Original Research Article

J. Computing & Int. Systems (2021) 240–245

Journal of Computing and Intelligent Systems

Journal homepage: www.shcpub.edu.in

ISSN: 2456-9496

CONTENT BASED IMAGE RETRIEVAL BASED ON PSO-K-MEANS CLUSTERING ALGORITHM

Denis R[#1], Franklin Joseph J[#2]

Received on 02[nd] SEP 2021, Accepted on 26[th] SEP 2021

Abstract — This paper presents an overview of various image retrieval based on content techniques. The paper begins by going through the fundamentals of CBIR. Color, Intensity, and form are the following features explored for Image Retrieval. We go through the resemblance tests that are used to make matches and recover images briefly. Successful indexing and quick scanning images focused on visual characteristics is another critical problem in CBIR. Schemes as an example of image segmentation, indexing also are discussed. The connection between the user and the retrieval system is critical for content-based image retrieval, so versatile query creation and adjustment are just possible to be achieved by including the consumer's retrieval method. Finally, appropriate feedback is answered, which helps in improving the performance of a CBIR scheme.

Keywords - CBIR, Image Processing, Indexing Methods, Retrieval Simulations.

I. INTRODUCTION

Images (or visuals) on a system artefacts are transforming into relevant conventional written content as information media spreads across our culture. The militarization of photography technologies, an advent as a result of the Information Superhighway of the global media system, the imminent integration of technology and television, including the increased adoption, proliferation of audio controllers and image sensors, are all factors contributing to this phenomenon. As the amount of visual information available has increased dramatically, systems to archive and retrieve digital image and video collections are in high demand. Both theoretical analysis and machine construction have advanced significantly over the last decade. However, many complex science issues draw scholars from various disciplines. Knowledge retrieval is the progression of converting a request into a logical list of references.

The first image extraction studies were conducted in the 1970s. 1979, Florence hosted a consultation on Storage Spatial Application Methods. Researchers have been interested in the implementation of information retrieval management's ability strategies since then. The plurality of existing approaches was based on the textual annotation of photographs rather than visual features. To put it another way, images remained only interpreted with text before being scanned via a text established method similar to the one used by conventional database management systems. The number of ordinal pictures generated through science, educational, medicinal, commercial, and additional applications accessible to consumers improved significantly in the 1990s due to developments on the Internet and emerging digital image machinery.

Encounters of text-based retrieval became more challenging. This requirement was the impetus for the creation of these techniques. The amount of academic publications on graphic arts knowledge retrieval, structure, indexing, user solicitation and collaboration, data analytics takes dramatically since 1997. Similarly, universities, government agencies, businesses, and hospitals have built a slew of academic and commercial retrieval systems.

II. RELATED WORKS

CBIR retrieves processed a set of pictures database by contrasting characteristics dynamically obtained from the segmented images, contrasting to systems' text-based approach. The most popular features are mathematical colour, texture, or shape measurements used in almost all existing CBIR systems [1].

The standard framework encourages consumers to request by sending an example of the kind of picture they are looking for, but some systems also allow other options such as palette collection or sketch input. The framework then shows the most widely used functions used for image extraction and those kept imageries whose feature values utmost diligently fit those of the query [2].

With the advent of computer vision technologies and the rise in the number of photographs captured by digital video cameras, searching vast image databases for images with user-specified characteristics has become much more relevant and challenging than ever before [3].

* Corresponding author: E-mail: [1]gajalakshmi@shctpt.edu, [2]mohanrajrameshc@gmail.com

[1]Asst.Professor, PG Department of Computer Science, Sacred Heart College (Autonomous)Tirupattur, 635601.

[2]Master of Computer Science,PG Department of Computer Science, Sacred Heart College (Autonomous)Tirupattur, 635601. India

Picture retrieval using text, which looks for photographs based on one or even more criteria. Keywords identified by the user was the most popular image searching tool in the past. However, there are times when keywords cannot adequately represent a database request. CBIR was created to reduce this issue by searching for samples based on a test image [4]. [5] Provides an overview of existing system designs, procedures, and methods for feature abstraction and corresponding image algorithms.

