Computers and Electrical Engineering 74 (2019) 281–291

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Hybrid ant colony optimization model for image retrieval using scale-invariant feature transform local descriptor☆

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ARTICLE INFO

Article history:
Received 16 October 2018
Revised 7 February 2019
Accepted 7 February 2019
Available online 13 February 2019

Keywords:
Document retrieval
Scale-invariant feature transform (SIFT)
local descriptor
Ant colony optimization (ACO)
Support vector machine (SVM)
Back propagation neural network (BPNN)

ABSTRACT

An organization uses a symbol as its representation in the market for ease of identification and uniqueness. Logos are used to identify and retrieve the materials, even in a complex environment for further analysis. Algorithms based on support vector machine and neural networks provide better results in retrieval of the document from small dataset. But in-large data sets the existing models lags in their classification performance. This proposed model uses ant colony optimization (ACO) along with the local descriptor scale-invariant feature transform (SIFT), as a hybrid model for retrieving document from dataset. This hybrid model enhances the performance of the retrieval model in terms of increased efficiency, leading to an accuracy of 95.86% with a high output precision of 97.67%.

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1. Introduction

In 20th century digital world, many organizations private and public sectors are interested in implementing their processes via digital models. They all have digital service rooms to reduce paperwork. Since a manual process is required to consolidate papers, these digital rooms are used to reduce this burden by improving efficiency and simplifying administration processes such as organizing, classifying and retrieving documents. An automatic indexing system is essential for this digital service, automatic classification and distribution of documents. The use of textual information for such process is complex, since all the documents are developed using the same format. Therefore, it is essential to identify the documents based on the logo or a symbolic representation in the layout. In some documents, a bar code or quick response (QR) code is used to give the details of the organization. This salient feature creates broad opportunity for content-based document image retrieval in analyzing documents.

The application of logo-based document retrieval is based on common pattern recognition processes, which differ from traditional processes mainly in the extraction portion. The usual recognition process starts with preprocessing, followed by extraction of a meaningful logo or symbol from the scanned document. After the extraction process, classification is performed to detect the logo and compare it with the existing database in a matching process. This includes a critical consideration of the recognition processes for machine-designed logos and manually designed logos. The current research in image processing and data retrieval is reviewed in order to identify the best retrieval model.

☆ Reviews processed and recommended for publication to the Editor-in-Chief by Associate Editor Dr. S. Smys.

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https://doi.org/10.1016/j.compeleceng.2019.02.006
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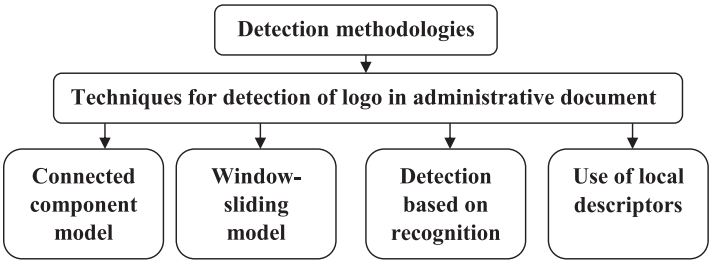


Fig. 1. Detection methodologies.

In document analysis, the process is described as two tasks, based on the interest of the researcher in the design process. The initial process is used to identify the logo and then a classification is performed, even if the obtained image is not present in the existing database. The second model uses a different process, as it extracts the logo, and then all the related documents are extracted based on the index values. In both processes, indexing plays a vital role and therefore it is considered an important feature for logo extraction. It is necessary to identify the detection procedure for a given document in order to summarize the documents.

In many logo recognition models, it is evident that the identification process is performed through segmentation. The steps involved in detection methodologies using common processes is given in Fig. 1. This figure shows techniques used in document detection based on various approaches, such as the connected component model, window-sliding model, detection based on recognition model and the use of local descriptors. The features for logo recognition is characterized based on the utilization of resources and are mainly classified into two categories, i.e., structural logo recognition and statistical logo recognition. Structural recognition considers the geometric relationship among the primitives and uses a graphical representation technique for recognition of shape and other contextual features. In the statistical recognition approach, enormous quantities of information from various sources are used. The local and global factors are considered based on the features, and these are categorized into local features and global features. The summations of extracted information from each input domain are considered as local features, whereas global features are concerned with the set of pixel values for a particular region of the document. Local features are used in the logo retrieval process due to their characteristics. The invariants, negative features, curvature and centroid point are considered with respect to local features in the detection model. For these descriptors, the total area and vertical gaps are considered in the detection, along with the color and other features. The bag-of-word features and the Fourier coefficients are considered in some cases in the logo detection model. In addition, many models, such as bispectral feature extraction, wavelet-based feature extraction, and two-level contour representation, are used in research studies related to logo detection. Classification is the next process in logo recognition, and this employs various models, such as those using nonparametric and parametric factors.

