents an ensemble of optimal AlexNet architecture with random forest (RF) classifier called EOANA-RF model to effective retrieve the images from the databases. Since AlexNet model does not offer superior results on large databases, the AlexNet architecture is optimized in three ways. Firstly, the average pooling undergoes replacement with max-ave pooling, Maxout is employed in fully connected (FC) layers and hidden layer is included to map high-dimension features to binary codes. Then, similarity measurement and RF based classification process takes place to retrieve the images related to the query image (QI) from the databases and classifies it. The performance of the proposed model undergoes validation using Corel10K dataset. The obtained simulation outcome verified the enhanced performance of the proposed model on the applied dataset.

KEY WORDS
Image retrieval, CBIR, Corel 10K, AlexNet, Similarity measurement

INTRODUCTION

In general, information retrieval as become an essential objective along with the requirements of multimedia data processing for detecting the practical information. Hence, image retrieval (IR) is been a typical and most organized tool. It is more essential to execute and enhance the tools used for IR to explore images present on internet in a productive manner. Many types of traditional IR system depends upon a keyword search which tends to several disadvantages like, maximum requirement of man power as well as dependency on personal aspect that generates improper outcome. In order to manage these limitations, a novel mechanism has been established named as CBIR method [1]. This model is comprised with collection of techniques which mainly focus in minimum level image features, for instance texture values, structure as well as color signature for retrieving images from database which are based on QI provided by a customer [2]. Previous CBIR models perform in an inconvenient form while using higher level methods that mainly aims in minimum and maximum level visual features that are not contributed in retrieval function. Hence, 2 modules has been enhanced initially, Region based image retrieval (RBIR) which is based on image representation to be divided as regions features that depends upon image perception by an user. Alternatively, Relevance feedback (RF) helps to assure the user inclination [3]. The core theme of CBIR technique is to retrieve the images which are relevant to QI [4].

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CBIR uses the model of query by example that helps in retrieving same images of input image using a definition regarding a QI missed by a user, also CBIR method has been operated by QI features extraction, once the system starts for extracting a feature. Feature vector has been estimated for the obtained features, CBIR shows all images present in a database along with a vector, after inputting the QI, CBIR model determines the feature vector to compare with alternate vectors saved for each image exist in a database, images which are comprised with higher features are same as QI has to be retrieved. To improvise the IR process the Region-based visual signatures [5] has been employed in image segmentation. According to the performance of optical system of a human, images should be differentiated as features of region by image similarity. Such models determine the segmented region features from the object level and implement at the granularity region where previous models are applied to image representation by applying global features. [6] implied as model to extract features by applying image binarization to improve the images retrieval as well as exploration with the application of CBIR. Many developers sampled the model by applying 2 public datasets which has limited the feature size of an image. Some of the statistical values which are relied on precision as well as recall measures applied for estimation purpose. The main demerit of this technique is to misclassify the QI that affects the function of image than other conventional techniques. [7] projected a method image representation as well as feature extraction under the application of bandelet transform, which is comprised with the information in the form of image. The artificial neural network (ANN) has been applied for used for IR process where the system functions were computed by the application of 3 public data sets such as: Coil, Corel, and Caltech 101. Here, the precision as well as recall measures were employed for estimating the retrieval efficiency. [8] projected a technique to conduct the IR process with help of statistical tests, like Welch's t-tests and F-ratio. These modules are structured input QI. In this approach, the whole image has been assumed to be textured image, whereas in structured image, the shape is divided as different regions according to the behavior. Initially, F-ratio test has been employed to pass the images to energy spectrum testing. Followed by, when images are effective in 2 tests then it is decided that images are identical. Otherwise, it is dissimilar. In order to calculate the performance validation Mean Average Precision score have been employed.

