Wiley
Journal of Electrical and Computer Engineering
Volume 2025, Article ID 3889925, 17 pages
https://doi.org/10.1155/jece/3889925

WILEY

Research Article

Multifeature Fusion for Enhanced Content-Based Image Retrieval Across Diverse Data Types

Punit Soni,[1] **Mandeep Singh**,[1] **Purushottam Sharma**,[2] **Tajinder Kumar**,[3] **Xiaochun Cheng**,[4] **Rajender Kumar**,[1] **and Mrinal Paliwal**[1]

[1]*Chitkara University Institute of Engineering and Technology, Chitkara University, Chandigarh, Punjab, India*
[2]*School of Computer Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India*
[3]*Department of Computer Science and Engineering, Jai Parkash Mukand Lal Innovative Engineering and Technology Institute, Radur, Haryana, India*
[4]*Computer Science Department, Bay Campus Fabian Way, Swansea University, SA1 8EN, Swansea, Wales, UK*

Correspondence should be addressed to Purushottam Sharma; puru.mit2002@gmail.com and Xiaochun Cheng; xiaochun.cheng@swansea.ac.uk

Received 19 January 2025; Accepted 24 April 2025

Academic Editor: Kanwarpreet Kaur

There is a growing trend for using content-based image retrieval (CBIR) systems these days because of the constantly growing interest in digital content. Therefore, the ability of the CBIR to perform the CBIR process will depend on the feature extraction process and its basis, for the retrieval will be done on. Numerous researchers put forward various techniques for feature extraction to enhance the nature of the system. Since features play a very key role in enhancing performance, various features can be used collectively to attain the requisite goal. To retain this in mind, we present in this paper a multifeature fusion system, where three features are integrated and form one feature to improve the situation of retrieval. For this purpose, scale-invariant feature transform (SIFT), speeded-up robust features (SURF), and histogram of oriented gradients (HOG) features are adopted. These features are common features that deliver information about the shape of the object and for matching purposes, two techniques of distance matching such as Euclidean and Hausdrauff distance are adopted. To assess the performance of the proposed multifeature-based CBIR approach, experiments were conducted with the usage of a MATLAB simulator. The Corel-1000 dataset, consisting of 10,000 images in 100 semantic classes, turned into applied, with each magnificence containing 100 images. A subset of 2500 images across 50 semantic classes was used to train the system. This research aligns with industry, innovation, and infrastructure by contributing to advancements in image processing and retrieval systems. Key characteristic descriptors, along with SIFT, SURF, HOG, texture, and multicharacteristic combinations, were extracted for retrieval functions. The results display that the usage of the Hausdrauff distance as a similarity degree outperforms Euclidean distance, accomplishing retrieval accuracies of 80.02% for HOG, 77.9% for SIFT, 79. 8% for SURF, 77.2% for texture, and 84.2% for multicharacteristic combinations, surpassing Euclidean distance results via 1.7%–3.6% across capabilities. These findings underscore the effectiveness of Hausdrauff distance in enhancing retrieval precision within the CBIR framework.

Keywords: CBIR; Euclidean; features; fusion; Hausdrauff; HOG; multifeatures; SIFT; SURF

1. Introduction

With the development of technology, most digital systems work using images for effective results. The system includes government, engineering, commerce, architecture, academics, fashion, hospitals, and journalism. The collection of these images is known as an image dataset that stores image data along with the extracted information [1]. Content-based image retrieval (CBIR) is one of the important systems nowadays and has many applications all around the world. Some of these applications are fashion and graphic designing, publishing and advertising, medical diagnosis, architectural and engineering design, remote sensing systems, and geographical information. One of the real-time applications of CBIR is discussed in which Google provides an option of image search either by image or content [2]. Similarly, many other search engines also opt for this feature.

CBIR is one of the most dynamic research themes in the research area of computer vision and has pulled in expanding consideration in hypothetical and handy research [3]. Although CBIR innovation has been broadly utilized in the past few eras, making a smaller and discriminative descriptor for enhancing variation, shape distortion, and foundation chaos is as yet a difficult issue.