The organization of the manuscript is as follows, Section 1 forms the introduction, Section 2 deals with related work, Section 3 gives detailed information on ant colony optimization in the document retrieval process, along with the scale-invariant feature transform local descriptor, Section 4 discusses and evaluates the results and Section 5 concludes the study.

2. Related work

Many research articles were studied before developing the proposed model. Since this is a developing research topic, the issues and the advantages of the various models are considered. This literature review section provides a clear idea of the issues present with respect to existing models and the necessity for the proposed optimization model. A content-based image retrieval system is described in [1] for a high-dimensional remote sensing image. This research model has limitations in terms of efficiency when handling large data sets. In [2], the issues regarding remote sensing images using a region-based retrieval model are reported. The proposed model uses graph theory as the experimental procedure for obtaining the regions of the data set for retrieving the actual image. The limitation of this model is that error convergence sometimes occurs due to the unsupervised process. The [3] advantages present in the content-based image retrieval model are highlighted, along with coding features. The proposed model in this research uses a diffusion process for truncating the features in the data set while retrieving the images.

In [4], the existing content-based retrieval model is used in peer-to-peer networks. The use of this retrieval model leads to better results in terms of precision, compared to other research studies at that time. The neural network model, which comprises the domain features for image retrieval, is described in [5]. The neural network follows the support vector machine (SVM) classifier, which produces better results than existing models. The proposed model combines this deep learning process with compressed features for obtaining improved results. The findings from [6] highlight the issues present in remote sensing image retrieval process. The usual processes of graph theory does not provide a suitable model in the case of image retrieval, and therefore it is enhanced by using a hybrid model.

A similar process is discussed in [7], where a graph-based ranking model is used for content-based image retrieval. This retrieval process assigns graph-based rankings and each rank value is used in other variables. Another issue identified in

[8] concerns logo recognition based on adaptive weighted pooling and convolution neural networks. The adaptive model [9] uses logo proposals for developing the proposed model. This is useful in terms of retrieval of images. A convolution neural network is used in [18] as a pretraining strategy. This system has input nodes from various sources and is responsible for all the processes within it. The proposed model uses a large data set, since the vehicle recognition model together with a convolution neural network provides a self-tunable multilayer network. It differentiates between text and image in a group of components, with an accuracy of 76.65%

Information given in [10] regarding fine-grained object classification for recognizing color patterns from the document. The process is classified only for the color, and the sensors are used to segment the original document and images into four regions, i.e., graphics, picture, text and background. In addition, [11] compares the proposed model with the existing model for image classification and retrieval. This image classification model is not only used for retrieval but also has the capability to improve the graphic sources into optical character recognition (OCR) sources. The rapid annotation using subsystem technology (RAST) algorithm is used to analyze the text blocks for recognizing the non-text and other blocks [17]. In [12], a neural network-based logo detection model uses second-order features for matching and retrieval. The proposed model mainly applies the Markov model for run length encoding and the Hough transform for segmentation of the photos' frames.

The findings from [13,15] concern the SVM, which can be used to solve the issues in image retrieval. The author proposed a model using artificial neural network (ANN) and support vector machine for the classification of the data set. The study in [14] classifies the data based on the features. Four stages occur in the ANN and SVM. The performance measures used in this study are accuracy, sensitivity, specificity and area under the curve. The authors developed a classification model using an input variable function, preprocessing and partitioning, setting of model parameters and implementation. In [23], a novel hybrid model is proposed for the classification of image set. In the data set, explanatory variables and one class variable is used. Almost every study uses explanatory variables and a class variable. A single classification technique [24] is not enough to produce improved results.

The findings in [25] consider the issues in a hybrid neural network model based on factors such as efficiency and accuracy. Edge detection for the networks is used, along with particle swarm optimization. This optimization model provides efficiency in terms of retrieval of images from the database. Scene-based logo retrieval is used in [16] for recognizing the images. In addition, a low-resolution logo-based vehicle is used in the random statistical process. In [19], the optimization model used in the common image retrieval process is highlighted. For the image processing application, this research model is useful for obtaining a clear idea of optimization models and their advantages for implementation in the document image retrieval. The ant colony optimization-based image classification model for medical images is also described in [20]. Since the use of the neural network classifier produces a better result, this optimization model is used to enhance the classification results. The implementation of ant colony optimization in network-based image processing applications is described in [21–23]. From all these studies it can be observed that none of the classification processes produces better results. Therefore, it is essential to optimize the classification results. From the above findings, the ACO is identified as a better optimization model for retrieving classifier results. Since it contains a fitness function, path identification strategies are useful, and these are also applied in the proposed document retrieval model. The advantage of using a local descriptor in the proposed model is that it provides a hybrid term for enhancing the results.

