Indonesian Journal of Electrical Engineering and Computer Science
Vol. 30, No. 2, May 2023, pp. 870~881
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v30.i2.pp870-881

Query-based image tagging model using ensemble learning with enhanced artificial bee colony optimization

Ravi Babu Devareddi[1], Atluri Srikrishna[2]
[1]Department of Computer Science and Engineering, College of Engineering, Acharya Nagarjuna University, Guntur, India
[2]Department of Information Technology, R.V. R. & J. C. College of Engineering, Chowdavaram, Guntur, India

Article Info

Article history:

Received Nov 6, 2022
Revised Dec 29, 2022
Accepted Jan 2, 2023

Keywords:

Artificial bee colony
Content-based image retrieval
Enhanced artificial bee colony
QbITM-ELEABC
Support vector machine

ABSTRACT

Digital images make up most multimedia data and are analysed in computer vision applications. Daily uploads of millions of pictures to Internet archives such as satellite image repositories complicate multimedia content and image graphs. As feature vectors, content based image retrieval (CBIR) and image classification models represent high-level image viewpoints. Observing photos recognizes objects and evaluates their significance for image enhancement. To access the visual information of big datasets, efficiently retrieve and query picture graphs. The artificial bee colony (ABC) algorithm is inspired by the foraging behaviour of honeybee swarms. ABC is susceptible to laziness in convergence and local optimums, just like other optimization methods. This study created an enhanced ABC (EABC) model to enhance precision. This study presents query-based image tagging model using ensemble learning with EABC (QbITM-ELEABC) for CBIR for appropriately tagging images based on the query image. We examine a number of convolutional neural network (CNNs) with varying topologies that can be trained on the dataset with varying degrees of similarity. As representations, each network extracts class probability vectors from images. The final image representation is created by combining the ensemble's class probability vectors with image.

Corresponding Author:

Ravi Babu Devareddi
Department of Computer Science and Engineering, College of Engineering, Acharya Nagarjuna University
Guntur, Andhra Pradesh, India
Email: ravibabu.devareddi@gmail.com

1. INTRODUCTION

Recent technological advancements have increased the use of digital cameras, smartphones, and the Internet. The growing amount of shared and archived multimedia data makes it challenging to find a suitable image. The most basic requirement in every image retrieval approach is to find and arrange similar photos [1]. Most internet search engines require captions to find images [2]. Keywords in search results can retrieve unrelated images. Human perception and manual labeling/annotation cause irrelevant output [3]. Initially, millions of image collections make manual labeling nearly impossible. Second, an automatic annotation system labels images based on their content [4]. Users can quickly find what they need in an extensive collection of images using image retrieval by searching for specific characteristics. Color-based image retrieval is efficient for a vast image collection, but it ignores that color is not a constant parameter; it is affected by surface properties, lighting, camera settings, and camera orientation. The user must submit a query image to retrieve the requested images. The extracted features are represented as feature vectors in the system. Next, indexing algorithms compare the query image's feature vectors to those in the database, allowing retrieval. Modern retrieval algorithms incorporate user relevance feedback to produce more relevant search results. Content based image retrieval (CBIR) retrieval performance depends on efficient feature representation and similarity metrics. The semantic gap was the model's biggest challenge [5].

Pixels collected by computers don't match high-level image concepts. The difficulty of CBIR with deep learning methods like convolutional neural networks (CNN) and annotated images [6] is examined. Automatic image annotation must recognize color, edges, texture, and shapes. User perceptions can affect retrieval [7]. Tagged CBIR uses visual analysis of the query image [8]. CBIR compares the visual content of the user query with the images in the archive, and proximity in the image feature vector offers a basis for finding similar images [9]. CBIR queries match visual attributes to rank results. QBIC and simplicity are image retrieval models, according to research. Healthcare, remote sensing, crime investigation, video processing, military surveillance, and textiles use CBIR and feature extraction.

Wang *et al*. [10] has been studied various tag data and visual aspects. Existing approaches often employ these optical characteristics alone or in a series, although this is not optimal. To understand the importance of pictures, they present a hyper graph-based method that fuses global and local visual information. The construction of a hyper graph begins with international and local visual aspects and information about tags. They suggest a pseudo-relevance feedback mechanism to produce the resulting false-positive pictures. The particle swarm optimization (PSO) technique is used to select the most informative grey, colour, and texture attributes [11].

An overview of CBIR systems and widely utilized features, along with a comparison of various weight assignment algorithms, is presented. The next issue highlighted because of their research is to automate the process of assigning weights to picture attributes using the CBIR system [12]. Optimizing the decision surface may classify the images in the dataset into two groups: those that are like the query image and those that aren't to solve the image retrieval issue. This issue is approached as an optimization problem, and the particle optimization process is used to find a solution. Nobody employs the PSO technique for direct feature weighting, even though it is popular in image retrieval and utilized by many companies [13]. Assessment of significant learning-based improvements for content-based picture retrieval during the last 10 years is presented in [14]. In addition, to have a deeper comprehension of the advancements being made, the currently applicable state-of-the-art methodologies are classified according to various criteria. This study uses a taxonomy that considers multiple types of supervision, networks, descriptor types, and retrieval types.

Eliminated the CNN's top layer to extract a feature from it, and further testing revealed that this feature was beneficial to the structural equation modeling (SEM) model. In addition, based on the previous experiences with standard K-nearest neighbor (KNN) models, they suggested a model solve the issue of concurrently addressing the image tag refinement and assignment while keeping the simplicity of the KNN model [15]. CBIR has practical applications in fashion image retrieval, human re-identification, e-commerce product retrieval, remote sensing image retrieval, and trademark image retrieval. Finally, they address CBIR's future research plans utilizing big data and deep learning approaches [16]. Tschandl *et al*. [17] used content-based image retrieval, or CBIR, to recover visually similar dermatoscopic pictures that include illness labels matching those labels and then compare this diagnostic accuracy to the predictions provided by a neural network.

Shankar *et al*. [18] completed their work on bringing clarity to a blurred image, conversion an image colorization using CNN [19], identifying facial features using Hausdorff distance [20]. Pair-wise comparisons of visual features led to a new method for automatic weighting. Their proposed method uses a hierarchical analytical procedure. UC Merced Land usage dataset contains 21 satellite picture classes [21], query processing for video using object-oriented approach [22], retrieving an image using genetic model [23], analyzing performance using social group optimization (SGO) and accelerated particle swarm optimization (APSO) for image denoising [24], and enhanced performance on object detection [25]. Study of Devareddi and Srikrishna [26], worked on CBIR for data analysis and did an edge-clustered segmentation-based model for image retrieval [27]. The analytical hierarchy process (AHP) and meta-heuristic optimization algorithms including particle swarm optimization (PSO), genetic algorithm (GA), and gray wolf optimization are providing backing for the technique (GWO) [28].