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[9] deployed an image descriptor for extracting texture and color as it has similar impact on CBIR. In [10], a local structure descriptor is deployed to process the IR. Local structure descriptor has been developed on the basis of local structures of colors where the combination of color, shape and texture are presented as a single unit to perform IR process. Also, a technique used for feature extraction that is capable of extracting local structure histogram with the application of local structure descriptor. [11] implied a model termed as IR using interactive genetic algorithm (GA) to calculate the maximum number of desired features and compares with the QI images. This method has been sampled under a set of 10,000 images to evident the effectiveness of a presented technique. [12] applied a CBIR mechanism by employing the combination of Speeded-Up Robust Features (SURF) as well as Scale Invariant Feature Transform (SIFT). Therefore, presentations of such local features are utilized to retrieve images as SIFT is robust in rotation and scale changing, while SURF is highly stringer for illumination difference. The combination of SURF and SIFT improves the CBIR efficiency. GA algorithm is used for optimization [13]. GA is very productive in identifying an optimal solution from a search space. To improve the function of meta-heuristic like GA, a local search mechanism is essential to assist the GA in searching the solution space instead of finding a search space. The best local search technique is great deluge algorithm (GDA). This GDA were established by [14] in the form of local search model. The main aim of this technique has been evolved from analogy of hill climbing and trying to travel in a direction of finding a way to maintain dry feet and water level is increasing by a GDA. Also, GDA has been included in GA when it is more efficient to produce best solution rather applying GA model [15].

This paper presents an ensemble of optimal AlexNet architecture with RF classifier called EOANA-RF model to effective retrieve the images from the databases. Since AlexNet model does not offer superior results on large databases, the AlexNet architecture is optimized in three ways. Firstly, the average pooling undergoes replacement with max-ave pooling, Maxout is employed in FC layers and hidden layer is included to map high-dimension features to binary codes. Then, similarity measurement and RF based classification process takes place to retrieve the images related to the QI from the databases and classifies it. The performance of the proposed model undergoes validation using Corel10K dataset. The obtained simulation outcome verified the enhanced performance of the proposed model on the applied dataset.S

MATERIALS AND METHODS

The working principle of the proposed EOANA-RF model is shown in Figure-1. Initially, the feature extraction process takes place on the images present in the database by the use of optimal AlexNet architecture. Then, the extracted features are stored in a repository. Upon providing the query image, the feature extraction process again takes place and similarity measurement is carried out to determine the resemblance between the extracted feature vectors if the QI and the feature vectors exist in the database. The images with higher resemblance will be retrieved. Afterwards, the retrieved images will undergo classification by the use of RF classifier where the retrieved images will be grouped into respective classes. The processes involved in the EOANA-RF model will be explained in the following subsections.

Optimized AlexNet model

Basic architecture: The presented system is based on AlexNet, which is said to be a traditional deep convolution neural network (DCNN). AlexNet is comprised with 5 convolution layers, 3 pooling layers and 3 FC layers. The convolution layers as well as pooling layers were applied for extracting image features while FC layers applies the convolution layers and pooling layers, that match a 2D feature vectors as ID feature vectors. Though it is existed with a semantic space which can be limited by including a depth of network, it improves the processing time simultaneously. The main goal is to reduce the semantic gap with the application of few optimizing process applied on the structure of AlexNet in case of accurate and compact image representation.

AlexNet can be optimized using convolutional layers and FC layers to attain particular middle-level feature descriptors.

- The max-ave pooling criterion is applied in pooling layers for the representation of local feature.
- Max-out activation has been completely employed in FC layers to fit the global feature.
- The hidden layer was included in FC layer to transform the global feature vectors as binary codes.

Top K images were ranged under the application of Hamming distance which is referred as retrieval outcome. This mechanism is named as Optimized AlexNet for Image Retrieval (OANIR).
Feature extraction: In case of semantic IR, exploring a best feature extraction as well as representation has been considered as a crucial procedure. Even though a conventional AlexNet are capable of performing best feature extraction, it has only minimum network depth which is assumed to be a major challenging operation. In OANIR system, few optimizations were developed with no improvement of network depth.

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Max -Ave pooling for local features: The main objective for pooling is to obtain the major features from combined features at the time of provisioning significant features and eliminating the unwanted features. Pooling is comprised with merits for optimal feature representation. It is considered to be more compact representation which is assumed to be an invariant to image conversion and robust for noise. To obtain a better image features, state-of-the-art deep learning (DL) techniques were added such as max pooling, spatial pyramid model as well as average pooling. In case of convolved matrix image features along with the size of p×k, for all p-dimensional feature vector v_i, it can be defined as 2 pooling types, namely, max pooling and average pooling as given in Eqs. (1) and (2),