3. Proposed work

The proposed model based on a local descriptor uses a local detector for exploiting the key points in the document. Shape, context and scale-invariant feature transform models are used in the model for defining the descriptors. In the logo detection, a set of cascading amplifiers is used in image scales and the logo matching is performed using SIFT, which helps in reducing the computation time even when the document contains multiple logos. A logo is spotted based on detecting the key point. For each logo, a key point is assigned and previously stored in the database. After obtaining the key points, the logo spotting process filters the nearest-neighbor values using homograph descriptors. The mathematical model of the proposed SIFT descriptor is given as the key point localization and description of an identified key point. It uses scale-space theory for obtaining the important key points for the image set, using kernels as multiple scales. It has an improved approach for simplifying the relevant scale into multiple scales. An image $x(m, n, q)$ is obtained, using convolution of the actual image with its Gaussian, given as

$$x(m,n,q) = \frac{1}{2\pi q^2} e^{-(m^2+n^2)/2q^2} \tag{1}$$

where $x(m, n, q)$ is the Gaussian kernel with parameter q^2, representing the factors for controlling the smoothness of the actual image. The difference in the scales of the image using the multiplicative factor is given as

$$y(m,n,q) = x(m,n,q) - x(m,n,q) * I(m,n) \tag{2}$$

In common processes, the image is divided into eight portions, and each image has a fixed resolution which is obtained from the above Gaussian values. In order to identify the key points, local minima and maxima are identified. For further accuracy and illumination changes, the key point is obtained using the expansion series for the real extreme values of that region. The gradient magnitude $g(m, n)$, expressed in terms of the image, is given as

$$g(m,n) = \sqrt{x(m+1,\ n,q) - x(m-1,\ n,q) + x(m,\ n+1,q) - x(m,\ n-1,q)} \tag{3}$$

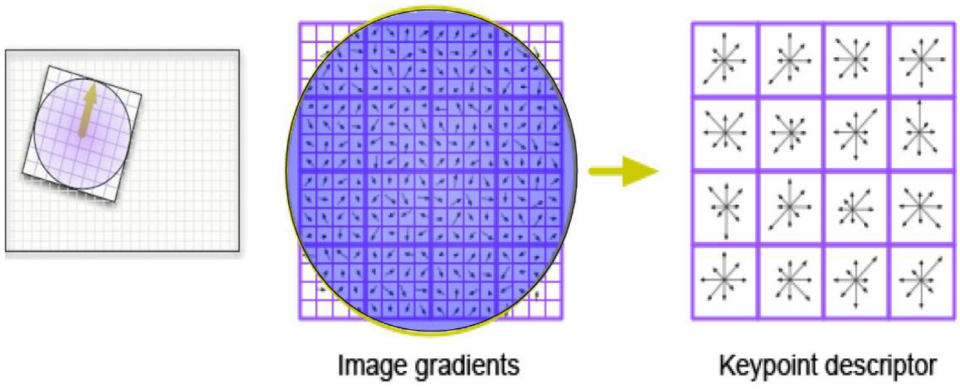


Fig. 2. SIFT visual illustration.

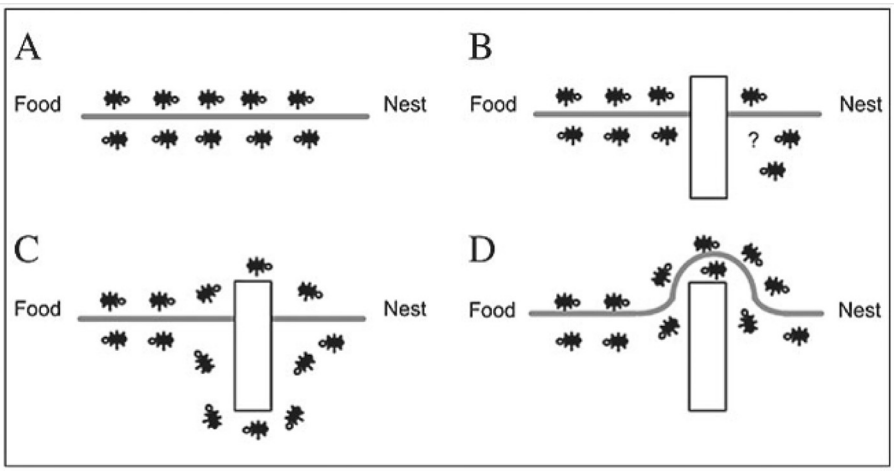


Fig. 3.1. Illustration of model of ACO minimization: (A) ants in a pheromone trail between nest and food, (B) an obstacle interrupting the trail, (C) ants finding two paths, (D) ants finding the shortest path.