During the most recent couple of years, because of progress in computerized image innovation, there has been an expedient development of advanced substances like images and recordings accessible to the client. The enormous quantities of images have made expanding difficult for computer system frameworks to look at and recover important images proficiently. People can perform image retrieval easily and quickly. The algorithmic portrayal of this errand for execution on computer systems has been extremely troublesome. To comprehend this trouble, content-based and substance-based are the two strategies embraced for search and retrieval in an image database. CBIR otherwise called query by image content (QBIC), content-based visual image retrieval (CBVIR) is the usage of computer vision to the image retrieval issue, that is, the issue of looking through the advanced images in the huge databases. The term "content-based" implies that search will naturally eliminate unwanted features by breaking down the real substance of the image for recovering images from an assortment instead of relying upon human-inputted metadata, for example, catchphrases and names. Execution of a CBIR framework utilizing one substance doesn't give adequate retrieval exactness [4]. The following sections of the paper discuss the basic process of the CBIR system, different features that can be used for matching purposes, and finally the proposed method and its evaluations [5].

2. Literature Work

With the rapid enlargement of virtual statistics and the demand for proficient retrieval structures, textual CBIR has evolved into a crucial era for handling huge-scale photo datasets [6]. CBIR structures rely upon various image features, including coloration, texture, form, and spatial relationships to provide more correct and relevant seek effects [7]. Current improvements in function extraction and multifunction fusion strategies have similarly more advantageous CBIR's functionality to deal with complicated datasets across various domains [8]. Unlike conventional CBIR strategies, CBIR automatically extracts those features from photos, minimizing the want for guide tagging and improving retrieval performance [9, 10]. Multifunction fusion, specifically, permits the combination of multiple descriptors to enhance system performance, especially in cases with illumination changes, cluttered backgrounds, or photograph distortions. By combining those function sets, CBIR structures can supply more specific effects and adapt to a broader variety of programs, from clinical imaging and far-flung sensing to e-commerce and virtual archiving [11, 12].

3. Motivation and Challenges

The motivation behind this research is to overcome the gap between feature extraction methods and similarity measurements, ensuring a more consistent and scalable CBIR framework. The suggested method is intended to enrich real-world applications, including remote sensing, medical imaging, and e-commerce where precise and effective image retrieval is essential. This work proposes to create a multi-feature fusion system to close the gap between traditional single-feature-based methods and similarity measures.

Implementing a multifeature fusion-based CBIR system presents some challenges. One of the primary difficulties is the feature selection and fusion complexity requires careful optimization to strike a balance between efficiency and redundancy. Another major challenge is handling the image condition variability which can affect feature extraction and matching accuracy is another significant challenge. Furthermore, optimization requires parameter tuning and scalability is still a problem as databases get bigger. Addressing these issues is a key to making the system practical for real-world applications.

4. Basic Process of CBIR

Detailed CBIR system is designed to retrieve the samples nearly related to the query samples and it works based on different phases like preprocessing, feature extraction, and similarity measure [42, 43]. CBIR requires a large set of datasets to retrieve data samples similar to the query of any user and this data should be organized or stored properly to maintain the performance of the system [44, 45].

The following steps are involved in the CBIR system:

a. *Dataset acquisition*: This is the first and most important step for any retrieval system. Here in CBIR, the image dataset is acquired and prepared to test the performance of the system. Some users use the default dataset instead of preparing their dataset.

b. *Query sample*: It is a sample uploaded by the user for which he/she requires some related data and based on various factors, CBIR retrieves images related to the query sample.

c. *Feature extraction*: Feature is the key component of any recognition system. Image samples have different features like key regions, texture, color, edge points, shape, and many more.

d. *Similarity measure*: Several different methods are used to measure the similarity of the query sample with the samples stored in the database. The commonly used methods are Euclidean distance, Manhattan distance, and chi-square distance. All the samples having less distance can be treated as similar to the query sample and top matches are retrieved by CBIR.

e. *Result calculation*: The performance of any CBIR system can be calculated based on different parameters namely, accuracy, specificity, and sensitivity.