Wang *et al*. [29] suggested a knowledge-fusion-based an artificial bee colony (KFABC). KFABC selects three distinct areas of expertise. The usage technique corresponding to each kind of knowledge is conceived and constructed. A learning system that may adaptively pick relevant information is suggested, and it does so by monitoring the current state of the search. KFABC's capacity to optimize 32 benchmark tasks is verified. It is time-consuming and costly to use human sensory assessment for traditional techniques of categorizing tea types, which rely primarily on the outward look of the tea leaves. This investigation successfully used a method for the exact and non-destructive categorization of tea types that used fluorescence hyper spectral imaging technology in conjunction with the competitive adaptive reweighed sampling (CARS)-ABC-support vector machine (SVM) algorithm [30]. Along with the updated mechanism of the ABC algorithm has high exploration performance; there is an issue with the algorithm's ability to converge on solutions [31]. Their work proposes the artificial bee colony algorithm for fitness weighted search (ABCFWS). Instead of the ABC algorithm's random search space, this alternative uses an intelligent one.

In this strategy, the fitness values of the food source and the chosen neighbor food source are used as weights, and a more balanced search space was identified in the direction of the food source with a higher fitness value. Rostami and Kaveh [32] have used the spectator bee from ABC. The migratory operators from biogeography-based optimization have been combined in the proposed hybrid biogeography based optimization (HBBO) to achieve optimum feature selection. After that, a SVM was used to categorize the pixels into distinct labels of land covers. Images from Google Earth, the Pauli RGB space, high-resolution imagery, and the National Land Cover Database were used to create representative samples of the ground reality (NLCD 2006). Ganesan and Santhanam [33], acquired the edge response of the picture. A kirsch mask is applied in each of the eight directions. After that, the encoding condition is used for both the edge information and the local intensity information to get a singular value for the descriptor. Finally, a novel learning method known as GMJAYA-ELM has been developed to categorize textures. This approach combines the Gaussian mutated JAYA (GMJAYA) with an extreme learning machine (ELM). In single-hidden-layer feed-forward neural networks, the GMJAYA is used to maximize the network's input weights and hidden biases.

In single-hidden-layer feed-forward neural networks, the GMJAYA is used to maximize the network's input weights and hidden biases. Optimization is essential in science and engineering. In the past 50 years, many optimization algorithms have been developed. Non exact, derivative-free solution strategies are gaining popularity as modern problems become nonlinear, heterogeneous, discontinuous, or dynamic. Evolutionary biology or swarm behavior inspired most of these techniques. Karaboga and Akay [34] defined ABC in 2005. The model of forage selection bee intelligence has three parts. Food employed and scout bees. ABC is a population-based meta heuristic algorithm inspired by honeybee swarm foraging. ABC's simplicity and applicability make it worthwhile for discrete and continuous optimization [35]. Here, soil moisture was modeled using four data-driven models: multilayer perceptron (MLP), adaptive neuro fuzzy inference systems (ANFIS), support vector regressio (SVR), and group method of data handling (GMDH). Particle swarm optimization was used to find the best structure for each of the four models [36]. Devi [37], various strategies of adaptive median filter (for pre-processing), discrete cosine transform based discrete orthogonal stockwell transform (for segmentation), and linear binary pattern (for feature extraction) are shown to process the trained dataset and given query.

This literature survey motivates us to improve the importance of the image retrieval system with the support of enhanced ABC (EBAC). Selection probabilities drive a search process that finds a new neighbor solution. A probability function is used to decide whether to accept a given key, regardless of whether it's the best image set. This research proposes a query-based image tagging model using ensemble learning with EBAC for content-based image retrieval. Section 2 discusses the proposed model for accurate image retrieval utilizing ensemble learning and ABC optimization. Section 3 compares the model to traditional models. The paper ends with section 4.

2. METHOD

The proposed method normalizes query image similarity to target database images. Fusion weights are adaptively assigned to improve image retrieval using the EBAC optimization algorithm. The machine learning technique known as ensemble methods aims to create a more accurate predictive model by combining multiple base models. By combining various models, superior predictive performance can be achieved compared to a single model. Lowering the decision tree's variance is possible using a Bagging ensemble model technique. For each iteration i, a subset or training set T_i, consisting of k tuples, is drawn from the more extensive collection Ds, with replacement. For each training set T_i, a classifier model C_i is then learned for image retrieval based on a query image.

In the proposed research, query image and dataset image features are extracted by using regrouping class-prior estimation (RECPE) algorithm [27] with support of the OPDED approach [38] and the interlinked feature query (IFQ) method is used to interlink features of an image. Thus, elements are trained to the ensemble model. An ensemble model of SVM and decision trees (DT) are considered for accurate image retrieval from datasets. The image features comparison is performed, similar images are extracted, and an image retrieved set is generated. The ABC optimization model is applied to update the retrieved image set. The bees at the ABC colony can be roughly divided into three categories: employed bees, onlookers, and scouts, as shown in Figure 1. For each potential food source, represented by an image like a query image, it is believed that only one artificial bee is engaged.

Therefore, the number of active bees in the colony is proportional to the number of potential food sources (images) in the area, represented by the images in the PatternNet dataset [39]. Employed bees dance here after returning from foraging at their designated food source (picture from the dataset) and before returning to the hive (retrieved dataset).