The orientation of the image is given as

$$Q(m,n,q) = \tan^{-1}\left[\frac{x(m,n+1,q) - x(m,n-1,q)}{x(m+1,n,q) - x(m-1,n,q)}\right] \tag{4}$$

The maximum orientation of each content item is obtained using the Gaussian window key point and the gradient magnitudes are also obtained using the same main orientation. The classification process concludes by defining the identified logo and its content, based on the retrieval. The accuracy of the system is obtained by calculating the error percentage, i.e., the percentage of errors in the proposed model.

Fig. 2 shows the SIFT visualization, which includes the process of identifying the local variables by rotating the local coordinates. The weighted Gaussian kernel is obtained for each block in the illustrative figure as a final descriptor with 128 dimensions. The ant colony optimization process is included in the SIFT descriptors model for obtaining improved results after the classification process. Neural networks in existing studies provide better results if they are combined with other models as a hybrid term. For optimization, this key point feature is considered and then the proposed model is defined using the basic strategy of ant colony optimization. The mathematical model for the ant colony optimization process is obtained using the assumptions, in order to formulate the proposed model in the logo-based document retrieval process.

The travelling process of ants searching for food is considered in the proposed model for obtaining the best portions of the document where the logo is located The ant identifies the shortest path from the food to its nest, as illustrated in Fig. 3.1.

The probability of the shortest path is evaluated based on successive iterations, and this natural model characterizes the process as a trail model for food transit from a particular place to the nest. The process of data size convergence and the essential coefficient parameters are considered for identifying the behavior. All motions of the individuals are obtained for movement from one place to another, and this movement is given as $\vec{x}_i$, with the next new location identified as $\vec{y}_j$. The

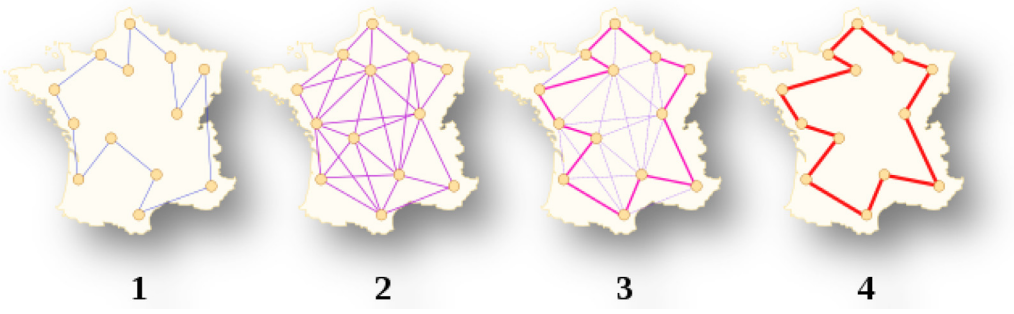


Fig. 3.2. Illustration of model of ACO minimization.

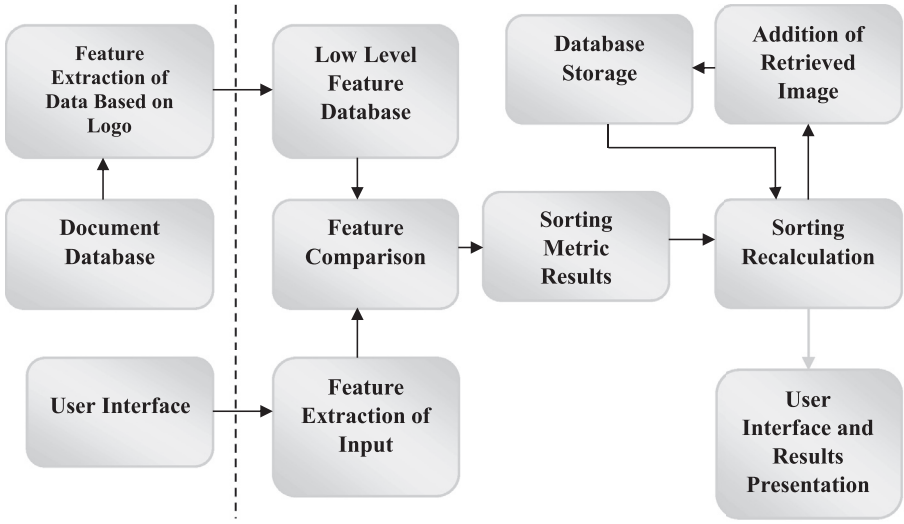


Fig. 4. Illustrative description of proposed model.