$$f_m(v) = \max v_i \tag{1}$$

$$f_a(v) = \frac{1}{p}\Sigma_{i=1}^{p} y_i \tag{2}$$

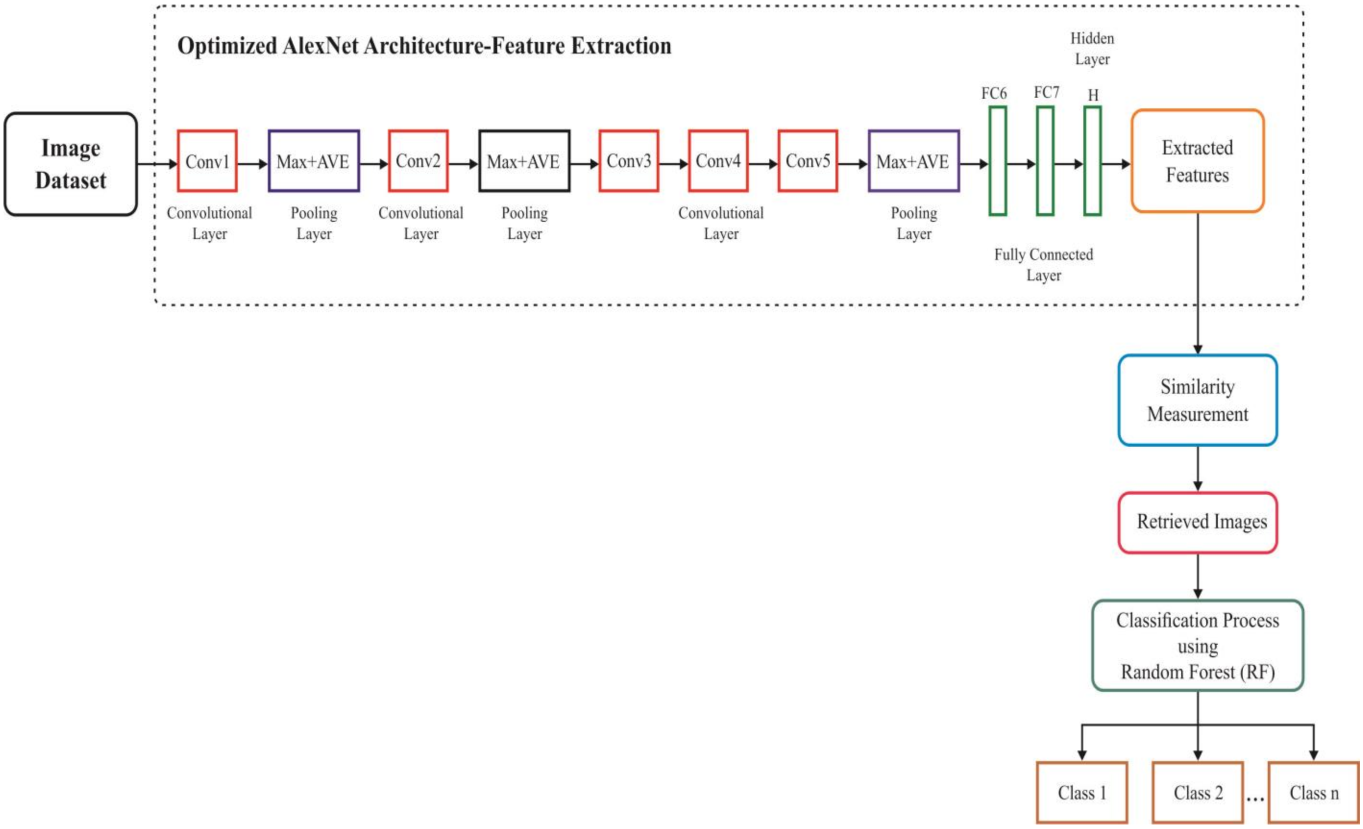

Fig. 1: Overall process of EOANA-RF model

Once the convolutional task is completed, distribution of image features for every patch could be named as exponential distribution along with a mean $E(X) = 1/\lambda$ and variance $D(X) = Var(x) = 1/\lambda^2$. Hence, the adjacent cumulative distribution function is $F(x;\lambda) = 1 - e^{(-\lambda x)}$. The maximum kurtosis from a provided exponential distribution is capable of modelling visual feature. The main feature acquired by a salient region is corresponding to maximum kurtosis present in a data distribution.

