Content Based Image Retrieval

ECE501- Digital Image Processing
End-Sem Report - Group 6

Dhriti Gandhi (AU2340030), Aneri Kabrawala (AU2340041), Renee Vora (AU2340059), Pushti Sonak (AU2340082)
School of Engineering and Applied Science (SEAS)
Ahmedabad University, Ahmedabad, India

***Abstract*—The growing need for reliable image retrieval in practical applications has increased due to the abundance of images available across various domains. Content-Based Image Retrieval (CBIR) is a method for this purpose, retrieving images within a pool of datasets based on their visual content (features). This work presents a classical CBIR system for retrieving similar images using colour, edge, shape, texture and feature fusion techniques. The effectiveness and accuracy of retrieval are used to evaluate the system's performance, highlighting the features that provide relevant search results.**

***Index Terms*—CBIR, feature fusion, colour histograms, cosine similarity, similarity scores, HSV, LBP, domain specific**

I. Introduction

In the current digital age, the internet is filled with images from every domain, and so are our personal devices. It is pretty challenging to retrieve and organise these images according to the practical applications. One of the traditional methods of image retrieval was through textual descriptions and assigned tags. However, such methods are ambiguous, require manual efforts, and yield results that are subjective, incomplete and inaccurate. Due to the increasing gap between image generation and its effective organisation, there is a high need for techniques that retrieve images based on their content rather than the text or tags associated with them. Content-Based Image Retrieval (CBIR) is a technique that solves this problem by using the actual features of the image, such as colours, textures, and edges, to search for images in a dataset. The extracted measurable features are compared within the set of images to find matches to retrieve similar images. CBIR has many applications, like effective image search, security and surveillance, medical imaging, and E-commerce.

A typical CBIR system involves several stages, including preprocessing, feature extraction, similarity measurement, and ranking. Accurate and effective retrieval depends on selecting the right features, the similarity metric used for comparison, and the choice of distance measure, such as Euclidean distance or cosine similarity.

This project tries to implement a CBIR system using classical image processing approaches. CBIR systems process a given dataset of images to extract meaningful features and retrieve similar images based on a query based on these features. Here, the features used for retrieval are: colour, shape, texture and a fusion of all three.

II. Methodology

The flowcharts below illustrate the flow of the program and algorithm used in the final model to generate the outputs. We have used a multi-stage processing pipeline, which consists of domain preprocessing, multi-layer feature extraction, feature fusion, and rank retrieval. We begin with a domain-based dataset, which we have taken from various Kaggle sources. The domains we selected are: Brain MRI (medical), Natural, and Paintings (Indian paintings and Oil paintings).

Domain preprocessing is performed on the dataset because images from different domains contain unique characteristics. Here is the preprocessing process-

- Natural images- Undergo aspect-ratio resizing, zero-padding to a fixed resolution, adaptive histogram equalisation (CLAHE) for contrast enhancement, and gamma correction.
- Brain MRI - Images are first converted to grayscale and then normalised to balance intensity variations inherent in medical scans.
- Paintings - Resize operations, contrast enhancement, and edge fusion are applied to emphasise artistic contours.

Each was preprocessed and saved to a different directory in the folder.

Before we proceed to feature extraction, we perform object-focused segmentation. This is done by detecting black borders and cropping them to remove padding modification. Then it is converted to HSV colour space, and a mask is generated by thresholding the Saturation and Value channels. We extract the largest connected component and isolate the primary object. This is then used as a region of interest and ensures extracted features have more of the actual subject than background noise. The next part is our core feature extraction. Three feature categories are computed for each image:-

- Colour Features - The image is converted into HSV and LAB colour spaces. Each image is divided into a 3×3 grid, and colour histograms are computed for each block in both colour spaces. These histograms are normalised and concatenated to form a robust spatial colour descriptor.
- Texture Features- Local Binary Patterns (LBP) are applied to grayscale (Mainly for MRI images) versions of the image. We are using an 8-point, 1-radius operator. LBP histograms are computed for each grid cell in a 3×3 division. The resulting texture descriptors are normalised and concatenated.
- Shape Features - From the grayscale image, we computed seven Hu Moments. These values are then converted using a log transformation and normalised. This enables them to remain stable and work easily with others.