Figure 1 explains the CBIR system extracts visual features (like color, texture, and shape) from the query image. It then compares these features with those in the database to retrieve visually similar images based on similarity measures.

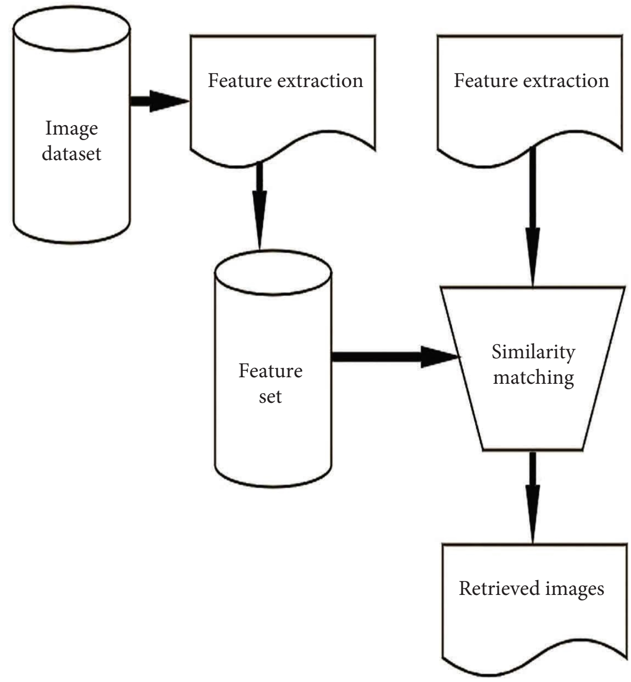


Figure 1: Basic process of CBIR system.

5. Different Methods of Feature Extraction

Features for images are the point of interest of the images, and it describes the image that further can be used for recognition/matching purposes. It is an important step for any recognition or retrieval system and needs to be efficient even in the condition of noise, and any kind of changes in the image samples.

There are some techniques proposed by different authors to extract features and then use them for CBIR systems. Some of these features are based on descriptors like scale-invariant feature transform (SIFT) [46], histogram of oriented gradient (HOG) [47], and speeded-up robust features (SURF) [48]. The other important features like shape [49], edge [50], and texture features [11] also have a great impact on the performance of the CBIR system. Moreover, hybrid feature extraction methods were also introduced by various authors [51–55].

a. *SIFT* [56]: It is one of the important feature extraction algorithms that detect the local feature from the sample image. The first step of this method is to construct scale spaces for the internal depiction of an image sample and then followed by the process of finding key points using the Laplacian of Gaussian (LoG) method. For an image "$I\,[m \times n]$", scale spaces are calculated using the following equation:

$$\mathrm{SS}(m, n, \alpha) = G(m, n, \alpha) * I\ (m, n). \tag{1}$$

Here, SS is the scale space, $(m,\ n)$ is the location coordinates, "α" is the scale parameter, and G is the Gaussian operator. Then, LoG is calculated as

$$\mathrm{LoG} = \alpha^2\left(\nabla^2 G\right), \tag{2}$$

where $\nabla^2 G$ is the difference between Gaussian. After key-point extraction, maxima, and minima points are stored for the further process from which if there is any kind of bad key point, then it will be removed first. It is mathematically defined as

$$D(k) = D + \frac{\partial D^{\tau}}{\partial k} + \frac{1}{2} x^{\tau} \frac{\partial^2 D}{\partial k^2} x. \tag{3}$$

Lastly, orientation is assigned to each of the extracted key points and then the final representation is formed with a unique set of features.