Let P implies a cardinality of pooling. The cumulative distribution of a max-pooled feature is given by

$$F(P) = \left(1 - e^{(-\lambda x)}\right)^P \tag{3}$$

The mean isolation is expressed as,

$$\mu_{m=}\left(H(P)\right)/\lambda \tag{4}$$

and variance is

$$\sigma_m^2 = \frac{1}{\lambda^2}\Sigma_{1=1}^{p}\frac{1}{l}\left(2H(l) - H(P)\right), \tag{5}$$

where $H(k) = \Sigma_{i=1}^{k}\frac{1}{i}$ is a harmonic series.Hence, for each P,

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$$\frac{\mu_1}{\mu_2} = \frac{\delta_1}{\delta_2} = \frac{\lambda_1}{\lambda_2} \tag{6}$$

The distribution might be optimally isolated when a scaling factor of a mean value is higher than scaling factor of SD. Moreover, as $H(p) = \log(P) + v + o(1)$, if $P \to \infty$, where v refers anEuler's constant, which can be represented as:

$$\Sigma_{1=1}^{P} \frac{1}{l}\left(2H(l) - H(p)\right) = \log(P) + O(1) \tag{7}$$

The distance from mean values are developed rapidly when compared with SD. Therefore, a crucial result could be attained if there is no smoothing performance, higher cardinalities gives best signal-to-noise ratio. A feature available in convolutional layer has related data, like position as well as relative position. If the distributions of image features are smooth and flat, max-pooling operation removes the associated local spatial data. Then, it influences the feature extraction and representation to a great extent. At this point, ave-pooling has the responsibility to manage locally correlated data. Thus, the pooling function can be written as,

$$f(v) = \alpha_1 \max v_i + \alpha_2 \frac{1}{p} \Sigma_{=1}^{P} y_i \tag{8}$$

where $\alpha_1 + \alpha_2 = 1$. For the training phase, it is pointed that the learned method is capable of providing best image features with all types of images. Fix $\alpha_1 = \alpha_2 = 0.5$ to improvise the robustness of a technique of input data while in a testing stage, 2 solutions are offered to resolve with diverse cases. If the input images are comprised with maximum quality pixels and only minimum noises, then it is fixed as $\alpha_1 = \alpha_2 = 0.5$ to validate the saliency feature and the average feature. While the input images are constrained with lower quality pixels and with a higher noises, then it is fixed as $\alpha_1 = 0.3, \alpha_2 = 0.7$ to focus on average features when compared with maximum kurtosis noise features that minimize the influence of image noises in extracting features. The MNIST and CIFAR-10 are existed with lower quality pixels whereas SUN397 and ILSVRC2012 are present with higher quality pixels.

Non-linear activation Maxout: The FC layers perform matrix multiplication, assumed to be more similar to feature space conversion. It is also used in data extraction as well as combination. Features in FC layers indicate global information. When merged with a non-linear mapping activation function, the FC layers triggers a non-linear conversion. The limitation of this function is that, it has lower data for spatial structure. These shortcomings can be resolved by using average pooling. Previous activation functions, such as Sigmod and ReLu, fits the 2D functions, and it shows that Max-out function can fit diverse dimensional function along with global approximation. It reaches a tremendous performance with dropout training. The Max-out technique is referred as a forward propagation structure with a largest resultant active form. In a provided input, the result for Max-out can be expressed as:

$$h_i(x) = \max_{j \in [1,k]} z_{ij} \tag{9}$$

where $z_{ij} = x^T W \ldots ij + b_{ij}, W \in \Re^{d \times k}$, and $b \in \Re^{m \times k}$ are learned parameters.The inclusion of Max-out parameters of a network tends to acquire maximum computation time for feature extraction. To attain major retrieval efficiency, the neural nodes present in FC6 and FC7 layers are reduced to 2048, and minimize the dropout value from 0.7 to 0.5. Finally, the sparseness image feature representation maintains the representation accuracy simultaneously. Binary code for large scale data: Here, the hidden layer pattern has been applied to reach the productive IR in large scale database. It undergoes mapping with high dimension features as compact binary codes as well as removes the unwanted features concurrently. Therefore, the activation function could be shown as:

$$a_n^H = \sigma(a_n^7 W^H + b^H) \tag{10}$$

where $\sigma(.)$ denotes a Sigmod logistic regression that manages the result from (0,1). a_n^7denotes the resultant feature vectors in FC7 layer, W^H represents weights, and b^H implies bias parameters of hidden layer. The binary code function is written as:

$$b_n = \begin{cases} 1 & a_n^H > 0.5 \\ 0 & a_n^H \leq 0.5 \end{cases} \tag{11}$$

Under the application of binary operation from a hidden layer, feature vectors undergoes mapping with binary codes. For IR process, OANIR network tends to extract image features for QI. Followed by, the result of hidden layer and binary codes were filtered with an activation function. Then, a same image has been ranged using Hamming distance of binary codes from QI as well as database images.

