IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Content Based Image Retrieval Using Color And Texture Features Derived By Machine Learning And Data Mining Techniques

[1]Syed Qamrul Kazmi, [2]Munindra Kumar Singh, [3]Saurabh Pal
[1]Research Scholar, [2]Assistant Professor, [3]Professor
[1]Department of Computer Applications,
[1]V.B.S Purvanchal University, Jaunpur, India

Abstract: The proliferation of digital cameras, social media platforms, and online image-sharing services has led to an enormous amount of images being created and shared every day. This explosion in the volume of images presents both opportunities and challenges, particularly in the field of content-based image retrieval (CBIR) and image management. We can have rich visual content, data input for various image related tasks and creating innovative applications. By applying cutting-edge machine learning and deep learning techniques as well as investigating cutting-edge indexing and retrieval strategies, researchers and developers are always attempting to improve CBIR algorithms. Large image files may now be stored and processed more effectively as an introduction of distributed storage and cloud computing technologies. The industry is developing quickly to take advantage of the potential provided by the abundance of visual content that is already available. This approach makes use of an image's size, texture, and dominating colors. The analysis of image data is the focus of the emerging data mining subfield known as image mining. Images can be retrieved from a vast dataset using a variety of techniques. However, they have some shortcomings. In order to extract data from images, this research uses image mining techniques including clustering and associations rules mining. Additionally, it combines multimodal elements including visual and textual components

***Index Terms* - Data Mining, Content based image retrieval, Clustering, Feature extraction**

I. INTRODUCTION

Using diverse methods from statistics, machine learning, and database administration, data mining is the act of identifying patterns, relationships, and insights inside huge databases. Data mining aims to extract useful and previously undiscovered information from data, which can then be applied to prediction, pattern identification, decision-making, and knowledge discovery. The following are important components of data mining: Data Collection and Integration: Gathering and combining data from multiple sources, such as databases, spreadsheets, text documents, photos, videos, and more[1]. Data preprocessing and cleaning refers to the processes of removing errors, missing numbers, and inconsistencies from the data as well as preparing it for analysis. Exploratory Data Analysis (EDA) is the process of examining the data to learn more about its composition, distribution, and potential trends. Visualization and elementary statistical analysis are frequently used in this. Finding the most pertinent features (attributes or variables) to be used in analysis and modeling is known as feature selection and engineering. Feature engineering may entail developing new features that more accurately depict the data's underlying patterns. Using models and algorithms use numerous statistical approaches, machine learning methods, and data mining algorithms to analyze the data in order to find patterns, connections, and trends. Decision trees, clustering, association rule mining [2] regression, and neural networks are examples of common algorithms. Exploratory Data Analysis (EDA) is the process of examining the data to learn more about its composition, distribution, and potential trends. Finding meaningful structures and patterns in the data, such as associations between groups of related data points, recurring patterns through time, and correlations between variables, is known as pattern recognition. Validation and evaluation: Using metrics, cross-validation, and other assessment approaches to rate the usefulness and importance of the patterns found. Thus, it is possible to prevent overfitting or chance from being the cause of the patterns. Interpretation and insight generation: analyzing patterns and insights to draw out useful information and insightful conclusions. Business judgments, scientific ideas, or forecasts can all be informed by these insights. Implementing the learned information into practical applications or systems is known as application and deployment [3]. This could entail utilizing the insights to improve products, procedures, and experiences. Data mining is frequently an iterative process where the outcomes are utilized to improve models and tactics. Models can be developed and updated when new data becomes available. The use of data mining is widespread in a number of industries, including commerce, medicine, finance, marketing, and more. Applications that are frequently used include market basket analysis, sentiment analysis, fraud detection, recommendation systems, and predictive maintenance. The emergence of big data and sophisticated machine learning algorithms has increased the capabilities of data mining, enabling businesses to derive more intricate and precise insights from massive and varied datasets.

The goal of image mining, sometimes referred to as picture data mining or image information mining, is to extract useful and insightful information from enormous collections of photos. It entails using image data mining tools to look for trends, correlations, and patterns in visual data. Given the abundance of digital photos and the need to get valuable insights from visual content, image mining is particularly crucial. Important elements of image mining include feature extraction, Pattern recognition, object detection and recognition, Content based image retrieval, Image classification, Image segmentation, Visual data exploration etc. Similar to traditional data mining, the method starts with the extraction of pertinent information from images. Color histograms, texture descriptors, shape details, object attributes, and other characteristics [11] may be included in these features [4]. Raw pixel data is converted into analytically useful numerical representations using feature extraction. Recognition of Patterns: Image mining algorithms look for structures and patterns inside images. This may involve locating objects, their spatial relationships, the textures of images, and other visually significant elements. Identification and localization of particular objects or entities within photographs is known as object detection and recognition. In areas like computer vision and autonomous systems, this is very crucial. Searching for photos in a database based on their visual content is known as content-based image retrieval (CBIR).