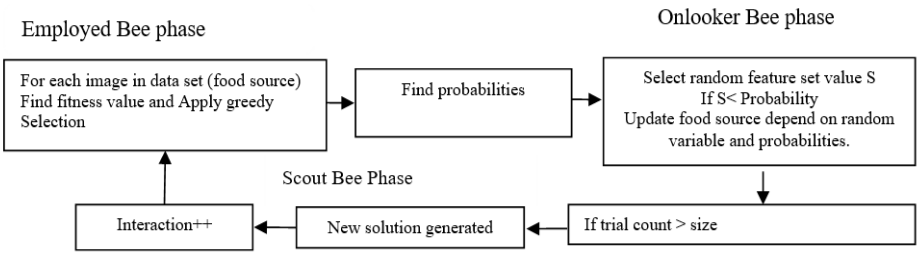


Figure 1. Typical system architecture for the proposed EABC approach

The fitness value is the type of food identified, considered, or discarded. The food considered is represented as the fitness value. The employed bee with depleted food (irrelevant images) works as a scout, investigating irrelevant images in the dataset to discover a new food source (new relevant images). The fitness value is the type of food identified, considered, or discarded. The food considered is represented as the fitness value. The employed bee with depleted food (irrelevant images) works as a scout, investigating irrelevant images in the dataset to discover a new food source (new relevant images). Onlookers observe the employed bees' dances and select their food sources (the relevant images) accordingly. The complete framework of the proposed model is shown in Figure 2. In this research, query based image tagging model using ensemble learning with EABC for a CBIR model is proposed for tagging the relevant images based on the query image (QbITM-ELEABC). The working process of the proposed model is explained in the algorithm QbITM-ELEABC.

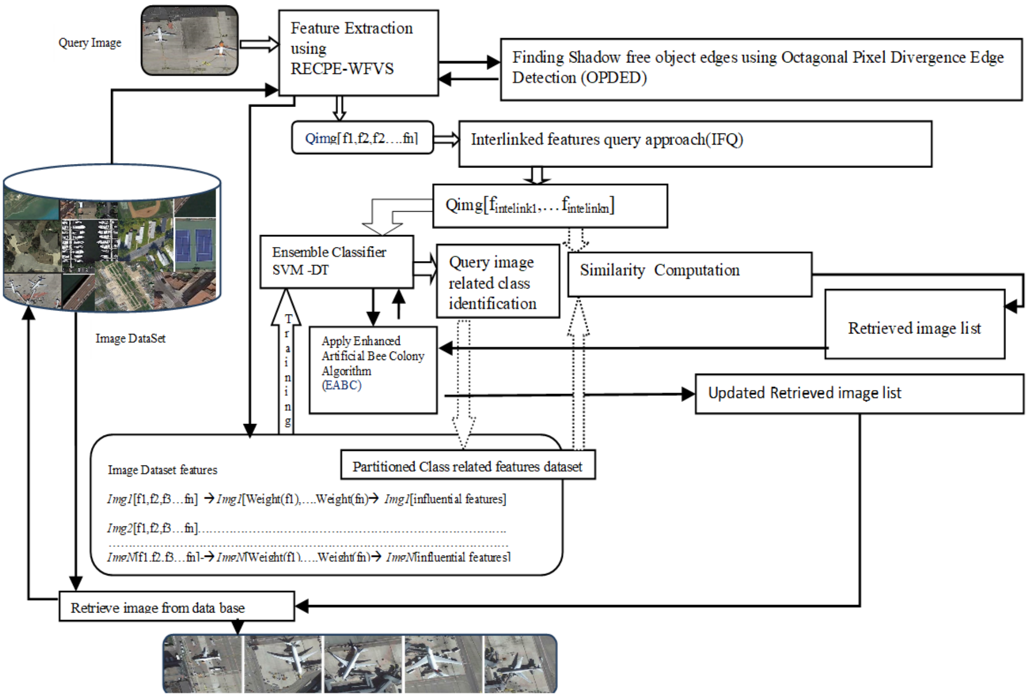


Figure 2. Proposed model framework

2.1. Proposed algorithm

In this paper, the QbITM-ELEABC algorithm is proposed, and the actual steps are described in algorithm 1. This algorithm considers an image as input; features are extracted from the given image and form the feature vector. The information from the feature vector is used to train the ensemble model. Later, enhanced ABC is used for the optimization model. Finally, have the model return the relevant images related to the query image.

```
Algorithm 1: QbITM-ELEABC (Query-based Image Tagging Model using Ensemble Learning with
Enhanced Artificial Bee Colony).
Input: PatternNet Dataset (IDset) and Query Image (Qi)
Output: Tagged Image Set (TIset)
Parameters used: Artificial Bee Colony (ABC), Support Vector Machine (SVM) and Decision
Trees (DT)
Step 1: Load the query image Qi (Qimg) and image dataset IDset (DSimg) and perform feature
        extraction.
Step 2: A similarity check has been done for query image features and image dataset
        features by performing Qsim and IDsim.
Step 3: Classification is done using the ensemble learning model (EnsembM(i)). It is
        applied to the feature similarity set and compares the images to get the best
        similar features.
          A. The Decision Tree model DecTreeGen( ) is applied to the feature subset to
             classify the relevant image feature sets using algorithm 2.
          B. The SVM model SVMClass( ) is applied to the feature subset to classify the
             relevant image feature sets using algorithm 2.
Step 4: To generate relevant images and to identify the best fitness function, apply the
        Enhanced ABC optimization algorithm.
        Initialization: Take the initial population as query image relevant feature set
        from Step3
             Repeat
          A. Employed bee: Execute a process of updating each solution in the solution
             population for each potential food source, represented by an image like a
             query image. Compute the fitness value for each relevant image with Eq.
             (10).
          B. Onlooker bee: Select solutions randomly based on their fitness values, then
             repeat each key update process. It observes the employed bees' dances and
             selects their food sources (the relevant images) accordingly. It finds
             using the Prob (p) function using Eq. (8).
          C. Scout bee: Choose one of the least active solutions and replace it with a
             new randomly generated solution. Investigating irrelevant images in the
             dataset to discover a new food source (new relevant images).
          D. Memories the best solution achieved
             Until (stop condition has been satisfied)
Step 5: The image tagging is applied on the final optimized images set obtained in step 4
        to link the relevant images based on the query image. The final retrieved set
        RIset is generated.
Step 6: Display the final image Tagged set that is the final search result based on the
        query image.
```

2.2. Algorithm explanation

In step 1, we need to load the query image Qi and image dataset IDset and perform feature extraction of the images initially by enhancing the query image quality as shown in (1) and for query image and dataset images as shown in (2) and (3) respectively.