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Query matching

Feature vector for QI as Q is denoted as $f_Q = \left(f_{Q_1}, f_{Q_2}, \ldots \ldots . . f_{Q_{Lg}}\right)$ has been attained after completing the feature extraction process. Likewise, every image present in a database has been presented with feature vector $f_{DB_j} = \left(f_{DB_{j1}}, f_{DB_{j2}}, \ldots \ldots f_{DB_{jLg}}\right); j = 1,2, \ldots \ldots, |DB|$. The main aim of this process is to select n best images which are same as QI. It involves in selecting n top images by estimating the distance from a QI and image in a database $|DB|$. To match these images, it is employed with 4 diverse similarity distance measures as given in the following.

$$\textit{Manhattan distance value}: \mathrm{D}(\mathrm{Q}, \mathrm{I}_1) = \sum_{\mathrm{i}=1}^{\mathrm{Lg}} |\, \mathrm{f}_{\mathrm{DB}_{\mathrm{ji}}} - \mathrm{f}_{\mathrm{Q},\mathrm{i}}| \tag{12}$$

$$\textit{Euclidean distance value}: \mathrm{D}(\mathrm{Q}, \mathrm{I}_1) = \left(\sum_{\mathrm{i}=1}^{\mathrm{Lg}} \left(\mathrm{f}_{\mathrm{DB}_{\mathrm{ji}}} - \mathrm{f}_{\mathrm{Q},\mathrm{i}}\right)^2\right)^{1/2} \tag{13}$$

$$\textit{Canberra distance value}: D(Q, I_1) = \sum_{i=1}^{Lg} \frac{|f_{DB_{ji}} - f_{Q,i},|}{|f_{DB_{ji}}| + |f_{Qi}|} \tag{14}$$

$$\mathrm{d}_1 \textit{ distance value}: D(\mathrm{Q}, I_1) = \sum_{i=1}^{Lg} |\frac{f_{DB_{ji}} - f_{Q,i}}{1 + f_{DB_{ji}} + f_{Q,i}}| \tag{15}$$

where $f_{DB_{ji}}$ denotes the i^{rh} feature of j^{rh} image present in database $|DB|$.

RF classifier

The RF classification method is a well-known approach for linear and non-linear classification issues which are relatively novel. Hence, it comes under the category of ML methods named as ensemble models. Ensemble learning is defined as a learning approach that contributes in various mechanisms that is applied for resolving an individual predictor. It is operated by producing several classification methods that learns and develops autonomous detection. Such prediction has been integrated as single prediction which has to be an optimal one when compared with prediction done by a classifier. RF is a considered to be an ensemble learning that applies ensemble of DTs. Gradient boosting employs a collection of weak learners and provides enhanced prediction accuracy. Therefore, the attained simulation outcome from a sample depends upon previously obtained result. In GD, the limitations of predictions are referred as negative gradients. For all steps, a novel tree has been fit to the negative gradients of existing trees.The RF classification model is comprised with an integration of tree classifiers in which every classifier has been produced under the application of random vector that is tested in an autonomous input vector, and every tree casts a single vote for well-known class that tends to classify the input vector. Hence, an RF classifier applied in this work has arbitrarily chosen features at all nodes to be used for tree development. Bagging is a technique used in generating training data set by randomly obtaining N examples, where N denotes the size of the actual training set which has been deployed for all selected feature combination. The constantly employed attribute selection values in DT establishment are IG, Ratio criterion and Gini Index. The given training set T, selecting in a random manner that belongs to few class C_i, the Gini index might be expressed as:

$$\sum\sum_{j\neq i}(f(C_i,T)/|T|)(f(C_j,T)/|T|) \tag{16}$$

where $f(C_i, T)/|T|$ implies the possibility of selected classC_i.