CBIR systems compare feature vectors of query images with those in the database using image mining techniques [5]. Image classification is the process of classifying photographs according to pre-established categories or classes. For image categorization, machine learning methods, particularly deep learning models, are frequently used. Identification and localization of particular objects or entities within photographs is known as object detection and recognition. In areas like computer vision and autonomous systems, this is very crucial. Image segmentation deals with the division of a picture into regions or segments with similar characteristics [12]. This is beneficial for dissecting various elements of an image independently [6]. Visual data exploration is the process of visualizing and examining enormous collections of photographs in order to find noteworthy trends, connections, or outliers. Using information from picture mining to inform judgments is known as "image-based decision support." Analyzing medical photographs, for instance, can help with disease diagnosis in the healthcare industry. This involves identification of images that drastically differ from the norm, which can be valuable in security and quality control applications. It can be seen in Anomaly Detection the Biomedical Image Analysis the Image mining is essential in the analysis of medical pictures for research and diagnostic purposes in disciplines like medicine and biology. Domain expertise, computer vision techniques, and machine learning algorithms are frequently combined to mine images. This multidisciplinary field combines elements of statistics, computer science, and visual perception [7]. As technology develops, image mining continues to be crucial in obtaining insightful information from the vast amount of visual data, enabling applications across a variety of sectors, including healthcare, entertainment, retail, and more.

II. Related Work

Nilanjana et al [3] suggested method for comprehensively describing content-based image retrieval using DL approaches.

Noise reduction has been applied to the input image in this case. FFCNN has been used to extract and classify the processed image. The image has been retrieved using the extracted characteristics to calculate the similarity index of the images using the ranking matrix and distance calculation.

Shahbaz Sikandar et al [1] used two pre-trained deep learning models, ResNet50 and VGG16, and one machine learning model, KNN, are used to create the hybrid deep learning and machine learning-based CBIR system. Using these two deep learning (DL) models, they applied the transfer learning technique to extract the features from the photos. The machine learning (ML) model KNN and Euclidean distance were used to determine how similar the images are.

Palwinder Kaur et al [2] discussed related data with the image, factors like shape, organization, and color of the objects contained in the images are also taken into account. These technologies are quicker and more effective than other traditional methods of picture retrieval. They used an approach in which Gabor filtering is used to extract features, and then lion optimization is used to further improve them [13] . In the end, SVM is used to optimize cuckoo search, and the decision tree approach is used to optimize lion search. The proposed method is evaluated using a number of parameters, and the findings demonstrate that Lion optimization produces better outcomes than cuckoo search optimization.

Preeti Chouhan et al discussed various methods like Neural networks, grouping, correlation, and association. Their approach makes use of an image's size, texture, and dominating colors. A feature called Gray Level Co-occurrence Matrix (GLCM) is used to analyze an image's texture. Features like color and texture are normalized. Using the texture and color features of the image coupled with the form feature, the image retrieval feature will be extremely sharp. Weighted Euclidean distance of the color feature is used to get features for similar sorts of picture shape and texture features.

Amna Sarwar et al to addressed the semantic gap issue and improve the effectiveness of content-based image retrieval (CBIR), we suggest a novel method built on the bag-of-words (BoW) model that performs visual words integration of the local intensity order pattern (LIOP) feature and local binary pattern variance (LBPV) feature. The suggested method builds a bigger size visual vocabulary that also comprises complimentary features from both descriptors by combining two smaller size visual vocabularies (one from each feature) that were created using LIOP and LBPV features. Because for effective CBIR, a smaller visual vocabulary increases recall while a larger visual vocabulary increases the CBIR's precision or accuracy. Comparative evaluation of the WANG-1K, WANG-1.5K, and Holidays image databases, the recommended strategy is tested. When compared to more contemporary CBIR algorithms, the experimental examination of the suggested method on these image databases demonstrates its superior performance.

III. PROPOSED METHODOLOGY

The suggested color, advanced texture, shape feature, and random forest classifier technique is shown in Figure 1. The overview of suggested form features and their extraction process is provided in the next section.