random distribution of the process and its stability are given as

$$\overrightarrow{y_{j,t}} = x\vec{l}_{i,t} + Real * Rand\ int[-1, 1] \tag{5}$$

If the stability of position $\overrightarrow{y_j}$ is better than the present position $\overrightarrow{x_i}$, the position is updated.

$$\overrightarrow{y_{j,t}}(p+1) = \vec{x}_{i,t}(p) + \left(\overrightarrow{y_{j,t}}(p) - \vec{x}_{i,t}(p)\right) * Rand\ int[0, 1] \tag{6}$$

The above process up to Eq. (6) is repeated many times and the positions are updated so that the distances between them are identified easily for each displacement. In all possible iterations, the position is changed from one place to another. The behavior of ants in forward movement by one step is given as

$$\overrightarrow{y_{j,t}}(p+1) = \vec{x}_{i,t}(p) + \left(\frac{\overrightarrow{y_{j,t}}(p) - \vec{x}_{i,t}(p)}{q_{i,t}}\right) * Rand\ int[0, 1] \tag{7}$$

where $\overrightarrow{x_i}$ is the initial position, $\overrightarrow{y_j}$ is the next or new or best position and q_i is the center position.

Fig. 3.2 shows an illustration of an ant colony optimization model which includes current position, next position and best position. The interaction behavior between them is considered globally. The Euclidean distance is calculated among all the ants for detecting neighbors' distances. For effective improvement in convergence rate, the possibility of reducing the computational load must be considered in all cases. The center, which is obtained previously, is calculated based on the intra-cluster values. The function is a minimum, given as

$$q(g_1, g_2, g_3, \ldots g_n) = \sum_{i=1}^{p} \left(\int \int_{x^3}^{\alpha} \|g_i - 1\| * q(x)/2 \right) \tag{8}$$

where a new cost facility is essential for identification of the minimum requirement for the acceleration constant. Fig. 4 shows an illustration of the proposed model.

Here, the risk analysis is described via the relation between the risk parameters and risk levels in the proposed model. The general rule statements are formulated as statements comprising the hyper chaos-based outline and implementation of the algorithm, as follows.

1. Input data set
2. Begin
3. Initialize input sequence *x, q*
4. Keyword search k={k1, k2, … kn}
5. Data values *x, y*, zin terms of *m, n, q*. Output sequence *y, q*
6. Read document image, calculate mean, standard deviation and intensity using eight neighbors
7. Set algorithm parameters, initialize ant array
8. Calculate heuristic values, initialize pheromone
9. Obtain the document and initialize variable with random values as step movements of ants, for each $k_i \in k$
10. Compare stability factor and optimal state availability

    Iteration time into 0&&Result, heap into q

11. If available

        go to next position
    else
        remain in the same position until next change occurs

12. End
13. Strategy policy (based on step 4)
14. Location is increased/decreased for new search
15. Obtain optimal solution for the new steps. Parameters are $q_{2,}q_{3,\ \ldots}\ q_n$

    for $x = Randint(q_n x)$

16. Select the random points $u^t, t = 1, 2, \ldots L_l$

        for $t = 1$ to x_l
    for the set $z_n = u^t, Z_m = z(p^i, q^j)$
    by computing the ant behavior with integer values

17. Perform the swarm move and create a suitable connection for the set

$$Z_\alpha = z\left(p_\alpha^i, q_\alpha^j\right)$$

18. If $Z_\alpha < Z_m$, *then* replace the corresponding position with the new position once from the function value.

Fig. 5 shows the process flow of the ant colony optimization in the proposed model. The process starts as described in the algorithm section and in the last stage, if the maximum number of iterations is reached, then the process is initiated again, until it reaches the best position as the final result. For the proposed model, the best logo-based retrieval is considered important.

4. Results and discussion

In general, for logo recognition and retrieval of images, the Unified Modeling Language data set (UMLD) is frequently used in many research studies. In addition, the Flickr logo collection and the Belga Logos dataset, are the other data models used in various studies. In the proposed model, the UML data set is used in the experimental process. This consists of 106 images of documents with logos present in them. The Belga Logos data set is used to compare the results in some cases. This data set consists of more than 10,000 images originating from companies that differ in terms of finance, culture, politics, etc. The proposed model is performed in MATLAB 14.1 installed on an Intel i7, 3.75 GHz processor. The computation times and accuracies are calculated for the proposed model by comparing them with existing models such as SVM classifier and neural network models. Moreover, the performance comparison has been made based on the accuracy of classification expressed in terms of precision and recall. Table 1 gives the parameters of the data set used in the proposed model, as initial values.