b. *HOG* [57]: This feature extraction method works on the principle of gradient descriptors and records the appearance and shape of the sample along with the distribution of the direction of edges and intensity gradients. Cells are the small connected regions in an image in which compilation of the histogram of the gradient is performed and then its concatenation results as a descriptor. This block is a larger region of a sample where the calculation of the intensity is done using contrast normalization. Like this, all the blocks of the samples are normalized first and it provides better results.

c. *SURF* [58]: SURF is an enhanced version of a SIFT algorithm and is comparatively faster. This approximation is done using LoG with box filters and works parallel for different scales. The other change in SURF is that it uses wavelets for direction orientation. SURF gives better performance in low illumination and external noise does not have any effect on the performance of SURF. For better results, images with a clear background may be preferred.

d. *Texture features* [5]: Granularity and repeated patterns on the image surface are referred to as texture features. These features can also be computed as a statistical texture analysis where some of the specific positions are selected and then the computation is done based on the statistical distribution of intensities. Statistical texture features can be classified into first-order, second-order, or higher-order derivatives. The GLCM method is used to extract second-order features like contrast, directionality, energy, entropy, coarseness, and correlation.

- *Coarseness*: It is defined by the scale and repetition rates of texture. It describes that for patterns with dissimilar arrangements; the greater its element size, the coarse it is, and can be figured as

$$\text{Coarseness }(I)=\frac{1}{W\times H}\sum_{x=0}^{W-1}\sum_{y=0}^{H-1}S_{best}(x,y). \quad (4)$$

Here, $S_{\text{best}}(x,y)=2^k$ and k is the value of maximizes $\max_{1\le k\le L}(E_{k,h}(x,y),E_{k,v}(x,y))$ in vertical and horizontal directions, $\in[1,L]$, where $2^L\le\min(W,H)$. The other factor $E_{k,h}(x,y)$ and $E_{k,v}(x,y)$ is an average at every pixel $I(x,y)$ of its neighborhood of the size $2^k\times 2^k$ and is computed from $A_k(x,y)$ by:

$$\begin{aligned}A_k(x,y)&=\sum_{i=x-2^{k-1}}^{x+2^{k-1}-1}\sum_{j=y-2^{k+1}}^{y+2^{k-1}-1}\frac{I(i,j)}{2^{2k}},\\ E_{k,h}(x,y)&=\left|A_k\left(x+2^{k-1},y\right)-A_k\left(x-2^{k-1},y\right)\right|,\\ E_{k,v}(x,y)&=\left|A_k\left(x,y+2^{k-1}\right)-A_k\left(x,y-2^{k-1}\right)\right|.\end{aligned} \quad (5)$$

- *Contrast*: It deliberates the $s=$ dynamic range of gray levels by distributing polarization of white and black pixels. Contrast can be computed as

$$\text{Contrast }(I)=\frac{\sigma}{\sqrt[4]{\alpha_4}}. \quad (6)$$

Here, σ is the standard deviation and $\alpha_4=\mu_4/\sigma^4$. μ_4 is the fourth instant around the mean value.

- *Directionality*: It computes the total degree of directionality from a histogram of local edge possibilities in contradiction to the angle of direction. The quantification of the perceptiveness of histogram crests measures the directionality by adding the second moment of every crest.

6. Proposed System

This CBIR system is proposed to extract different types of image data from a large dataset based on the multifeature fusion method where SIFT, HOG, SURF, and texture features are extracted and then the combination of these is applied to achieve better performance in terms of accuracy. This proposed system works under two main phases: (a) training phase and (b) testing phase. In the training phase, all the acquired data will be trained using different methods, and then its different features are stored for future purposes. The testing phase extracts the best matches with the provided query image based on fused features. The details of these phases are given below:

a. *Training phase*: The process of the training phase is shown in Figure 2. In this phase, the input image is first selected from the database and then preprocessing is performed to enhance the quality of the sample. It is an important step to restore the smoothness and sharpness of an image to improve the performance of the recognition system. For this purpose, a two-dimensional statistical sequence filtering method is used. After filtration, the feature extraction step is performed where different features are extracted namely, SIFT, SURF, HOG, and texture features. In this proposed work, the work is done on multifeatures where key-point features are collected together and form a feature set for all the filtered input samples.