We then move to feature fusion. And use weighted feature fusion. The formula for feature fusion is:

$$F = 0.4(\text{Color}) + 0.4(\text{Texture}) + 0.2(\text{Shape})$$

The final fused vector is stored in the dataset feature matrix. Finally, we preprocessed the query image using the same steps to generate its feature vector, computed the cosine similarity between the query vector and all dataset feature vectors, and then ranked the images based on the similarity scores. The top-K most similar results are retrieved, saved, and displayed for observation.

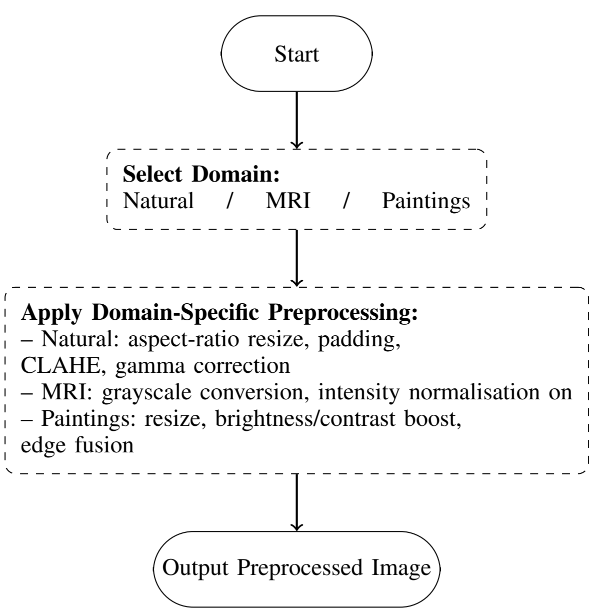


Fig. 1: Preprocessing Flowchart

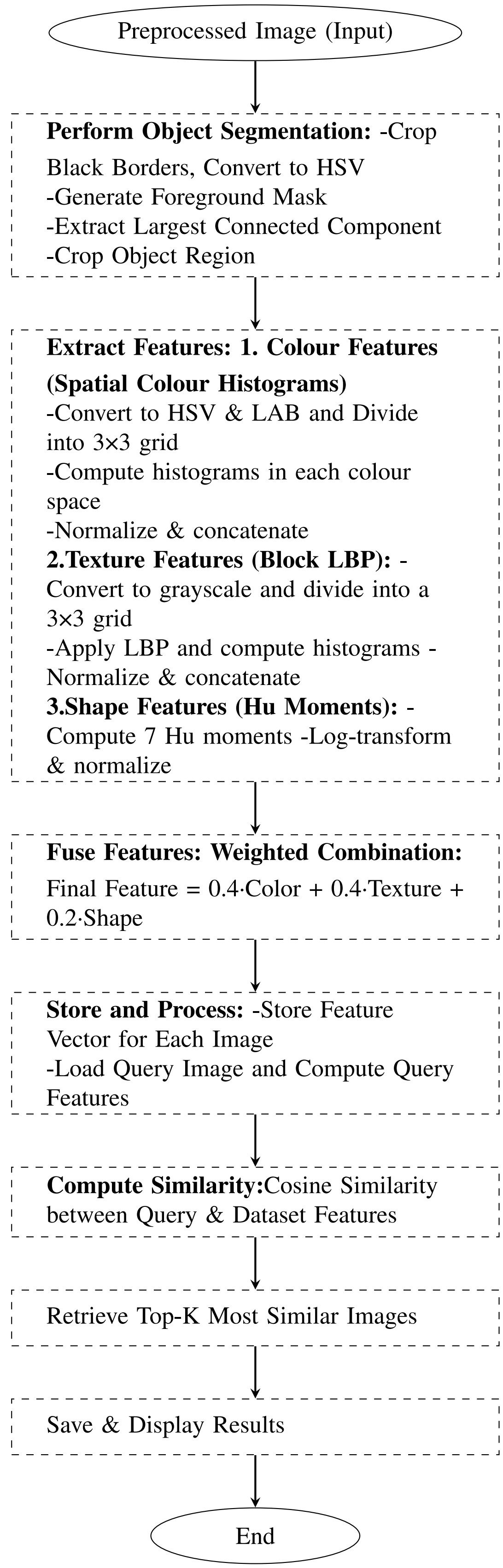
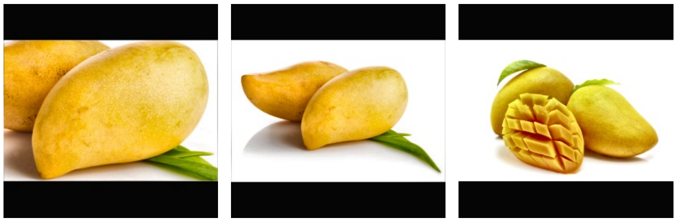