Fig. 6 shows the comparison of various logo-based document retrieval ratios. The proposed model is compared with the SVM model and the back propagation neural network model. The results show that the proposed hybrid ant colony optimization model has better performance compared with the SVM and BPNN model in terms of efficiency. The efficiency increase is almost 50% better than the existing traditional methods. Hence the claim is proved in terms of efficiency. It is

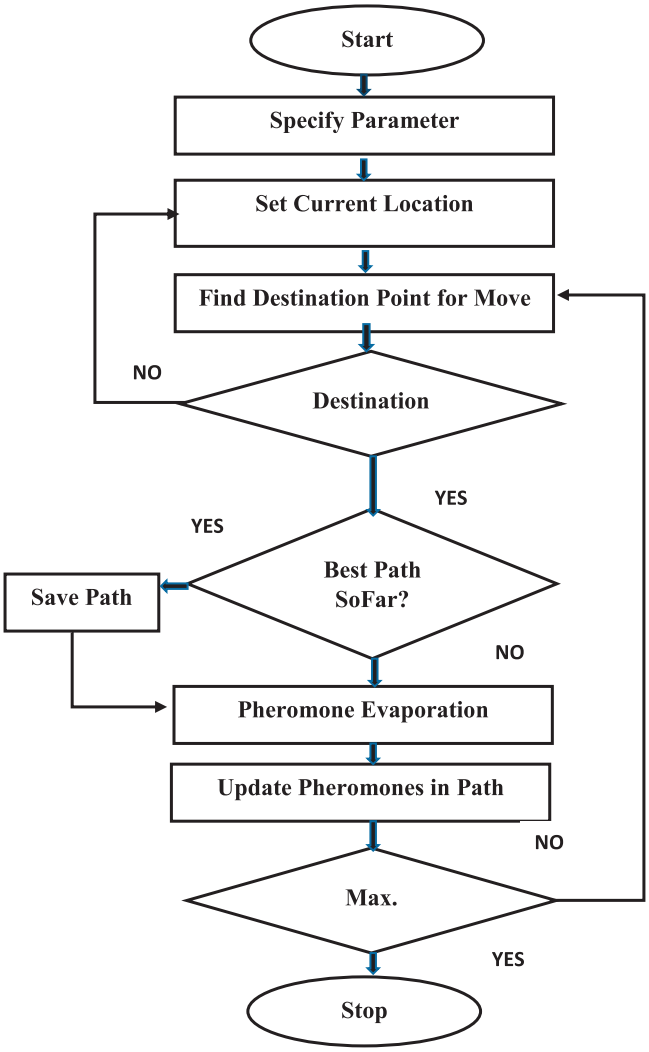


Fig. 5. ACO process flow.

Table 1
Parameters in the proposed experiment.

S. no.	Parameters	Value
1	Total no. of ant(s)	50
2	No. of iterations	50
3	Initial pheromone MatrixValue	0.001
4	Number of construction steps	80
5	Movement steps	700
6	Pheromone amount for each region	0.5,1,1.5
7	Pheromone decay coefficient	0.5

very evident from the results shown in the graph below in Fig. 6. i.e., the optimized model provides better results than the classification model, even though the classifier performs better than other models.

Fig. 7 shows the precision values for the various methods used in the study. The proposed model precision value is compared with those of the existing models SVM and BPNN, and it is clearly observed that the values for the proposed model are better than those of the other two models. As the precision values decreases, the number of returned documents increases.

Fig. 8 shows the comparison of simulation time for the proposed model and the other models, in terms of overhead values.