$$I=\{I_1,I_2,I_3,\ldots,I_k\}. \quad (7)$$

For instance, an image set. The extraction of different features will be done using the following:

$$f'=f_{\text{SIFT}}=\text{SIFT}\{I_1,I_2,I_3,\ldots,I_k\}, \quad (8)$$

$$f''=f_{\text{SURF}}=\text{SURF}\{I_1,I_2,I_3,\ldots,I_k\}, \quad (9)$$

$$f'''=f_{\text{HOG}}=\text{HOG}\{I_1,I_2,I_3,\ldots,I_k\}. \quad (10)$$

Multifeature fusion (f_M) uses the above features and aggregates them to form a single feature vector. Before aggregation, normalization is required with which all the feature vectors are brought to the same dimension and are calculated using the following:

$$\begin{aligned}f_M&=f_{\text{SIFT}}\cup f_{\text{SURF}}\cup f_{\text{HOG}}\\ &=\begin{bmatrix}f'_{11}&f'_{12}&\cdots&f'_{1n}\\ f'_{21}&f'_{22}&\cdots&f'_{2n}\\ \vdots&\vdots&\cdots&\vdots\\ f'_{m1}&f'_{m2}&\cdots&f'_{mn}\end{bmatrix}\cup\begin{bmatrix}f''_{11}&f''_{12}&\cdots&f''_{1n}\\ f''_{21}&f''_{22}&\cdots&f''_{2n}\\ \vdots&\vdots&\cdots&\vdots\\ f''_{m1}&f''_{m2}&\cdots&f''_{mn}\end{bmatrix}\cup\begin{bmatrix}f'''_{11}&f'''_{12}&\cdots&f'''_{1n}\\ f'''_{21}&f'''_{22}&\cdots&f'''_{2n}\\ \vdots&\vdots&\cdots&\vdots\\ f'''_{m1}&f'''_{m2}&\cdots&f'''_{mn}\end{bmatrix}\\ &=\begin{bmatrix}f'_{11}\cup f''_{11}\cup f'''_{11}&f'_{12}\cup f''_{12}\cup f'''_{12}&\cdots&f'_{1n}\cup f''_{1n}\cup f'''_{1n}\\ f'_{21}\cup f''_{21}\cup f'''_{21}&f'_{22}\cup f''_{22}\cup f'''_{22}&\cdots&f'_{2n}\cup f''_{2n}\cup f'''_{2n}\\ \vdots&\vdots&\cdots&\vdots\\ f'_{m1}\cup f''_{m1}\cup f'''_{m1}&f'_{m2}\cup f''_{m2}\cup f'''_{m2}&\cdots&f'_{mn}\cup f''_{mn}\cup f'''_{mn}\end{bmatrix}.\end{aligned} \quad (11)$$