Visual contents of photographs are indexed as features of the CBIR framework model. Color, texture, form, and colour layout are examples of these characteristics (both colour features and spatial relations) [6]. For potential use, the functions are saved in an image function archive. When a query image is provided, a pre-established algorithm retrieves the structures of the request image to the database, resulting in similar images being returned for the query image [7].

Colour is one of the most common decreased image properties, unaffected by image scale or orientation [8]. Colour graph of data, colour probability distributions and chromaticity identifier are examples of standard colour features used in CBIR (DCD). The much more famous colour depiction seems to be the graph, then it lacks spatial detail. Gotlieb et al. [9]

anticipated a search feature focused on running thread of varying proximity amounts for object-oriented image retrieval. [10] First, to obtain images less than the demand of an exceptional object, break the photo into certain sub-blocks, then use similarity matrix analysis and colour area detail. The likelihood of discovering colour pairs at a given pixel size is described by a colour correlogram, which also provides spatial detail. As a result, the colour correlogram outperforms the colour histogram in retrieval precision [11]. A colour auto qualitative strategy is a kind of colour distribution of values that only records the dimensional correlation of identical colours.

The linear block algorithm (LBA) is colour thresholding and calculation tool for chromaticity extraction. To increase the extraction system's precision, colour scales and confidence interval are used to display the object's advanced equipment, though this image pixel is mainly used to depict the image's unique characteristics. Colour features with a smaller number of features are defined as dominant colours. This approach can significantly reduce image retrieval time and improve retrieval performance. Humans consider the relationships between colours and textures vital as we describe image features. [12]. They suggested a texture-based image retrieval method that incorporates wavelet decomposition [13] and the gradient vector [14]. With each image, the device includes coarse image features and an acceptable feature descriptor. Both descriptors are constructed from the original image's wavelet [15] coefficients. The coarse feature descriptor is used first to filter out unsuitable pictures automatically, and then the exemplary feature descriptor is used to select the genuinely matched images.

III. PROBLEM STATEMENT AND PROPOSED WORK

Erstwhile, CBIR structures know how to be divided into two groups based on the script and pictorial. Text material search schemes, for starters, terms and annotations are also used to label. If suitable text explanations for images in an image database are included, text functionality may be handy as a query. Giving appropriate definitions, on the other hand, must be performed manually, which time is consuming. A visual question can be phrased in a variety of ways anticipated a search feature focused on running thread of varying proximity amounts for object-oriented image retrieval.

[10] First, to obtain images less than the demand of an exceptional object, break the photo into certain sub-blocks, then use similarity matrix analysis and colour area detail. The likelihood of discovering colour pairs at a given pixel size is described by a colour correlogram, which also provides spatial detail. As a result, the colour correlogram outperforms the colour histogram in retrieval precision [11]. A colour auto qualitative strategy is a kind of colour distribution of values that only records the dimensional correlation of identical colours. The linear block algorithm (LBA) is colour thresholding and calculation tool for chromaticity extraction. To increase the extraction system's precision, colour scales and confidence interval are used to display the object's advanced equipment, though this image pixel is mainly used to depict the image's unique characteristics. Colour features with a smaller number of features are defined as dominant colours. This approach can significantly reduce image retrieval time and improve retrieval performance.

Humans consider the relationships between colours and textures vital as we describe image features. [12]. They suggested a texture-based image retrieval method that incorporates wavelet decomposition [13] and the gradient vector [14]. With each image, the device includes coarse image features and an acceptable feature descriptor. Both descriptors are constructed from the original image's wavelet [15] coefficients. The coarse feature descriptor is used first to filter out unsuitable pictures automatically, and then the exemplary feature descriptor is used to select the genuinely matched images.

III. PROBLEM STATEMENT AND PROPOSED WORK

Erstwhile, CBIR structures know how to be divided into two groups based on the script and pictorial. Text material search schemes, for starters, terms and annotations are also used to label.