$$Pixset_M = 255-.\left(\frac{[\lambda_x(T)-\lambda_y(T+1)]}{[\theta x(x,y)-\theta_y(x+1,y+1)]}\right) + Th \tag{1}$$

$$Q_{img} = \frac{\sum_{(x,y\in Qi)} |Pixset(x,y)-\max(x,y)|^2}{\sum_{(x,y\in Qi)} \theta(x,y)^2+\min\text{ (PixSet(x,y))}} \xleftarrow[\text{(x,y)}\leftarrow\text{max (Pixset)}]{} \tag{2}$$

$$DS_{img} = \frac{\sum_{(x,y\in IDset)} |Pixset(x+1,y+1)-\max(x+1,y+1)|^2}{\sum_{(x,y\in IDset)} \theta(x+1,y+1)^2+\min\text{ (PixSet(x+1,y+1))}} \xleftarrow[\text{(x+1,y+1)}\leftarrow\text{max (Pixset)}]{} \tag{3}$$

The algoirtm1 generated feature vectors for the query and data set images. Now the query image feature extraction and the image considered from the image dataset feature extraction are performed to perform the similarity check for accurate extraction as done in step2. Here query image and dataset images for similarity are calculated as shown in (4) and (5). Hence feature similarity checking is performed as shown below.

$$IDsim(Fsubset(i), Fsubset(i+1)) = \sqrt{min(\,x,y) + \frac{\lambda}{2}} \tag{4}$$

$$Qsim(Fsubset(i) = \sqrt{\sum_{i=1}^{min\{x,y\}} \lambda_i^2 (max(\,x,y))} \in IDsim(Fsubset(i)) \tag{5}$$

While (Qsim = = IDsim) and set Flag counter F ← 1.
do
Imgset[M]=IDsim(i)
F=F+1
Done

After similarity comparison, it generates a relevant feature similarity set. Then, the ensemble learning model (SVM-DT) is applied to the feature similarity set that considers the images having the best similar features, as shown in step 3. The ensemble model is used on the final similarity feature set, as shown in (6) and (7).

$$Im\,s\,etx, y = \sum_{r=1}^{M} \sum_i min(\sum_{r=1}^{M} pixset(Qimg)-min(x-1,y-1)\, max \tag{6}$$

$$EnsembM(i) = \sum_{r=1}^{M} \theta(x,y) + \frac{max(Im\,set(x-1,y-1))}{size(Im\,gset)} + max \sum_{r=1} Im\,s\,et(x+1, y-1) * \frac{corr(Fset(x-1),Fset(y+1))}{F} \tag{7}$$

In step 3 (A), The decision tree and in step (B), the SVM models are applied to the feature subset for accurate query-based image retrieval by using model 1 and model 2, respectively show in algorithm 2. Finally, Iset is generated by using this ensemble model.

Algorithm 2: Classification models (Decision Trees and Support Vector Machine) to retrieve the similar images

Model 1: *Decision Tree Classification*

```
DecTreeGen (Imgset, Fsubset, R, Max(R),Min(R))
{
 If(Max(Fsubset(i))<Min(Fsubset(i))εR)
 leafImg=getImage(Imgset(i))
 leaflab=rel
 return leafImg
 end if
rootImg=getImage(Imgset(i))>Fsubset(N)
rootImg.compare(leafImg)=split(Imgset(i),Fsubset)
 for each R in Fsubset(N)
ChildImg←Img.compare(rootImg,Imgset(i+1))
       If Fsubset(Img(i+1))>(Fsubset(Img(i))
       rootImg.split(Img(i+1)
    Add the relevant image as a child image to
         generate the set as ISet(N)
 End for
}
```

Model 2: *SVM Classification*

```
SVMClass (Fsubset,X,Y,R,ISet)
{
Input: Array of Features (Fsubset), X,
Y},{R},{ISet}
Output: Image Set (ISet)

Train the SVM model (r←(Fsubset(i))
 For j in Fsubset
 For i in Imgset
 If ((X[i]* Y[j])+R)<Th
 Ir(i)←R+j+len(Fsubset)* (X[i]* Y[j])
    Iset(i)←Ir(i)+R+j+len(Fsubset)*
(X[j]* Y[i])*(2*(1/corr(Ir(X-i), Ir(Y-
              j))))
 End if
 End For
 End For
}
```

We classified the similar image feature sets most relevant to the query image feature vector from the above step. In step 4, the Enhanced ABC optimization algorithm is applied to the final ensemble feature set for identifying the best fitness function for relevant image retrieval. The food source with the higher fitness value and the selected neighbor food source are considered for image tagging as in step 4(A). In step 4(B), a random initial population is considered and then generates opposing solutions for each position in the initial population and then conduct the EABC's initial population by selecting solutions with higher fitness from the two different people generated with a random source to enhance the model with relevant images as the resultant set. The enhanced optimization model is applied to the similarity feature final set, and the best image set is considered based on the fitness function. Initially, use a random spray of H percent of the population to the solution space, and then determine their fitness values set as {F1, F2…. Fn}.

After these populations are placed in the solution space, they are referred to as employed bees. The population searching probability is defined as shown in (8).

$$Prob(p) = \sum_{p=1}^{L} \frac{\lambda(Y_p)*\lambda(Y|X_p)}{\sum_{p=p+1}^{L} \frac{\lambda(Y|X_p)}{\lambda(Y_p)}} \tag{8}$$

Here λ represents the probability condition, X, Y are the image coordinators in the image set. Perform probability iteration of the image set comparison, and the given food source is selected. Those food sources are given up if the employed bees' fitness values don't increase for a continuous predefined number of iterations, called final limit (FL), and the workers then take on the role of scouts. FL is as shown in (9).

$$FL(XY)=(1-\lambda+Th)\times x_{P,P+1}+\lambda\times\mu_{x,y}\times(Y_{p+1}-X_p) \quad (9)$$

After the final limit is calculated, the fitness value is calculated using (10) and (11).

$$FitnessV\big(Prob(p)\big) = \frac{\sum_{p=p+1}^{L} \frac{\lambda(Y|X_p)}{\lambda(Y_p)}}{1+\frac{1}{\lambda}} \quad (10)$$

$$Fit(p) = \begin{cases} \frac{1}{1+FitnessV(p)} \; if\; FitnessV \geq 0 \\ FitnessV \; if \; FitnessV < 0 \end{cases} \quad (11)$$

Calculate the fusion weights for the final limit set, and based on the fusion weights, multi-search is based on the fitness value. The fusion weights are calculated as shown in (12).

$$FWeightset\big(Fit(p)\big) = \begin{cases} \frac{(FitnessV_{p+1}*Y)-(FitnessV_p*X)}{\lambda} \; if\; FitnessV_{P+1} \geq FitnessV_P \\ \frac{(FitnessV_{p-1}*X)-(FitnessV_{p+1}*Y)}{FitnessV(p)+FitnessV(p+1)} \; otherwise \end{cases} \quad (12)$$