3.1 Texture Based Feature Extraction

The process of extracting features from an image's texture patterns is known as "texture-based feature extraction" in computer vision and image analysis. The term "texture" describes the visual patterns that appear repeatedly in a certain area of an image, such as the grain in wood, the wrinkles on a garment, or the waves on the lake. Texture characteristics are important for a variety of tasks, including as object detection, image classification, and segmentation. They record information about the spatial distribution of intensity values in an image. Texture-based feature extraction is a process in computer vision and image analysis [8] that extracts features from the texture patterns of an image. There are numerous approaches and methodologies for extracting texture-based features:

Statistical Procedures:

Gray Level Co-occurrence Matrix (GLCM): The GLCM calculates the likelihood of occurrence of pairs of pixel intensities inside an image at a particular spatial relationship. The GLCM can be used to extract texture features such as contrast, homogeneity, energy, and entropy. Gray Level Run Length Matrix (GLRLM): Like GLCM, GLRLM computes and quantifies the frequency of runs of pixel values along distinct directions [14].

Methods Using Filters:

Gabor filters are specifically intended to capture various frequency components in an image. Because these filters are sensitive to direction and scale, they can capture a variety of texture patterns [9] . Local Binary Pattern (LBP): By comparing intensity values, LBP encodes the associations between a core pixel and its neighbors. The resulting pattern is used to describe the region's texture.

Methods Based on Transforms:

Discrete Wavelet Transform (DWT): The DWT divides a picture into separate frequency components at different scales. The wavelet coefficients that result can be used as texture characteristics. Texture Spectrum Analysis entails translating a picture into the frequency domain in order to identify information related to the distribution of energy across various frequency components [15] . When executing texture-based feature extraction, it is critical to select the method that is most suited to your task and dataset. Furthermore, integrating numerous texture features or combining them with other types of features can result in more robust and accurate results in a variety of computer vision applications. The Gray Level Co-occurrence Matrix (GLCM) elements are calculated by counting the occurrences of pixel pairs with certain intensity values [10] and a defined spatial relationship in an image. Typically, the GLCM is computed for a given displacement (distance) and direction .Let's call the GLCM G, and G(i, j) is the number of pixel pairings (p, q) with intensities i and j at a given displacement and orientation.

Mathematically, the formula for computing GLCM elements is as follows:

$$\sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j}$$

Returns a measure of how correlated a pixel is to its neighbor over the whole image. Range = [-1 1] Correlation is 1 or -1 for a perfectly positively or negatively correlated image. Correlation is NaN for a constant image.