RESULTS

In this section, the experimental validation of the proposed EOANA-RF model takes place. The dataset used, results offered by the EOANA-RF model and the comparative analysis is carried out in the following subsections.

Dataset used

The important points of proposed EOANA-RF methods are applied for testing in contrast to a standard Corel10K dataset [16]. The used dataset is constrained with a collection of 10,908 distinct images. A group of 100 classes are present in an employed dataset and 100 images have been exploited in all classes. This model utilizes a group of ten classes where everyone holds a set of100 images. The images

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are divided into different groups from animals, sports, food, etc. Only few testing images from the dataset is depicted in Figure-2.

Fig. 2: Sample Test Image.

Fig. 3: (a) Query Image (b) Retrieved Images.

Figure-3 depicts the qualitative results analysis of the EOANA-RF model on the applied Corel10K dataset. It is shown that the EOANA-RF method effectively retrieves a set of images for the applied QI.

Result analysis

Figure-4 offer the outcomes obtained by the EOANA-RF method interms of precision and recall under a set of ten classes. On the applied set of images under Buses class, the EOANA-RF model attains a maximum precision and recall of 95.67% and 86.13% respectively.

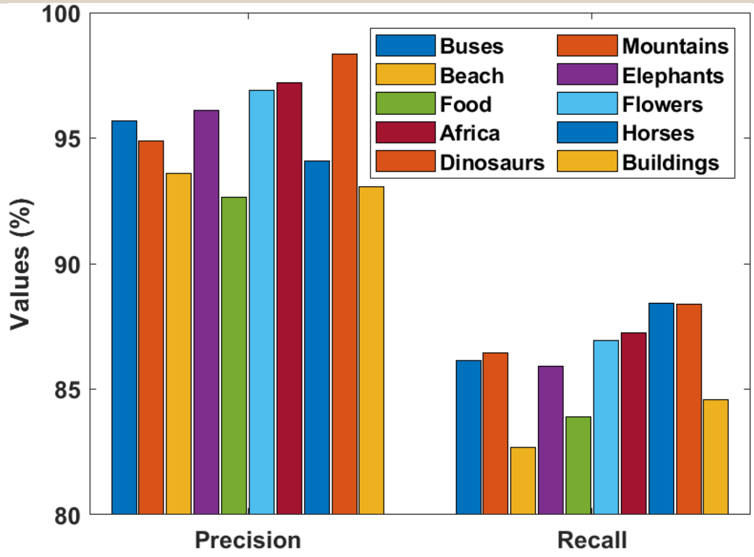

Fig. 4: Results of Proposed EOANA-RF Method in terms of Precision and Recall

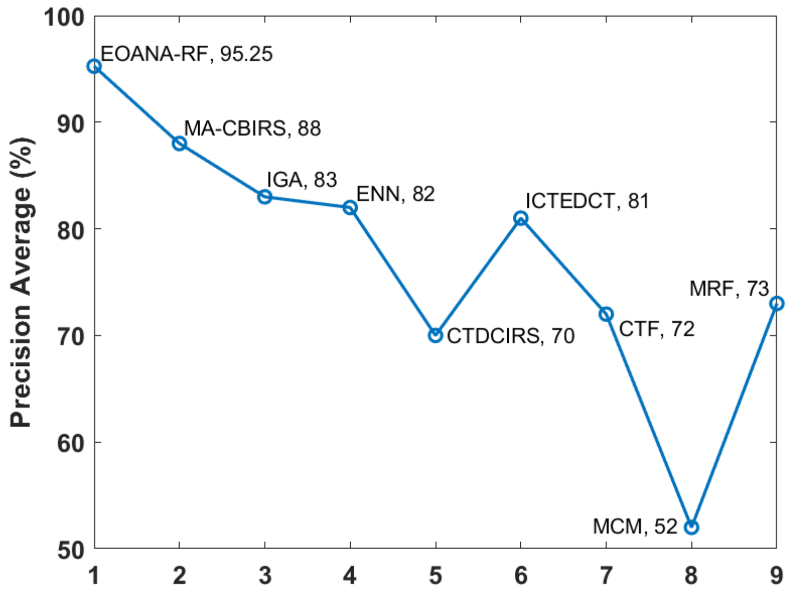

Fig. 5: Average precision analysis

Simultaneously, the MA-CBIRS model attempts in showing competing simulation outcome by attaining maximum average precision of 88%.On the same way, the previous IGA model seeks to average precision rate of 83% and the ICTEDCT techniques refers slightly better results with average precision of 81%.Similarly; the traditional MRF model demonstrates worst retrieval process by reaching very less average precision value of 73%. Therefore, poor retrieval outcome is produced by used CTF, CTDCIRS and MCM techniques by accomplishing minimum average precision rate of 72%, 70% and 52% correspondingly. The maximum average precision value of 95.25% is provided by EOANA-RF model which illustrates the stable retrieval outcome on the applied images. In order to ensure the uniform retrieval performance on the used test images, an average recall measure can be estimated for each applied methods [Figure-5].

Discussion