If suitable text explanations for images in an image database are included, text functionality may be handy as a query. Giving appropriate definitions, on the other hand, must be performed manually, which time is consuming. A visual question can be phrased in a variety of ways.

A successful query approach would feel intuitive to the user while still gathering enough data to extract beneficial results. A representation of the target image is used as a query in visual query-based systems. Image properties such as colours and textures, the majority of which can be retrieved automatically, are used to retrieve related images with the illustration. The traditional CBIR system has two main functions. The first is an image enhancement (IE), which entails creating an image signature or feature vector from a collection of features to epitomize each image's content in the registry truthfully.Function direction is usually hundreds of elements in size, much smaller than the original image. The second issue is a parallel calculation, which entails measuring an aloofness flanked by the test and each representation in a folder depending on monograms to find the top "nearest" images.

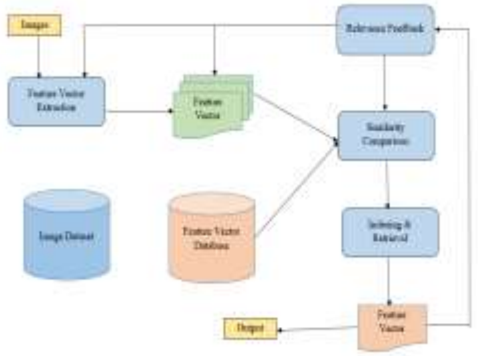


Figure 1. Block Diagram for CBIR

IV. FUNDAMENTAL ASPECTS OF CBIR

The primary method behind CBIR systems is feature extraction and representation. Features, as previously stated, are image properties extracted using image handing out systems are colour, intensity detail. Color, Intensity, and form are three essential characteristics of depictions that have been widely researched in the literature. However, there is no single "best" function that consistently produces correct outcomes in all situations. Since perceptual subjectivity pervades this issue, In order to provide adequate recognition accuracy, a set of features is typically needed.

4.1 Colour Feature

Colour, the simple constituent of images, is the first yet most basic function for image indexing and salvage. The colour gen present in the image is the starting point for all other data derived from image recognition algorithms.Zhao et al. [16] suggest yet another method where both colours' location significantly impacts image reclamation. For image retrieval, a quick algorithm is proposed that could include many spatial colour features. Area and place [17], which refer to including both the null and phases, are these characteristics. Weight of all element knows how to determine the resemblance of two images by calculating the moments of each colour field.

Many retrieval systems have successfully used colour moments, notably [18-22], when an image only comprehends an object. Each duplicate's colour histogram is in the archive. The filter of a picture is a review of the colours present and their proportions. They are easy to calculate and unaffected by colour.

The operator may indicate each colour and pattern necessary proportion (for example, 75 per cent olive avocado, 25 per cent red) or upload an example picture mainly during the initial search, and a colour picture is located from the data [23]. In any case, the matching procedure returns photos with histograms of colour most closely fit the query's criteria. When it comes to many photographs in an image archive, histogram comparison will saturate the discrimination. The joint histogram technique [24] is used to solve this mystery. Since contour information extraction systems use a single colour histogram derived from an image, which necessitates spatial awareness of the image's colours, two images of very different appearances likely have the same colour histogram. Harkat et al. [25] propose this scheme that uses several histograms to account for the spatial details of colours to solve this issue.

4.2 Intensity Feature

Intensity is characterized in computer vision as whatever is what is left because after colour, and localized form was determined taken into account, or via terms like form and arbitrariness. It does not seem to be very convenient to retrieve pictures of shape and texture similarities.

However, comparing photographs based on texture similarities can help discriminate between identical colour areas [26].Intensity exemplification techniques are divided into two categories: structural and mathematical.

The morphological operator with the adjacency graph [27] is two structural tools for defining texture. They fit well with a variety of textures. Statistical approaches template can be explained using Fourier scaling function, professional and non-matrices, change classification techniques, Tamura function, [28-29] Word putrefaction, Markov random field [30], fractal model, and inter processing techniques like Gabor and discrete wavelet.