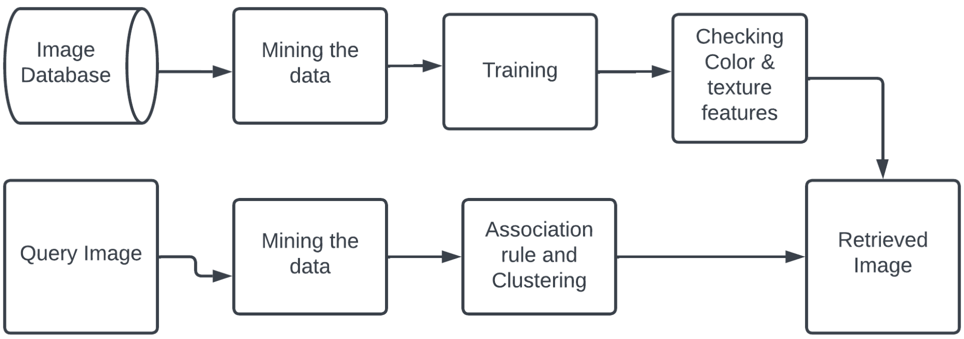

Fig: 1 Proposed CBIR system

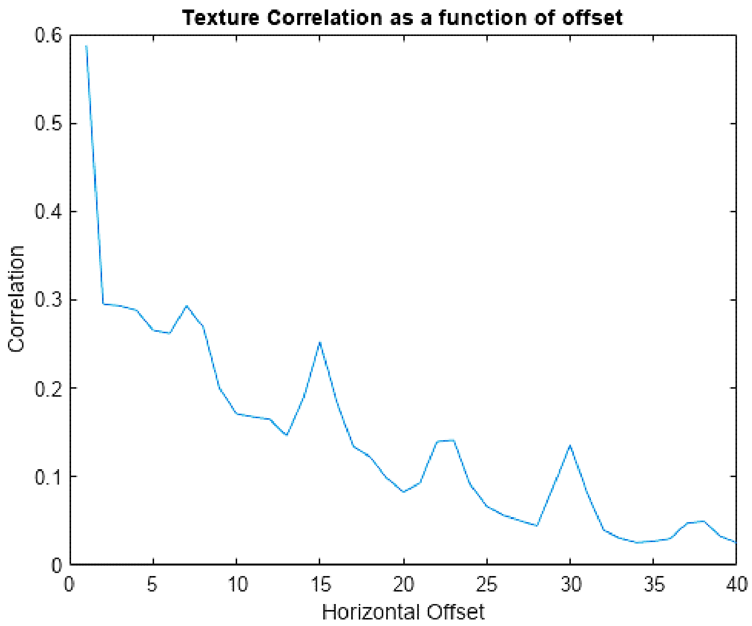

Fig: 2 Comparison of correlation with offset

Weighted Euclidean Distance

The standardized Euclidean distance between two dimensional vectors can be written as:

$$d_{\mathbf{x,y}} = \sqrt{\sum_{j=1}^{J} \left(\frac{x_j}{s_j} - \frac{y_j}{s_j}\right)^2}$$

Where sj is the j-th variable's sample standard deviation. We don't need to deduct the j-th mean from xj and yj because they will cancel out in the end. Differencing. (1.1) can now be rewritten in the following equivalent manner [16]:

$$d_{x,y} = \sqrt{\sum_{j=1}^{J} \frac{1}{s_j^2}(x_j - y_j)^2} = \sqrt{\sum_{j=1}^{J} w_j(x_j - y_j)^2}$$

Where wj = 1/sj is the inverse of the j-th variance. wj as a weight attached to the j-th variable: in other words

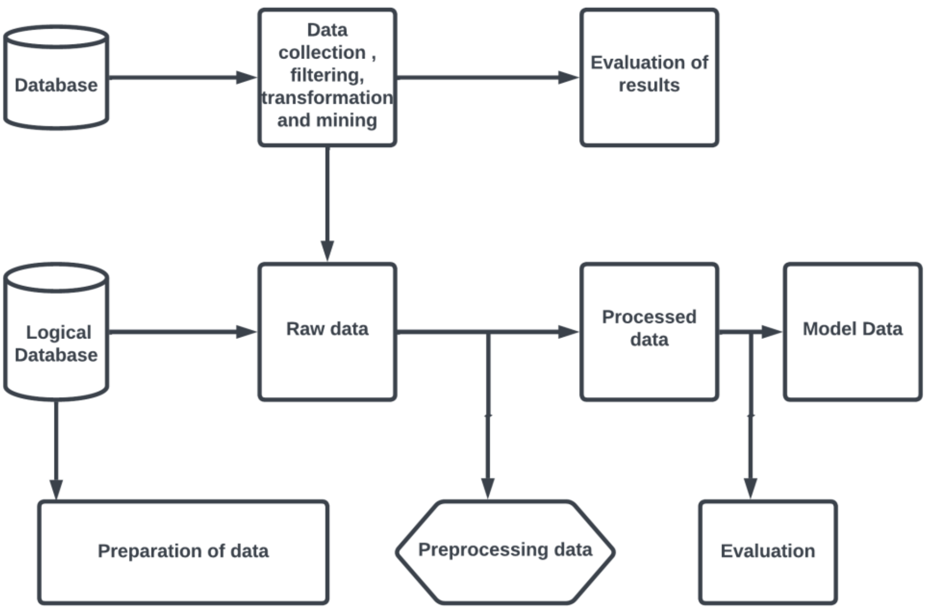

Fig : 3 Data mining technique

3.11 **Evaluation of Performance**

Precision is the most commonly used measures for performance evaluation CBIR system. The Precision is calculated as follows:

$$\text{Precision} = \frac{\text{Number of relevant images retrieved}}{\text{Number of retrieved images}} \quad (3)$$

In general, any CBIR approach returns a fixed number of positive integer pictures. This is known as the system's scope. A

precision value is assigned to each image in the database, which is then averaged across all photos in the database. The greater the scope, the more relevant photos are retrieved, resulting in lower precision numbers.

$$TPR = \frac{TP}{Actual\ Positive} = \frac{TP}{TP + FN}$$

$$FNR = \frac{FN}{Actual\ Positive} = \frac{FN}{TP + FN}$$

$$TNR = \frac{TN}{Actual\ Negative} = \frac{TN}{TN + FP}$$

$$FPR = \frac{FP}{Actual\ Negative} = \frac{FP}{TN + FP}$$

IV. RESULTS AND DISCUSSION

4.1 Results of CBIR approaches

In this section, we present all of our findings, including the best architecture, our CBIR system's retrieval performance in

relation to sample query images taken from our datasets, the precision of category-level image retrieval for our datasets, and a comparison of the proposed method's precision with that of some other recent CBIR approaches.