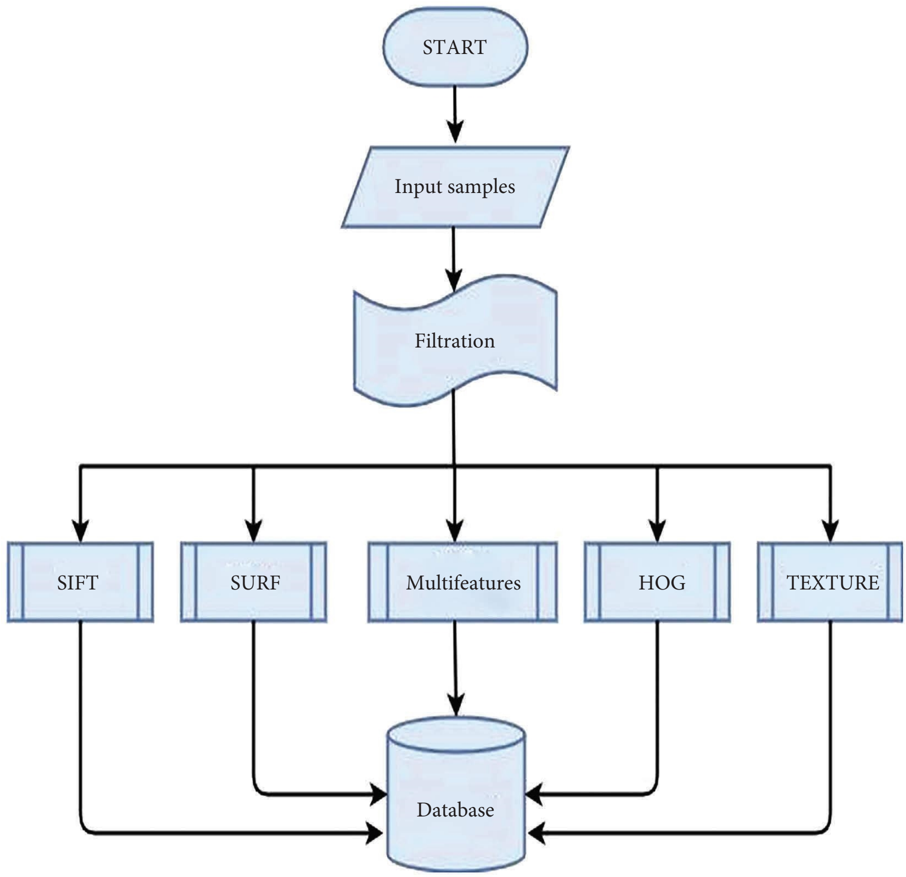


Figure 2: Training phases of proposed CBIR.

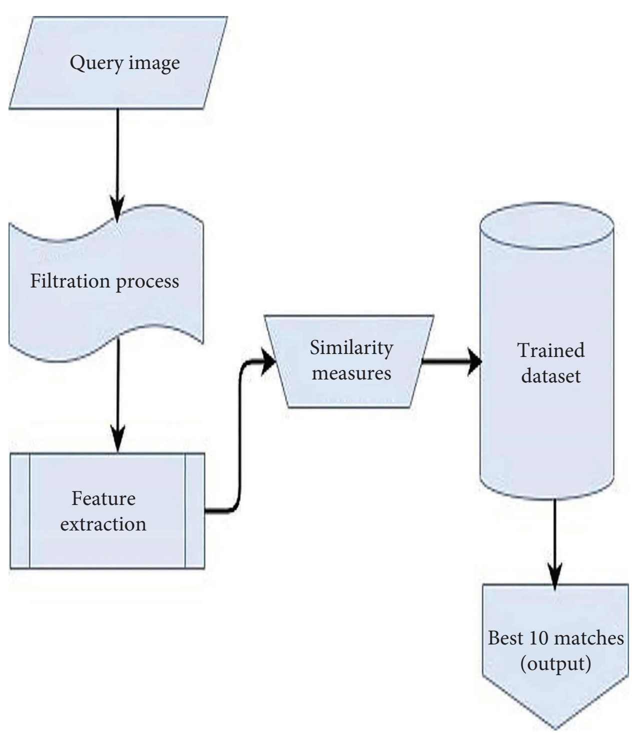


Figure 3: Testing phases of proposed CBIR.