The majority of patch characterization research in image retrieval is focused on computational or generative approaches. The Markovian analysis (first published in 1973 by Haralick) and its extended variants are basic texture properties. A sliding mask is used to calculate the property for retrieval.

Wavelets have gotten much attention. Because of their proximity and compression capacity, they have been frequently considered. Many wavelet transformations are composed of semantically associated groups of dilations or dilations and rotations. The fundamental stages, wavelet transformations used to characterize texture [31], often in tandem with a Markov decision analysis. New transformations, most notably fractals, have been studied as well. Provides a thorough comparison of texture classification methods that primarily depend on transform-based properties.

Regularity, Coarseness, line likeness, directionality, contrast, and roughness are all Tamura characteristics developed based on psychological observations of human texture perception. Several well-known image extraction systems from the beginning, such as QBIC [32] and Photobook, used the first three components of Tamura functionality. Another technique for defining textures in terms of tactile properties is word decomposition [33]. Image features, especially texture features, were extracted using the Gabor filter.

They suggest a novel approach for more accurately describing spatial characteristics. This prototypical is also resistant to scrambling, revolution, and poignant. Segments are subjects of images in the suggested process, and all images are segmented into multiple bits. With the boost of user engagement, the ROI (Region of Interest) [34] strategy was used to separate the ROI region.

4.3 The proposed CBIR algorithm

The following step in the training methodology is to extract images that are close to the query image.

Input: colour image in the dataset

Output: n images obtained that are close to the query image

Step 1: As a question, pick a single colour picture.

Step 2: Extract colour and intensity features from the dataset images.

Step 3: In the database, build the function vector that reflects the value of objects.

Step 4: Using the suggested PSO-k-means clustering algorithm, divide the face image of images stored in the database into various classes.

Step 5: To find the shortest distance, measuring the difference between the search query image and each cluster's centroid.

Step 6: Find the top n images closest to the query image from the best cluster.

III. FUTURE ENHANCEMENT

The relationship between the user and the retrieval system is critical for content-based image retrieval, so versatile query creation and adjustment can solitary be achieved in including mainly in retrieval, the user plays an important role. The main emphasis in most knowledge extraction frameworks is divided into two sections: a question structure portion and a questionnaire layout section.

A user may choose the kind of pictures they want to download from the archive in several ways. Class searching, query by definition, query by image, and request by example are common request formations. The term "category surfing" refers to search the archive by image category. Photos in the collection are grouped into various groups based on their textual or visual quality for this reason. A query by category aims to retrieve images based on the logical explanation that each image with in database has. The goal of parsing by illustration and image is to create a diagram or provide a sample image that can be used to extract images of similar visual features from the dataset.

V. EXPERIMENTAL RESULT

Our proposed scheme to test and record the results in this section. We discuss the findings, make observations, and equate our method to other systems. The image database was clustered using Particle swarm optimization and the k-means clustering algorithm, and we presented our scheme.
As an offline step, we run the based method on the database and use the clusters to find images related to the query image. The distance between the query image and the centroid of each cluster is calculated to accomplish this.

This limitation is that specific images of each category are inappropriately grouped and have colour and Intensity features identical to the query image.

Precision and recall for CBIR

Precision and recall are the most widely used success metrics in the CBIR. The precision description displayed the number of appropriate images retrieved to the total number of images retrieved. As a result, precision is a metric for retrieval accuracy, and the equation is as follows:

$$\Gamma(t) = \frac{\sigma_B^2(t)}{\sigma_T^2}$$

$$\sigma_B^2(t) = \omega_1\ (t)\{\mu_1(t) - \mu_T\}^2 + \omega_2\ (t)\{\mu_2(t) - \mu_T\}^2$$

$$S_{H_1H_2}\ = \sum_{j=1}^{n^3} \min\left(H_{1j}, H_{2j}\right)$$

The ratio of recalled relevant images to the total number of relevant images in the database is used to define recall. As a result, recall is a metric of retrieval robustness, and the equation is as follows:

$$S = S_{HH'}$$

$$S = k_1S_1 + k_2S_2$$

S1 & S2 are parallels among consistent sub-regions I1 and I'1, and I2 and I'2, respectively. The weights K_1 and K_2 are strong-minded using the power of the separation (t) in

$$k_1 = 1 - a_1e^{-(\Gamma(t) - \Gamma_{min})}$$

$$k_2 = 1 - a_2e^{-(\Gamma(t) - \Gamma_{min})}$$

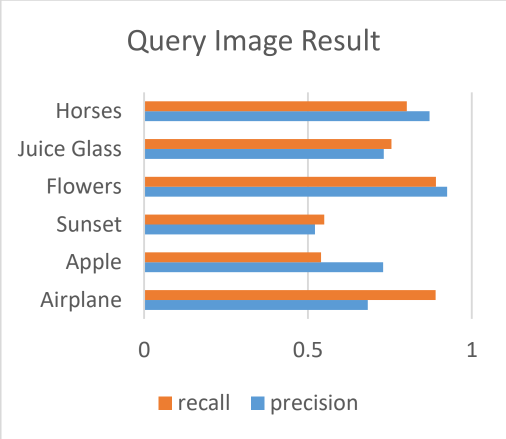
Since the precision score is 1.0 in CBIR, any image retrieved by search is significant, but it cannot tell if the search returns all of the images relevant to the query.

Furthermore, since the recall score is 1.0, any relevant image retrieved by the quest is sufficient, but it cannot remember the sum of irrelevant images.

$$recall = P(B|A) = \frac{P(A \cap B)}{P(A)} = \frac{a}{a+c}$$

$$precision = P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{a}{a+b}$$

The suggested design is compared to other schemes.



We are confident that our proposed solution is preferable to another current algorithm in most groups that view images using colour and intensity features while using the same database for testing.

VI.CONCLUSION

Since the 1990s, CBIR has become a very involved and flagship program rapidly evolving study field. Both theoretical analyses, machine construction, significant improvement has been made over the last decade. The widespread proliferation of CBIR is fueled by technological sensors, the Web, and the decreasing cost of storage devices. Given the scale of these powers, this mechanism will continue to grow in all directions, including new audiences, contexts, and ways of use, new modes of interaction, larger data sets, and new issue approaches.Optical content summary, resemblance reserve metrics, indexing pattern, and operator engagement existed all adopted as essential strategies for CBIR. Colour, Intensity details are the most common visual attributes used here. The resemblance distances amid filmic elements can be calculated in a variety of ways. Specific metrics include the Distance measure, Minkowski type angle, Kullback-Leibler divergence, quadratic form distance, and Jeffrey variance. Until now, the Minkowski and quadratic form distances were the most commonly used picture grouping distinctions. Spitting image taxonomy, effective normalization of pictorial extracted features is critical. Breadth decline is usually done until creating a query scheme, initially reduce the number of attributes in the appropriate graphic rewards.The bulk of current methods concentrate on reduced characteristics. Instead, new methods depend heavily on low-level functions, and CBIR offers an intelligent and automated approach for effective image searching. Human interpretation does not always fit the similarity tests between image elements.

While the images that users seek are contextually and perceptually similar, the retrieval effects of low-level feature-based recovery frameworks are often flawed and unstable. Although relevance system ensured the bridge between information processing and simplified data management, the issue remains unsolved, identifying further research.

REFERENCES

[1]. Smeulders, A. W. M., Worring, M., Santini, S., Gupta, A., & Jain, R. (2000). Content-based image recovery at the end of the early years. IEEE Connections on Pattern Inquiry and Machine Intelligence, 22(12), 1349–1380. doi:10.1109/34.895972

[2]. Zachary, J. M., & Iyengar, S. S. (n.d.). Content-based image retrieval systems. Chronicles 1999 IEEE Convention on Application Definite Systems and Software Engineering and Technology. ASSET'99 (Cat. No.PR00122). doi:10.1109/asset.1999.756762