Fig. 2: CBIR Flowchart

III. Results

We considered three types of images in our project: Natural images, Paintings, and Brain MRIs. The results of our Content-Based Image Retrieval (CBIR) system are presented below, featuring one representative query image from each category along with the corresponding retrieved images.



(a) Query (b) Rank 1 (c) Rank 2

(d) Rank 3 (e) Rank 4 (f) Rank 5

Fig. 3: Query Image from Natural Folder

(a) Query (b) Rank 1 (c) Rank 2

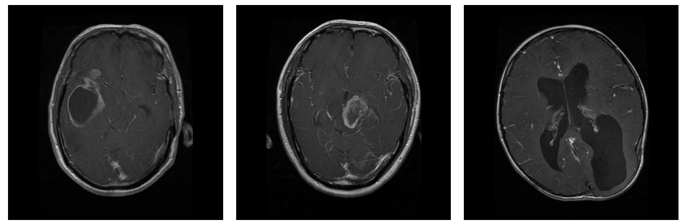
(d) Rank 3 (e) Rank 4 (f) Rank 5

Fig. 4: Query Image from Natural Folder

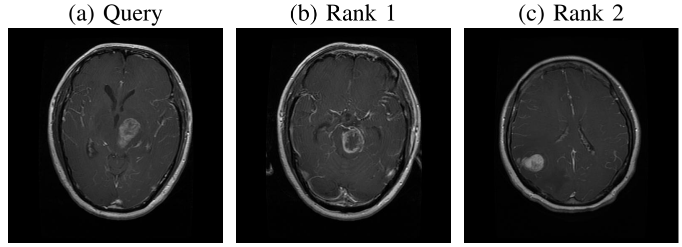
(a) Query (b) Rank 1 (c) Rank 2

(a) Rank 3 (b) Rank 4 (c) Rank 5

Fig. 6: Query Image from Paintings Folder



(a) Query (b) Rank 1 (c) Rank 2



(d) Rank 3 (e) Rank 4 (f) Rank 5

Fig. 7: Query Image from brainMRI Folder

Performance Metrics

Query	Precision	Normalised Recall	F1-Score
q_Mango_29.jpg	0.80	0.444	0.571
Butterfly.jpg	0.80	0.444	0.571
q_pichwai5.jpg	0.60	0.176	0.273
q_Tr-gl_0060.jpg	1.00	0.051	0.097

Comparison with colour and texture

Metric	Color	Texture	Combined
Precision	0.74	0.23	0.31
Normalised Recall	0.56	0.19	0.25
F1-Score	0.41	0.1	0.13

IV. Discussions

The results section presents the output obtained for a query image from every domain using our traditional CBIR system, based on colour, texture, and shape. These features are combined using weighted similarity scores (0.4 for texture, 0.4 for colour, and 0.2 for shape). These weights influence the results obtained across various categories.
For the natural image query, the top four ranks give mango images that have similar yellow colour distributions, textures, and round-like shapes. The image at rank five is a desert, which could be due to the dominance of the colour feature.