Figure-6 defines the investigation of IR process of various methods with respect to average recall. The figure clearly points that the projected EOANA-RF mechanism gives maximum retrieval final outcome with the average recall of 86.07%.Concurrently, the MA-CBIRS model attempts in showing reasonable result than other techniques with average recall measure of 70%. In line with this, the classical IGA approach seeks for an average recall value of 69%. The ENN and CTDCIRS models providemoderate outcomeswith same average recall measure of 16%. Similarly, the previous ICTEDCT and MCM methods depictan impractical retrieving performance by reaching a least average recall of 14%. But, poor retrieval results are produced with the application of CTF technique by achieving minimum average recall value of 10%. The highest average recall value of 50.73 by a deployed RCM model displays its reliable retrieving outcome on the applied images.

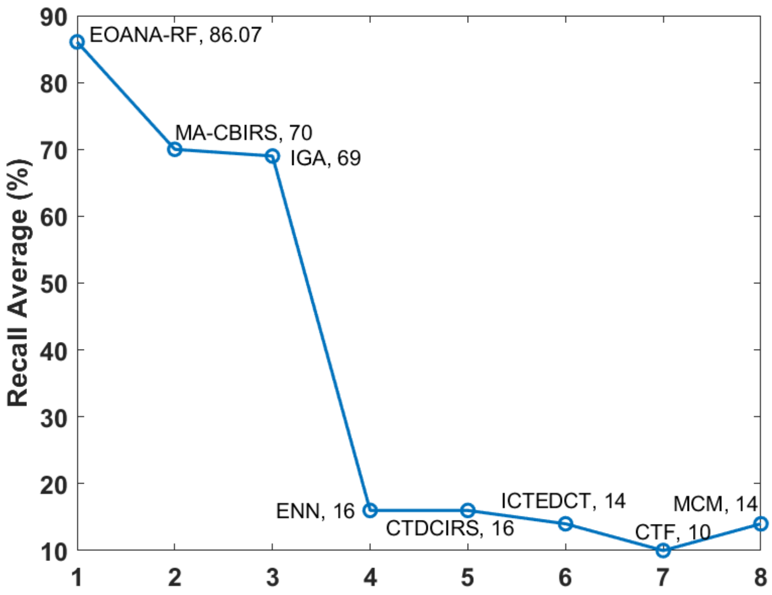

Fig. 6: Average recall analysis.

After observing the above-mentioned figures, it is obviously clear that the proposed model provides supreme retrieval and classification results over the compared methods in a significant way. It is verified from the maximum average precision and recall values of 95.25% and 86.07% respectively.

CONCLUSION

This paper has presented an effective EOANA-RF model to attain efficient retrieval of images from the databases. As AlexNet method is not capable in providing qualified results in case of large databases, the AlexNet architecture has been optimized in 3 ways. Initially, the feature extraction process takes place on the images present in the database by the use of optimal AlexNet architecture. Then, the extracted features are stored in a repository. Upon providing the query image, the feature extraction process again takes place and similarity measurement is carried out to determine the resemblance between the extracted feature vectors if the QI and the feature vectors exist in the database. The images with higher resemblance will be retrieved. Afterwards, the retrieved images will undergo classification by the use of RF classifier where the retrieved images will be grouped into respective classes. The performance of the proposed model is validated by applying Corel10K dataset. Hence, experimental values shows the improved results of the projected system has reached to a higher average precision and recall values of 95.25% and 86.07% correspondingly. In future, the performance of the proposed system can be improvised under the application of hyper parameter tuning models.

CONFLICT OF INTEREST

The authors have expressed no conflict of interest.

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None

FINANCIAL DISCLOSURE

None

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