Throughout the study, we draw on two independent datasets, each with its own collection of categories and image types. The suggested models partition the datasets into training and test images using 80% of the training photos and % of the test images. The first data set is Corel 5K, which contains 5000 images divided into 50 categories.

Figure 4: Sample images from Corel 5k

The second dataset is Corel-10k. Corel-10k consists of 100 classes, 100 images per class and total number of images is 10000;

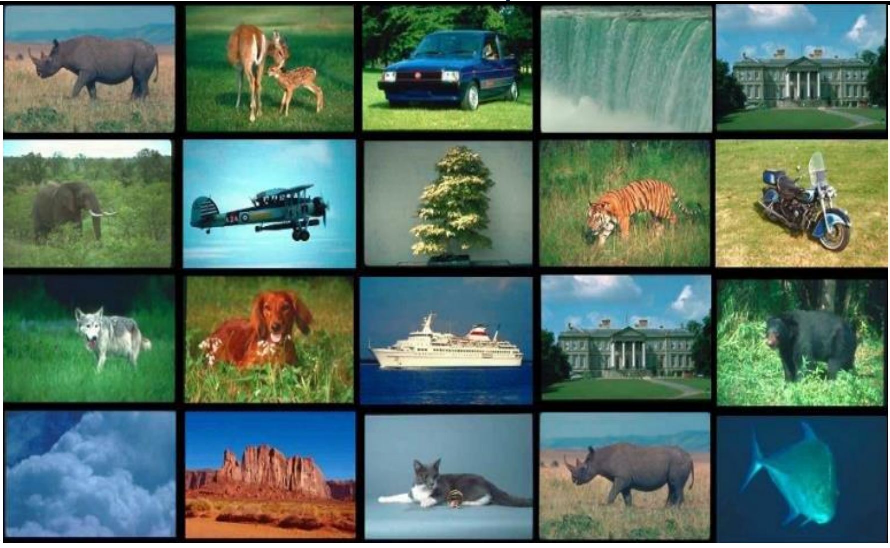

Figure 5: Example of classes from Corel-10k dataset

4.2 Result comparison with other recently proposed algorithms

The proposed method outperformed other methods as compared in the Table 1. The precision % obtained for the Corel 5k dataset was 98.42 where as for Corel 10k dataset the average precision % achieved was 99.10.

Table 1: Result comparison of proposed model with other methods

Methods	Average Precision % Corel 5k	Average Precision % Corel 10k
Proposed Method	**98.42**	**99.10**
Nilanjana et al	95.00	95.40
Shahbaz et al	96.23	96.15
Palwinder et al	89.30	92.20
Preeti Chouhan et al	94.37	89.45
Amna et al	96.67	97.10
Mahmood et al	95.70	96.25

The Comparison of average precision between our proposed method and recent papers' methods were carried on a scope of 20 on Corel 5k and Corel 10k datasets. Both the datasets are publicly available on Kaggle website.

V. Conclusion

In summary, the image attributes are represented using low-level visual elements such as color, texture, spatial layout, and shape. Image datasets cannot be represented using a single feature representation due to their diversity or nonhomogeneous picture qualities. It has been observed that using low-level features in fusion is one method for improving CBIR and picture representation performance. Only one feature is not capable for finding the best results. Thus semantic gap can be reduced by combining different local features, which represent the image in the form of patches, and performance can be improved by combining local and global features. Combination of local and global features is also one of the directions for future research in this area. Previous CBIR and image representation re-search works with traditional machine learning algorithms that have yielded promising results in a variety of applications.)The optimization of feature representation in terms of feature dimensions can provide a powerful framework for the learning of classification-based models while avoiding over fitting concerns. Recent CBIR research has switched to the use of deep neural networks, which have demonstrated good results on numerous datasets and outperformed handcrafted features subject to network fine-tuning.