[3]. Yamamoto, H., Iwasa, H., Yokoya, N., & Takemura, H. (n.d.). Centred on spatial colour distributions similarities in the retrieval of images Procedures, the International Conference on Image Storage and Interpretation is in its tenth year. doi:10.1109/iciap.1999.797718

[4]. Pass, G., & Zabih, R. (n.d.). Histogram refinement for content-based image retrieval. Proceedings Third IEEE Workshop on Presentations of Computer Vision. WACV'96. doi:10.1109/acv.1996.572008

[5]. W.Hsu, T.Chua, H.Pung. In ACM Multimedia Conference, An advanced colour-spatial approach to content-based image retrieval is presented, pp.305-313, 1995.

[6]. Zhang Lei, Lin Fuzong, & Zhang Bo. (n.d.). A CBIR method based on the colour-spatial feature. Proceedings of IEEE. IEEE Region 10 Conference. TENCON 99. "Multimedia Knowledge for Asia-Pacific Information Infrastructure" (Cat. No.99CH37030). doi:10.1109/tencon.1999.818376

[7]. Krishnamachari, S., & Chellappa, R. (1997). Multiresolution Gauss-Markov random field models for texture segmentation. IEEE Transactions on Image Processing, 6(2), 251–267. doi:10.1109/83.551696

[8]. Gimel'Farb, G. L., & Jain, A. K. (1996). On retrieving surfaced images from an image database. Pattern Recognition, 29(9), 1461–1483. doi:10.1016/0031-3203(96)00011-8

[9]. Gotlieb, C. C., & Kreyszig, H. E. (1990). Texture descriptors based on co-occurrence matrices. Computer Vision, Graphics, and Image Processing, 51(1), 70–86. doi:10.1016/s0734-189x(05)80063-5

[10]. Hsin-Chih Lin, Ling-Ling Wang, & Shi-Nine Yang (1997), Colour image retrieval based on hidden Markov models, IEEE Transactions on Image Processing, 6(2), 332–339. doi:10.1109/83.551706.

[11]. Long, F., Zhang, H., & Feng, D. D. (2003). Fundamentals of Content-Based Image Retrieval. Signals and Communication Technology, 1–26. doi:10.1007/978-3-662-05300-3_1

[12]. Srinagesh, K. Aravinda, G. P. Saradhi Varma, A. Govardhan and M. Sree Latha, "A modified shape feature extraction technique for image retrieval", International Journal of Emerging Science and Engineering, pp. 9-13, 2013

[13]. Sheikh, A. R., Lye, M. H., Mansor, S., & Ahmad Fauzi, M. F. (2011). A content-based image retrieval system for marine life images. 2011 IEEE 15th International Symposium on Consumer Electronics (ISCE). doi:10.1109/isce.2011.5973777

[14]. Agarwal, S., Verma, A. K., & Dixit, N. (2014). Content-Based Image Retrieval using Color Edge Detection and Discrete Wavelet Change. 2014 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT). doi:10.1109/icicict.2014.6781310

[15]. Sahu, M., Shrivastava, M., & Rizvi, M. A. (2012). Image Mining: A New Approach for Data Mining Based on Texture. 2012 Third International Conference on Computer and Communication Technology. doi:10.1109/iccct.2012.11

[16]. Zhao, H., Kim, P., & Park, J. (2009). Feature Analysis Based on Edge Extraction and Median Filtering for CBIR. 2009 11th International Conference on Computer Modelling and Simulation. doi:10.1109/uksim.2009.40

[17]. Setiawan, A. W., Mengko, T. R., Santoso, O. S., & Suksmono, A. B. (2013). Colour retinal image augmentation using CLAHE. International Conference on ICT for Smart Society. doi:10.1109/ictss.2013.6588092

[18]. Yadav, G., Maheshwari, S., & Agarwal, A. (2014). For a real-time video device, a contrast-limited adaptive histogram equalization-based enhancement is used. 2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI). doi:10.1109/icacci.2014.6968381