The bees perform the multi-level search operation to update the search operation in searching the relevant images based on query image features. As in step 4(C), no more similar images (food sources) exist. Then, in (10) and (11) are repeated until the best fitness value I considered, and the image set is generated. In step4 (D), the best solution is memorized. After applying optimization on a similar image feature set, obtain the most accurate image feature sets relevant to the query image. Image tagging is used to the final optimized image set to link relevant images depending on the query image, and RIset is formed to obtain images from the data set. The image tagging is performed as shown in (13).

$$ITag\big(FTset(M)\big) = \left(\frac{FL}{2\lambda}\sum_{r=1}^{M}\Big(M_{FitnessV} - \max\big(Prob(p)\big) + \max\big(FWeightset(Fit)\big)\Big)^2\right) + \frac{\max\big(FWeightset(Fit(p))\big)}{\lambda} \begin{cases} QIset \leftarrow 1 \; if \; ITag(r)\varepsilon Imgset(r) \\ QIset \leftarrow 0 \; Otherwisse \end{cases} \quad (13)$$

The generated image tagging list displays the images from the dataset relevant to the query image.

3. RESULTS AND DISCUSSION

In Swarm intelligence, a group of low-level intelligent individuals has learned to cooperate and organize effectively. It demonstrates that there is no central authority or universal model and naturally exhibits scattered and self-organizing properties. CBIR and image classification-based models represent high-level picture visualizations as feature vectors. The proposed model is implemented in python and executed in Anaconda Spyder. Images are often depicted as finite-dimensional vectors. Feature vector dimension affects storage, retrieval precision, and retrieval time. PatternNet dataset is used, as shown in figure 3. Experimentation and simulation evaluate the work's effectiveness and capabilities. This simulation explains the findings for the many modules used, such as feature extraction, similarity score computation, and normalization using the EABC optimization technique. This research proposes a QbITM-ELEABC for CBIR. The proposed model is compared to colour, grey, texture, shape, and random forest classifier with optimized PSO (CGATSFRFOPSO).

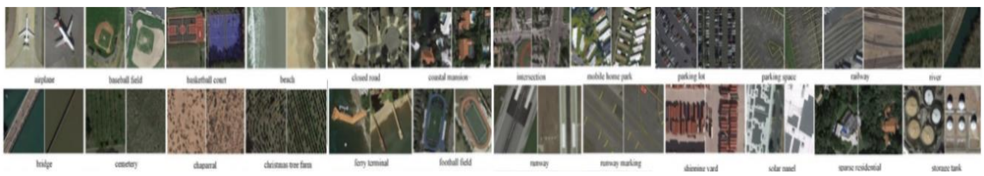
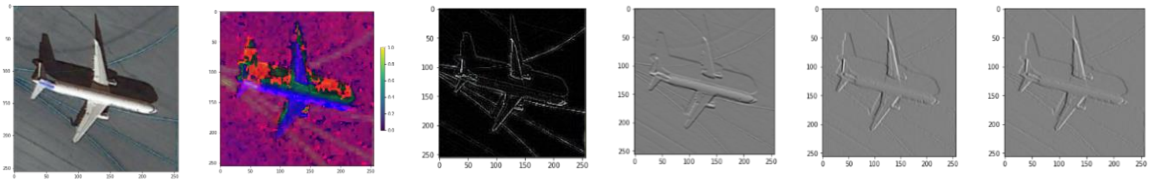


Figure 3. PatternNet sample images of 24 classes out of 38

All images from the dataset are loaded, and each image is analyzed for CBIR. The image transformation for the query image operations is shown in Figure 4. The images considered will undergo image processing by converting them into the grey level, shown in Figure 4(a). Then, the segmentation is performed for accurate pixel extraction from each image, as shown in Figure 4(b). As well as for finding the edges of the image with vertical segmented edges, horizontal segmented edges and homogeneity evaluation in the kernel as shown in Figures 4(c)-(f), respectively. The extracted features are trained to the ensemble model using the ensemble learning model (SVM-DT).



(a) (b) (c) (d) (e) (f)

Figure 4. Image transformation to (a) original image (RGB), (b) HSV converted image, (c) edge transformation, (d) horizontal segment edges, (e) vertical segment edges, and (f) homogeneity evaluation in the kernel

The data set pixel values is displayed in Figure 5, maximum and minimum pixel range is considered from the images in the dataset, and the average pixel value for CBIR is calculated. The max pixel set and min pixel set from the PatternNet dataset are calculated and represented in Figure 5(a). The pixel matrices are then further converted into true false sets, and these values are compared with the query image for precise retrieval of images of the same kind. The extracted pixel values are shown in Figure 5(b). The true and false set of the pixel matric representation is also shown in Figure 5(c).

```
Max Pixel CLuster is [197, 199, 255, 202, 225, 229, 175, 213, 209, 253, 173, 217, 207
Min Pixel CLuster is [0, 6, 10, 7, 3, 8, 12, 14, 11, 2, 4, 1, 27, 5, 13, 9]
```

(a)

```
 [109 110 109 ... 105 105 105]       [109 110 109 ... 105 105 105]
 [109 111 111 ... 106 105 104]  ...  [109 111 111 ... 106 105 104]
 [111 113 112 ... 106 105 104]]      [111 113 112 ... 106 105 104]]
[[105 123 134 ... 110 115 117]      [[107 144 238 ... 127 133 137]
 [106 113 120 ... 105 110 113]       [102 148 207 ... 125 132 137]
 [111 111 113 ... 101 105 109]       [133 185 193 ... 122 128 134]
```

(b)

```
Database Image Feature Set
[array([[False, False, False, False, False, False, False, False],
        [ True,  True,  True,  True, False,  True,  True, False],
        [ True,  True,  True,  True,  True,  True,  True, False],
        [ True,  True,  True,  True,  True,  True,  True, False],
        [ True,  True,  True, False, False,  True,  True, False],
        [False,  True,  True,  True,  True, False,  True, False],
        [False,  True,  True,  True, False, False, False, False],
        [ True,  True, False, False, False, False, False, False]]),
 array([[False, False, False,  True, False, False, False, False],
        [ True, False, False,  True,  True,  True, False,  True],
        [ True,  True, False, False, False, False,  True,  True],
        [ True, False, False, False, False, False, False,  True],
        [ True, False,  True, False, False, False, False,  True],
        [ True,  True,  True,  True,  True,  True,  True,  True],
        [False, False, False,  True, False,  True, False,  True],
        [False, False, False, False, False, False, False,  True]]),
```

(c)

Figure 5. Dataset matrix representation for (a) min and max pixel set, (b) dataset pixels, and (c) image feature true false set

The primary goal is to get the same level of detail using fewer features. Binarization, thresholding, scaling, normalizing, and other images preprocessing techniques are applied to the sampled image before features are extracted. Figure 6 represents the graph for accuracy levels of a picture of the traditional and proposed models with Table 1 values. Feature descriptors are algorithms that take input images and generate feature descriptors or vectors. The query-based image feature extraction is proposed, and existing models are shown as a graph in Figure 7 using Table 2.