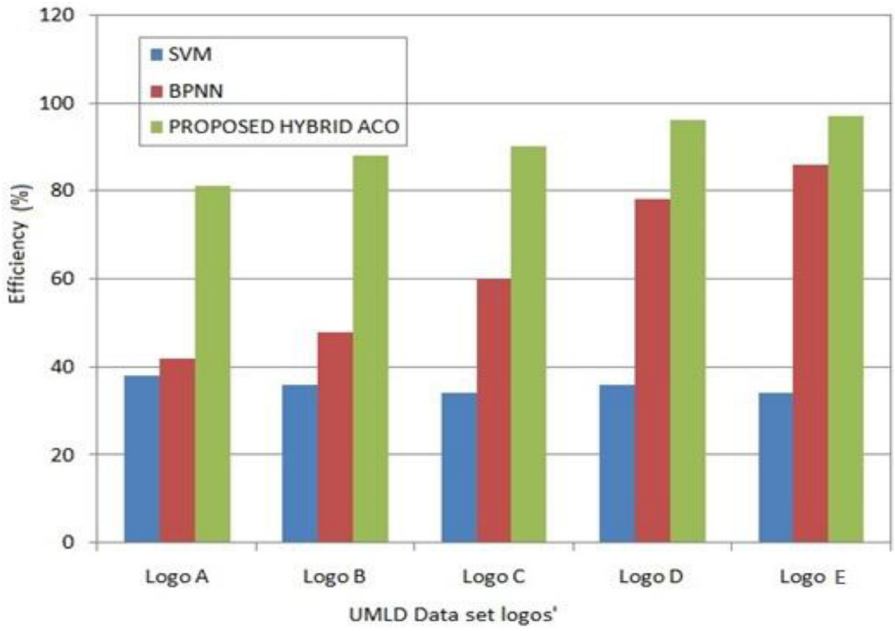


Fig. 6. Efficiency comparison of proposed model.

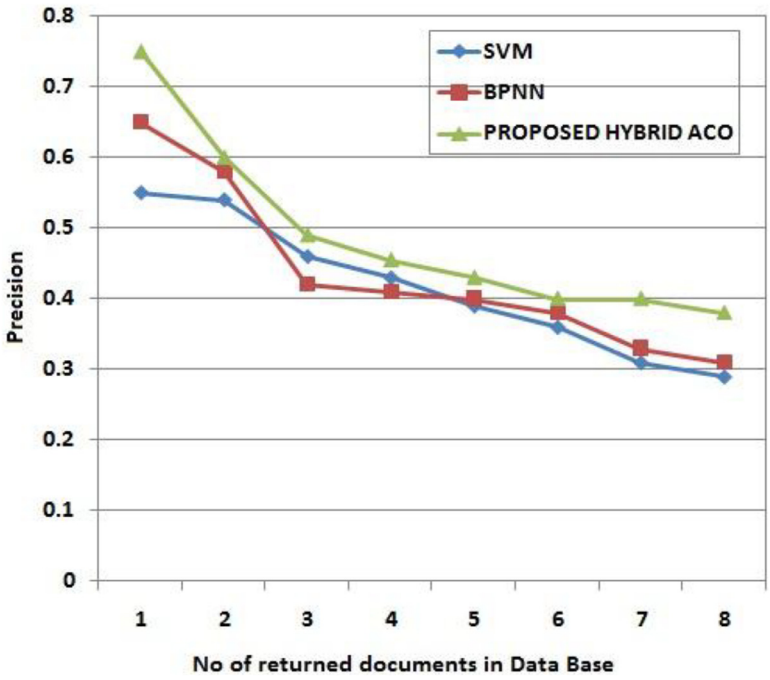


Fig. 7. Precision comparison for proposed model.

Fig. 9 shows a comparison chart for precision values and total recall values for the proposed model and existing models. The graph indicates that the proposed model has high precision values, as shown by the green line. The other two models have lower precision values for the same data set.

From the experimental results, it is observed that the proposed logo detection model provides better results for all aspects, compared with existing models. The overall process is compared with the back propagation neural network (BPNN) model.

The experimental process was performed with the above parameters for both the BPNN model and the proposed model. Results obtained in terms of computation time, efficiency and precision accuracy are listed and compared in Table 2. It is