The query image of butterfly has sharp stripes and colour features. As the weight of both colour and texture features is high, it gives consistent and accurate results. The rank 5 is that of rose, as the shape of its petals is similar to the shape of butterfly wings and the similarity in background colour.
In the case of paintings, images are retrieved based on similar styles, such as those featuring colours and shapes like leaves, flowers, and animals. Texture weight helps in retrieving paintings with similar background patterns and strokes.
This system performs better for the MRI images affected by cancer. MRI images are grey-scaled and lack texture variations, which is why normal brain MRI images tend to be weighted towards colour in the feature vector. Although an equal weight is assigned to the texture component, it yields appropriate results, as cancer-affected brain images exhibit high intensity and texture variations.

In the performance metrics and comparison table the recall values for some cases are relatively low because the total number of relevant images varies considerably across categories. For instance the medical images collection contains 100 relevant images for each subcategory while the natural images dataset contains only 10 per subcategory. This difference affects the recall calculation because when the total number of relevant images is large obtaining a limited number of correct matches results in poorer recall.

V. Conclusion

In this project, we created a Content-Based Image Retrieval system that retrieves photos based on their visual content. In order to discover and rate photos that visually resemble a query image across three distinct domains—natural photographs, paintings, and MRI scans—our approach collects and combines attributes that describe the colour, texture, and shape of images.

Our tests demonstrated that the system performs well in capturing dominant visual characteristics. Colour played a key role in retrieving visually similar objects for natural images, while texture and shape further refined the results. In paintings the combination of colour and shape helped in identifying similar artistic styles and texture contributed to matching patterns and strokes. Most robustly, the system performed well on MRI images, successfully highlighting the affected regions of cancer thus demonstrating the potential of CBIR in medical image analysis.

This concludes the project by demonstrating that with proper combination and weighting, traditional image processing techniques can enable picture retrieval tasks. CBIR is useful for organising, searching, and analysing large picture collections, as the combination of several attributes ensures that a system can adapt to different kinds of images.

References

[1] C. Knoblock, "An example of Content-Based Image Retrieval," *ResearchGate*, [Online image]. Available: https://www.researchgate.net/profile/Craig-Knoblock/publication/221607221/figure/fig3/AS:305582780239874@1449868020143/An-example-of-Content-Based-Image-Retrieval.png. [Accessed: Oct. 12, 2025].

[2] H. Farsi and S. Mohamadzadeh, "Colour and texture feature-based image retrieval by using Hadamard matrix in discrete wavelet transform," *IET Image Processing*, vol. 7, no. 3, pp. 212–218, Apr. 2013. doi: https://doi.org/10.1049/iet-ipr.2012.0203.

[3] K. Haridas and A. Selvadoss Thanamani, "Efficient Content-Based Image Retrieval System in Visual Words, Colour and Edge Directive Descriptors and Fuzzy Colour and Texture Histogram," *International Journal of Innovative Research in Computer and Communication Engineering*, 2007. [Online]. Available: https://www.rroij.com/fuzzy-color-texture-histogram. [Accessed: Oct. 12, 2025].

[4] M. Singha and K. Hemachandran, "Content-Based Image Retrieval using Colour and Texture," *Signal & Image Processing: An International Journal*, vol. 3, no. 1, pp. 39–57, Feb. 2012. doi: https://doi.org/10.5121/sipij.2012.3104. Available: https://aircconline.com/sipij/V3N1/3112sipij04.pdf.

[5] R. Kumar and N. Murthy M. S., "Enhanced Content-Based Image Retrieval Using Integrated Colour and Texture Features," *International Journal on Science and Technology*, vol. 16, no. 1, Jan. 2025. doi: https://doi.org/10.71097/ijsat.v16.i1.1418.

[6] A. Jg117, "CBIR-50 Dataset," 2023. [Online]. Available: https://www.kaggle.com/datasets/ameyaditya/cbir-50. [Accessed: Nov. 15, 2025].

[7] A. J. G., "Indian Paintings Dataset," 2023. [Online]. Available: https://www.kaggle.com/datasets/ajg117/indian-paintings-dataset. [Accessed: Nov. 15, 2025].

[8] M. Nickparvar, "Brain Tumor MRI Dataset [Data set]," *Kaggle*, 2021. doi: https://doi.org/10.34740/KAGGLE/DSV/2645886.