The image retrieval system solves the issue of finding relevant images in image databases according to user specifications by using low-level visual cues extracted from the images themselves. The image similarity of features in the query image and the images in the dataset are compared, and the relevant images are tagged with the query. As proposed, the image similarity is calculated in time levels, and existing models are shown in Figure 8 with Table 3 values.

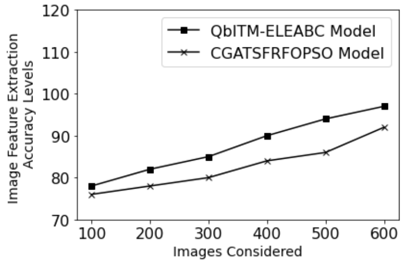


Figure 6. Image feature extraction accuracy levels

Table 1. The performance of feature extraction accuracy levels

No. of images	QbITM-ELEABC model	CGATSFRFOPSO model
100	78	76
200	82	78
300	85	80
400	90	84
500	94	86
600	97	92

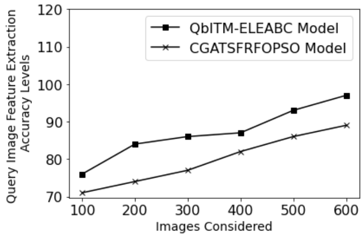


Figure 7. Query image feature extraction accuracy levels

Table 2. The performance of query image feature extraction accuracy levels

No of images	QbITM-ELEABC model	CGATSFRFOPSO model
100	76	71
200	84	74
300	86	77
400	87	82
500	93	86
600	97	89

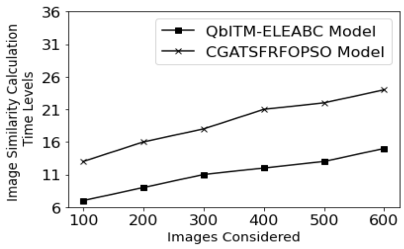


Figure 8. Image similarity calculation time levels

Table 3. The performance of image similarity is calculated in time levels

No of images	QbITM-ELEABC model	CGATSFRFOPSO model
100	7	13
200	9	16
300	11	18
400	12	21
500	13	22
600	15	24

To effectively address a given computational intelligence challenge, ensemble learning generates and combines numerous models in a planned manner for image retrieval by tagging images. Figure 9 represents the ensemble learning process in image tagging accuracy levels shown in Table 4 of the proposed and existing models.

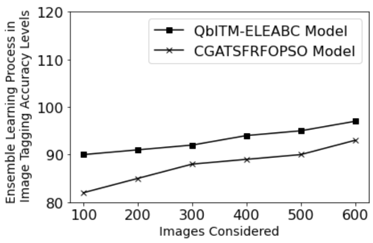


Figure 9. Ensemble learning process in image tagging accuracy levels

Table 4. The ensemble learning process in image tagging accuracy levels

No of images	QbITM-ELEABC model	CGATSFRFOPSO model
100	90	82
200	91	85
300	92	88
400	94	89
500	95	90
600	97	93

This new optimization method, the EBAC algorithm, combines the fusion weights with multi-level search used in the system implementation to produce a novel approach to retrieving images by performing image tagging. The optimization accuracy level in image retrieval process is shown in Table 5, and the graph representation is in Figure 10. The relevant images are displayed in Figure 11, based on the query image as shown in Figure 11(a), and the extracted images are shown in Figure 11(b). The proposed model extracts the most relevant images from the PatternNet dataset considered.

Table 5. The optimization accuracy level in image retrieval process

No of images	QbITM-ELEABC model	CGATSFRFOPSO model
100	89	78
200	92	81
300	93	83
400	96	85
500	97	87
600	98	91

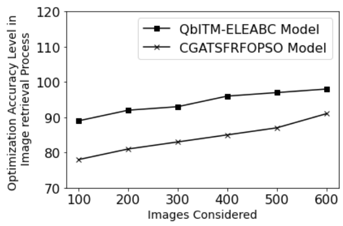
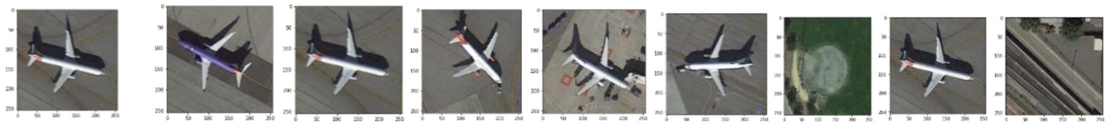


Figure 10. Optimization accuracy level in image retrieval process



(a) (b)

Figure 11. Extracted image set relevant to (a) query image and (b) retrieved images

4. CONCLUSION

It is impossible to represent images using a single feature representation because of their diversity or non-homogeneous image qualities. Including low-level characteristics in fusion can help improve CBIR and picture representation performance. As the image is represented as patches, the gap can be narrowed by combining specific local information, improving performance. Traditional machine learning algorithms have been used to study CBIR and take its inspiration with good results in several fields. For learning classification-based models, a practical framework for optimizing feature representation can be provided by maximizing the number of feature dimensions. For CBIR, recent studies have focused on using deep neural networks, which have demonstrated exemplary performance on numerous data and outperformed classifiers subject to fine-tuning. A novel optimization strategy, the ABC algorithm, combines fusion values in the system implementation to produce an entirely new image retrieval method. In this research, query based image tagging model using ensemble learning with EBAC for a CBIR model is proposed for tagging the relevant images based on the query image. The findings prove that a query image's color and texture attributes help locate related images. The proposed method has achieved an average precision of 89% for detailed images and 96% for simple ones. This model can be improved by incorporating additional low-level variables, such as shape and spatial placement. Improvements in image retrieval systems can be attributed to technological developments, such as expanding storage capacities and higher internet speeds.