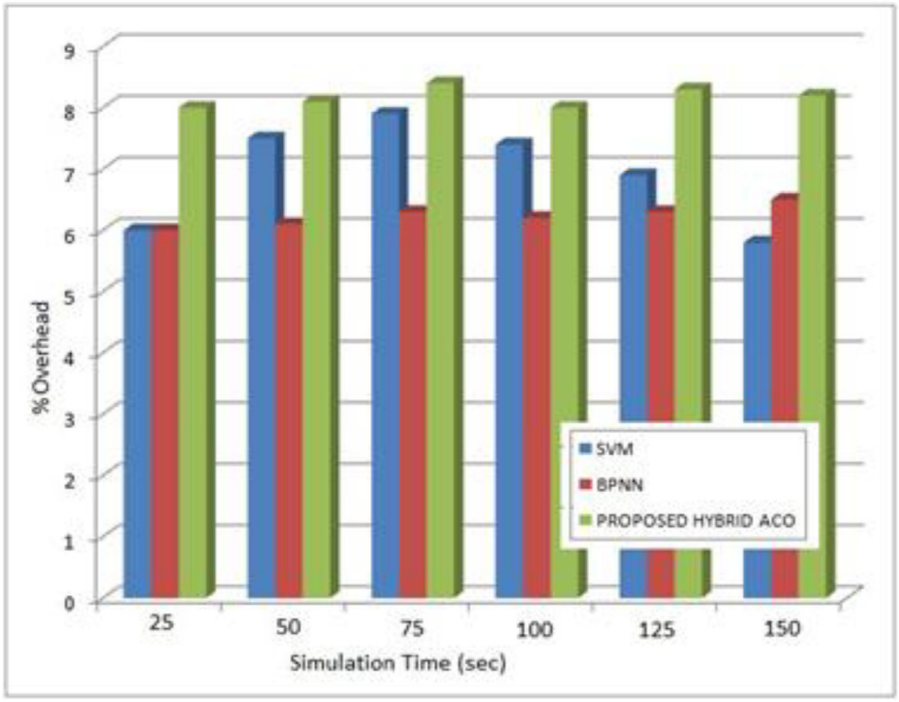


Fig. 8. Simulation time comparison for proposed model.

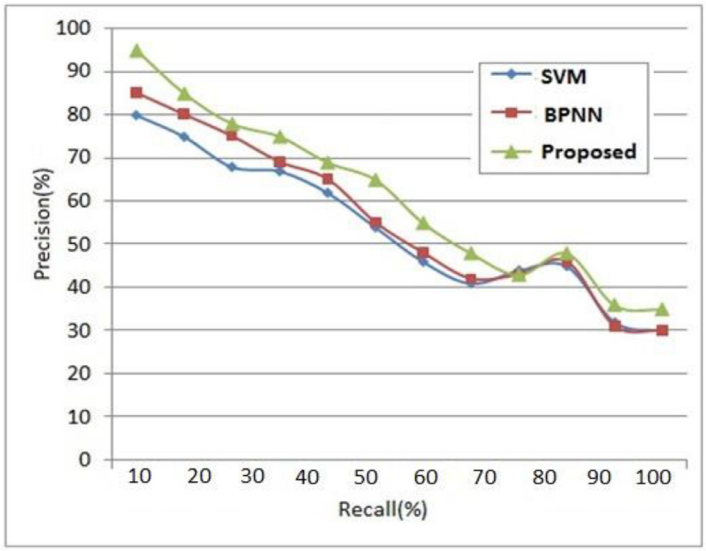


Fig. 9. Precision vs. recall percentage for proposed model, compared with other models.

Table 2
Performance comparison for proposed model.

S. no.	Parameter	BPNN model	Proposed model
1	Computation time	50s	30s
2	Error convergence	0.00043	0.0000012
3	Accuracy	90.65%	95.86%
4	Efficiency	85.788%	97.67%

Table 3
Comparison of logo detection rates.

S. no.	Logo type	Number of documents	Detection ratio		
			SVM	Hybrid SVMD-DLNN (BPNN)	Hybrid ACO
1		60	81	93	94
2		80	75	86	92
3		90	76	89	93

observed that the proposed model has better efficiency compared with the existing SVM and neural network models. The performance of the entire model is improved due to its smart utility management. The final analysis concerns the detection rate for the extraction of logos, as listed in Table 3.

It can be seen from the above table that the proposed hybrid ACO is able to detect the highest number of logos from the given set of documents, tested for three different logo cases. It can be seen that the proposed ACO outperforms the existing techniques, including the hybrid deep learning neural network (DLNN), for all evaluation metrics considered.

5. Conclusion

This research paper deals with a hybrid evolutionary and nature-inspired algorithm for automatic extraction of logos from a list of documents. In the experimentation process support vector machine, deep learning neural network trained by back propagation neural network and the proposed ant colony optimization were utilized to validate the results for three logos sets. It can be seen from the analysis that the proposed nature-inspired algorithm has a greater classification and detection accuracy, amounting to nearly 95%, with an overall efficiency of 97% in the shortest time of 30 s. Ant colony optimization is also found to exhibit lower system overheads, with a reduction of nearly 40%. This improvement in evaluation metrics over existing techniques is largely attributed to the optimization mechanism employed in ant colony optimization, which is a probabilistic model and aids in computing the shortest scheme for extracting the logo, simultaneously incurring the lowest overhead for the system. The food foraging behavior of ants was utilized in the extraction mechanism, leading to improved efficiency. Future work could be focused on increasing the number of test sets and incorporating multiple features into the given test documents.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.compeleceng.2019.02.006.

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