[19]. Bhairannawar, S., Patil, A., Janmane, A., & Huilgol, M. (2017). Colour image enhancement using Laplacian filter and contrast limited adaptive histogram equalization. 2017 Innovations in Power and Advanced Computing Technologies (i-PACT). doi:10.1109/ipact.2017.8244991

[20]. Kharel, N., Alsadoon, A., Prasad, P. W. C., & Elchouemi, A. (2017). Early diagnosis of breast cancer using contrast limited adaptive histogram equalization (CLAHE) and Morphology methods. 2017 8th Global Conference on Information and Communication Systems (ICICS). doi:10.1109/iacs.2017.7921957

[21]. Xie, P. (2012). The Study of Image Feature Extraction Based on Independent Component Analysis. 2012 International Conference on Computer Science and Service System. doi:10.1109/csss.2012.100

[22]. Suolin Duan, Tingting Xu, Wei Zhuang, & Dan Mao. (2014). the feature abstraction of ERD/ERS signals based on the wavelet package and ICA. Proceeding of the 11th World Congress on Intelligent Control and Automation. doi:10.1109/wcica.2014.7053677

[23]. Estrin, S., Martinez-Cancino, R., Makeig, S., & Gilja, V. (2018). Improving Classification Accuracy in Cortical Surface Recordings Using ICA-Based Features. 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC). doi:10.1109/smc.2018.00556

[24]. Ibrahim, M. F. I., & Al-jumaily Adel Ali. (2016). ICA based feature learning and feature selection. 2016 5th International Conference on Electronic Devices, Systems and Applications (EDSA). doi:10.1109/icedsa.2016.7818563

[25]. Harkat, A., Benzid, R., & Saidi, L. (2015). Features extraction and classification of ECG beats using CWT combined to RBF neural network optimized by cuckoo search via levy flight. 2015 4th International Conference on Electrical Engineering (ICEE).

[26]. R. Babers, N. I. Ghali, A. Hassanein, N. M. Madbouly, “Community Finding Based on Lion Optimization Algorithm”, 2015 11th International Computer Engineering Conference (ICENCO), pp. 1-6, 2015.

[27]. Yazdani, M., & Jolai, F. (2016). Lion Optimization Algorithm (LOA): A nature-inspired met heuristic algorithm. Paper of Computational Design and Engineering, 3(1), 24–36. doi:10.1016/j.jcde.2015.06.003

[28]. Salesi, S., & Cosma, G. (2017). A novel extended binary cuckoo search algorithm for article selection. 2017 2nd Global Conference on Knowledge Engineering and Applications (ICKEA). doi:10.1109/ickea.2017.8169893

[29]. Zawbaa, H. M., Emary, E., & Parv, B. (2015). Feature selection based on the antlion optimization algorithm. 2015 Third World Conference on Complex Systems (WCCS). doi:10.1109/icocs.2015.7483317

[30]. Sugamya, K., Pabboju, S., & Babu, A. V. (2016). A CBIR classification using support vector machines. 2016 International Conference on Advances in Human-Machine Interaction (HMI). doi:10.1109/hmi.2016.7449193

[31]. Tripathi, N., Sharna, P., & Gupta, M. (2016). A new technique for CBIR with contrast enhancement using multi-feature and multi-class SVM classification. 2016 International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES). doi:10.1109/scopes.2016.7955805

[32]. Anjali, T., Rakesh, N., & Akshay, K. M. P. (2018). An Original Based Decision Tree for Content-Based Image Retrieval: An Optimum Classification Approach. 2018 International Conference on Communication and Signal Processing (ICCSP). doi:10.1109/iccsp.2018.8524326

[33]. Zhou, Z., & Zhang, Y. (2013). Integration of association rule and decision tree for high-resolution image classification. 2013 21st International Conference on Geoinformatics.doi:10.1109/geoinformatics.2013.6626123

[34]. Lawrance, R., & Shanmugarajeshwari, V. (2017). An assay of teachers’ attainment using decision tree-based classification techniques. 2017 International Conference on Circuit, Power and Computing Technologies (ICCPCT). doi:10.1109/iccpct.2017.8074382