REFERENCES

[1] A. P. Byju, B. Demir, and L. Bruzzone, "A progressive content-based image retrieval in JPEG 2000 compressed remote sensing archives," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 58, no. 8, pp. 5739–5751, Aug. 2020, doi: 10.1109/TGRS.2020.2969374.

[2] D. Xue *et al.*, "An application of transfer learning and ensemble learning techniques for cervical histopathology image classification," *IEEE Access*, vol. 8, pp. 104603–104618, 2020, doi: 10.1109/ACCESS.2020.2999816.

[3] A. Khan, A. Javed, M. T. Mahmood, M. H. A. Khan, and I. H. Lee, "Directional magnitude local hexadecimal patterns: a novel texture feature descriptor for content-based image retrieval," *IEEE Access*, vol. 9, pp. 135608–135629, 2021, doi: 10.1109/ACCESS.2021.3116225.

[4] A. Ahmed and S. J. Malebary, "Query expansion based on top-ranked images for content-based medical image retrieval," *IEEE Access*, vol. 8, pp. 194541–194550, 2020, doi: 10.1109/ACCESS.2020.3033504.

[5] J. Ramalhinho, H. F. J. Tregidgo, K. Gurusamy, D. J. Hawkes, B. Davidson, and M. J. Clarkson, "Registration of untracked 2D laparoscopic ultrasound to C.T. images of the liver using multi-labelled content-based image retrieval," *IEEE Transactions on Medical Imaging*, vol. 40, no. 3, pp. 1042–1054, Mar. 2021, doi: 10.1109/TMI.2020.3045348.

[6] A. Ahmed, "Implementing relevance feedback for content-based medical image retrieval," *IEEE Access*, vol. 8, pp. 79969–79976, 2020, doi: 10.1109/ACCESS.2020.2990557.