REFERENCES

[1] Sikandar, S.; Mahum, R.; Alsalman, A. A Novel HybridApproach for a Content-Based Image Retrieval Using Feature Fusion. Appl.Sci. 2023, 13, 4581. https://doi.org/10.3390/app13074581

[2] Palwinder Kaur, Dr. Rajesh Kumar Singh, INTERNATIONAL JOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH VOLUME 9, ISSUE 01, JANUARY 2020 ISSN 2277-8616

[3] Nilanjana Saha, P. Thiruvannamalai Sivasankar, Rahama Salman, Badria Sulaiman Alfurhood, Aishwary Awasthi, & Sukhwant Singh Bindra. (2022). Novel Technique in Content Based Image Retrieval using Classification by Deep Learning in Artificial Intelligence. International Journal of Intelligent Systems and Applications in Engineering, 10(2s), 256 –. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2395

[4] Mehmood, Z., Mahmood, T. & Javid, M.A. Content-based image retrieval and semantic automatic image annotation based on the weighted average of triangular histograms using support vector machine. *Appl Intell* **48**, 166–181 (2018). https://doi.org/10.1007/s10489-017-0957-5

[5] Rashno, A., & Sadri, S. (2017). Content-based image retrieval with color and texture features in neutrosophic domain. In 3rd International Conference on Pattern Analysis and Image Analysis, IPRIA 2017 (pp. 50–55). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/PRIA.2017.7983063

[6] Wayne Niblack et al. "The QBIC Project: Querying Images by Content, Using Color, Texture, and Shape." In: vol. 1908. Jan. 1993, pp. 173–187.

[7] Zahid Mehmood, Toqeer Mahmood, and Muhammad Arshad Javid. "Content-based Image Retrieval and Semantic Automatic Image Annotation Based on theWeighted Average of Triangular Histograms Using Support Vector Machine". In: Applied Intelligence 48.1 (Jan. 2018), pp. 166–181. ISSN: 0924-669X. DOI: 10.1007/s10489- 017-0957-5. URL: https://doi.org/10.1007/s10489-017-0957-5

[8] Smarajit Bose et al. "Improved Content-Based Image Retrieval via Discriminant Analysis". In: International Journal of Machine Learning and Computing 7 (June 2017), pp. 44–48. DOI: 10.18178/ijmlc.2017.7.3.618.

[9] MILAN R. SHETAKE, SANJAY. B. WAIKAR, CONTENT BASED IMAGE & VIDEO RETRIEVAL, International Journal of Advances in Electronics and Computer Science, ISSN: 2393-2835 Volume-2, Issue-9, Sept.-2015.

[10] Mr. K. Kiran , M. Harsha Vardhan, N. Mounika , M. Lalitha , L. Bharath , CONTENT-BASED IMAGE RETRIEVAL SYSTEM, Journal of Engineering Sciences Vol 14 Issue 07,2023.

[11] Manimala Singha and K.Hemachandran, Content Based Image Retrieval using Color and Texture, Signal & Image Processing : An International Journal (SIPIJ) Vol.3, No.1, February 2012.

[12] Manoharan Subramanian , Velmurugan Lingamuthu , Chandran Venkatesan , and Sasikumar Perumal, Content-Based Image Retrieval Using Colour, Gray, Advanced Texture, Shape Features, and Random Forest Classifier with Optimized Particle Swarm Optimization, International Journal of

Biomedical Imaging Volume 2022, Article ID 3211793, 14 pages https://doi.org/10.1155/2022/3211793

[13] Yin-Fu Huang and Bo-Rong Chen, Content-Based Image Retrieval System for Real Images, EPiC Series in Computing Volume 41, 2016, Pages 95{108 GCAI 2016. 2nd Global Conference on Articial Intelligence.

[14] K. Haridas, Dr. Antony SelvadossThanamani, Efficient Content Based Image Retrieval System in Visual Words, Color and Edge Directive Descriptors and Fuzzy Color and Texture Histogram, International Journal of Innovative Research in Computer and Communication Engineering (An ISO 3297: 2007 Certified Organization) Vol. 2, Issue 10, October 2014.

[15] Shubhi Misra, Atul Kumar Verma, Content Based Image Retrieval Using K-Means Algorithm, International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 7 (2018) pp. 5562-5564 © Research India Publications. https://dx.doi.org/10.37622/IJAER/13.7.2018.5562-5564.

[16] Pooja B. Shaha, Malvika U. Saraf, MINING OF IMAGES USING RETRIEVAL TECHNIQUES, IJRET: International Journal of Research in Engineering and Technology eISSN: 2319-1163 | pISSN: 2321-7308.

[17] Xiaoqing Li, Jiansheng Yang, Jinwen Ma, Recent developments of content-based image retrieval (CBIR), Neurocomputing 452 (2021) 675–689, 2020