[7] J. Y. Choi and B. Lee, “Combining of multiple deep networks via ensemble generalization loss, based on MRI images, for alzheimer’s disease classification,” *IEEE Signal Processing Letters*, vol. 27, pp. 206–210, 2020, doi: 10.1109/LSP.2020.2964161.
[8] C. Peng, H. Jiang, and L. Qu, “Deep convolutional neural network for passive RFID Tag localization via joint RSSI and PDOA fingerprint features,” *IEEE Access*, vol. 9, pp. 15441–15451, 2021, doi: 10.1109/ACCESS.2021.3052567.
[9] X. Li *et al.*, “COCO-CN for Cross-lingual image tagging, captioning, and retrieval,” *IEEE Transactions on Multimedia*, vol. 21, no. 9, pp. 2347–2360, Sep. 2019, doi: 10.1109/TMM.2019.2896494.
[10] Y. Wang, L. Zhu, X. Qian, and J. Han, “Joint hypergraph learning for tag-based image retrieva,” *IEEE Transactions on Image Processing*, vol. 27, no. 9, pp. 4437–4451, Sep. 2018, doi: 10.1109/TIP.2018.2837219.
[11] M. Subramanian, V. Lingamuthu, C. Venkatesan, and S. Perumal, “Content-based image retrieval using colour, gray, advanced texture, shape features, and random forest classifier with optimised particle swarm optimization,” *International Journal of Biomedical Imaging*, vol. 2022, pp. 1–14, Apr. 2022, doi: 10.1155/2022/3211793.
[12] M. K. Ahirwal, N. K. Rout, and M. Atulkar, “A review on content-based image retrieval system: present trends and future challenges,” *International Journal of Computational Vision and Robotics*, vol. 11, no. 5, p. 461, 2021, doi: 10.1504/IJCVR.2021.10040487.
[13] F. Jafarinejad and R. Farzbood, “Relevance feedback-based image retrieval using particle swarm optimization,” *Journal of AI and Data Mining*, vol. 9, no. 2, pp. 245–257, 2021, doi: 10.22044/jadm.2020.9014.2037.
[14] S. R. Dubey, “A decade survey of content based image retrieval using deep learning,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 32, no. 5, pp. 2687–2704, May 2022, doi: 10.1109/TCSVT.2021.3080920.
[15] Y. Ma, Y. Liu, Q. Xie, and L. Li, “CNN-feature based automatic image annotation method,” *Multimedia Tools and Applications*, vol. 78, no. 3, pp. 3767–3780, Feb. 2019, doi: 10.1007/s11042-018-6038-x.
[16] X. Li, J. Yang, and J. Ma, “Recent developments of content-based image retrieval (CBIR),” *Neurocomputing*, vol. 452, pp. 675–689, Sep. 2021, doi: 10.1016/j.neucom.2020.07.139.
[17] P. Tschandl, G. Argenziano, M. Razmara, and J. Yap, “Diagnostic accuracy of content-based dermatoscopic image retrieval with deep classification features,” *British Journal of Dermatology*, vol. 181, no. 1, pp. 155–165, Jul. 2019, doi: 10.1111/bjd.17189.
[18] R. S. Shankar, G. Mahesh, K. V. S. S. Murthy, and J. Rajanikanth, “A novel approach for sharpening blur image using convolutional neural networks,” *Journal of Critical Reviews*, vol. 7, no. 7, pp. 139–148, Apr. 2020, doi: 10.31838/jcr.07.07.22.
[19] R. S. Shankar, G. Mahesh, K. V. S. S. Murthy, and D. Ravibabu, “A novel approach for gray scale image colorisation using convolutional neural networks,” in *2020 International Conference on System, Computation, Automation and Networking (ICSCAN)*, Jul. 2020, pp. 1–8, doi: 10.1109/ICSCAN49426.2020.9262377.
[20] D. R. Babu, R. S. Shankar, G. Mahesh, and K. V. S. S. Murthy, “Facial expression recognition using bezier curves with hausdorff distance,” in *2017 International Conference on IoT and Application (ICIOT)*, May 2017, pp. 1–8, doi: 10.1109/ICIOTA.2017.8073622.
[21] N. K. Rout, M. K. Ahirwal, and M. Atulkar, “Analytic hierarchy process-based automatic feature weight assignment method for content-based satellite image retrieval system,” *Soft Computing*, Jun. 2021, doi: 10.1007/s00500-021-05937-5.
[22] R. S. Shankar, A. B. Krishna, J. Rajanikanth, and C. H. S. Rao, “Implementation of object oriented approach to query processing for video subsequence identification,” in *2012 National Conference on Computing and Communication Systems, NCCCS 2012 - Proceeding*, Nov. 2012, pp. 126–130, doi: 10.1109/NCCCS.2012.6412979.
[23] R. S. Shankar, K. Sravan, L. V Srinivas, and D. Ravibabu, “An approach for retrieving an image using genetic algorithm,” *International Journal of Latest Trends in Engineering and Technology*, vol. 9, no. 2, 2017, doi: 10.21172/1.92.10.
[24] V. M. Gupta, K. Murthy, and R. S. Shankar, “A novel approach for image denoising and performance analysis using SGO and APSO,” *Journal of Physics: Conference Series*, vol. 2070, no. 1, p. 012139, Nov. 2021, doi: 10.1088/1742-6596/2070/1/012139.
[25] R. S. Shankar, L. V Srinivas, P. Neelima, and G. Mahesh, “A framework to enhance objectetection performance by using YOLO algorithm,” in *2022 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*, Apr. 2022, pp. 1591–1600, doi: 10.1109/ICSCDS53736.2022.9760859.
[26] R. B. Devareddi and A. Srikrishna, “Review on content-based image retrieval models for efficient feature extraction for data analysis,” in *2022 International Conference on Electronics and Renewable Systems (ICEARS)*, Mar. 2022, pp. 969–980, doi: 10.1109/ICEARS53579.2022.9752281.
[27] R. B. Devareddi and A. Srikrishna, “An edge clustered segmentation based model for precise image retrieval,” *Indian Journal of Computer Science and Engineering*, vol. 13, no. 3, pp. 769–782, Jun. 2022, doi: 10.21817/indjcse/2022/v13i3/221303094.
[28] N. K. Rout, M. K. Ahirwal, and M. Atulkar, “Content-based medical image retrieval system for skin melanoma diagnosis based on optimized pair-wise comparison approach,” *Journal of Digital Imaging*, pp. 1-14, Oct. 2022, doi: 10.1007/s10278-022-00710-y.
[29] H. Wang *et al.*, “Artificial bee colony algorithm based on knowledge fusion,” *Complex & Intelligent Systems*, vol. 7, no. 3, pp. 1139–1152, Jun. 2021, doi: 10.1007/s40747-020-00171-2.
[30] H. Ahmad, J. Sun, A. Nirere, N. Shaheen, X. Zhou, and K. Yao, “Classification of tea varieties based on fluorescence hyperspectral image technology and ABC-SVM algorithm,” *Journal of Food Processing and Preservation*, vol. 45, no. 3, Mar. 2021, doi: 10.1111/jfpp.15241.
[31] Y. Celik, “An enhanced artificial bee colony algorithm based on fitness weighted search strategy,” *Automatika*, vol. 62, no. 3–4, pp. 300–310, Oct. 2021, doi: 10.1080/00051144.2021.1938477.
[32] O. Rostami and M. Kaveh, “Optimal feature selection for SAR image classification using biogeography-based optimization (BBO), artificial bee colony (ABC) and support vector machine (SVM): a combined approach of optimization and machine learning,” *Computational Geosciences*, vol. 25, no. 3, pp. 911–930, Jun. 2021, doi: 10.1007/s10596-020-10030-1.
[33] A. Ganesan and S. M. Santhanam, “Local neighbourhood edge responsive image descriptor for texture classification using Gaussian mutated JAYA optimisation algorithm,” *Arabian Journal for Science and Engineering*, vol. 46, no. 9, pp. 8151–8170, Sep. 2021, doi: 10.1007/s13369-021-05417-w.
[34] D. Karaboga and B. Akay, “Artificial bee colony (ABC) algorithm on training artificial neural networks,” in *2007 IEEE 15th Signal Processing and Communications Applications*, Jun. 2007, pp. 1–4, doi: 10.1109/SIU.2007.4298679.
[35] C. Zheng, L. Zhu, Z. Cheng, J. Li, and A.-A. Liu, “Adaptive partial multi-view hashing for efficient social image retrieval,” *IEEE Transactions on Multimedia*, vol. 23, pp. 4079–4092, 2021, doi: 10.1109/TMM.2020.3037456.
[36] N. Behnia, M. Zare, V. Moosavi, and S. J. Khajeddin, “An inter-comparison of different PSO-optimized artificial intelligence algorithms for thermal-based soil moisture retrieval,” *Earth Science Informatics*, vol. 15, no. 1, pp. 473–484, Mar. 2022, doi: 10.1007/s12145-021-00747-7.
[37] N. B. Devi, “Satellite image retrieval of random forest (rf-PNN) based probablistic neural network,” *Earth Science Informatics*, vol. 15, no. 2, pp. 941–949, Jun. 2022, doi: 10.1007/s12145-021-00759-3.

[38] R. B. Devareddi and A. Srikrishna, "Interlinked feature query-based image retrieval model for content-based image retrieval," *Indian Journal of Computer Science and Engineering*, vol. 13, no. 5, pp. 1426–1436, Oct. 2022, doi: 10.21817/indjcse/2022/v13i5/221305013.
[39] W. Zhou, S. Newsam, C. Li, and Z. Shao, "PatternNet: a benchmark dataset for performance evaluation of remote sensing image retrieval," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 145, pp. 197–209, Nov. 2018, doi: 10.1016/j.isprsjprs.2018.01.004.

BIOGRAPHIES OF AUTHORS

Mr. Ravi Babu Devareddi received his B.Tech. (Computer Science Engineering) Degree in 2005 from Andhra University, obtained M.Tech. (Computer Science& Technology) Degree from Andhra University in 2009 and doing Research in Computer Science and Engineering in Acharya Nagarjuna University, Guntur, India. My current Research Interests are in Internet of Things, Image Processing, Computer Vision and Artificial Intelligence. He can be contacted at email: ravibabu.devareddi@gmail.com.

Dr. Atluri Srikrishna received her AMIE (ECE), Institute of Engineers, Kolkata, India. She obtained her M.Tech. Degree JNTUH, Hyderabad, Andhra Pradesh, India and her Ph.D. Degree from JNTUK, Kakinada, Andhra Pradesh, India. She is currently working as a Professor & Head in the Department of Information Technology, R.V.R. & J.C. College of Engineering, Chowdavaram, Guntur, India. Her current Research Interests are in Image Processing & Computer Vision, Information Security and Algorithms. She can be contacted at email: atlurisrikrishna@gmail.com.