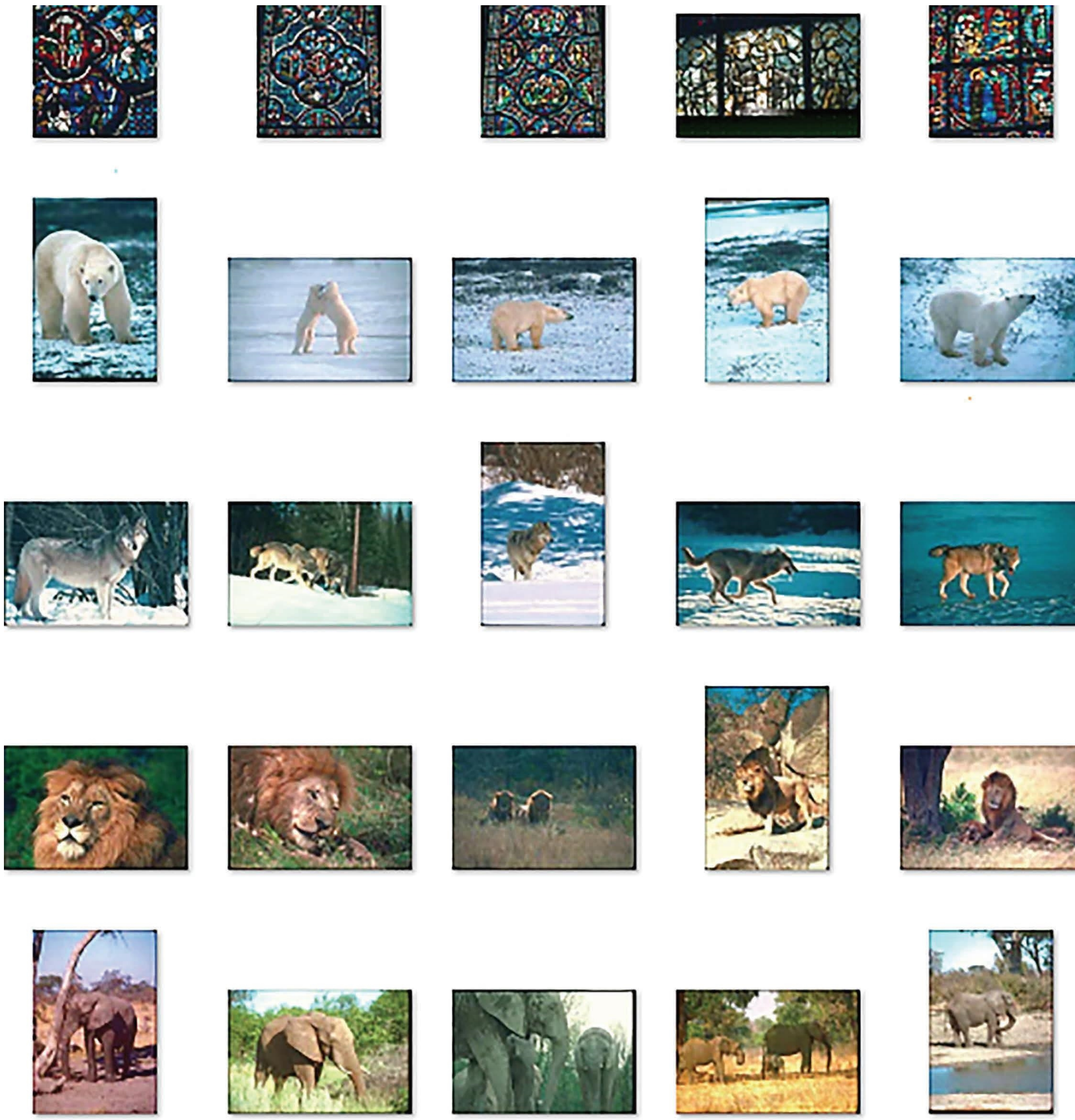


Figure 4: Sample dataset images.

Figure 2 illustrates that the proposed CBIR system undergoes training by extracting features from labeled images and learning patterns using a deep neural network. These learned features are then used to build an index for efficient image retrieval during the query phase.

b. *Testing phase*: In this phase, a query image is passed to the system where filtering is performed first on the query sample, and then feature extraction is performed. These extracted features are then matched with the database based on two different distance-based measures, namely Euclidian distance and Hausdorff distance. Minimum distance means similar to the sample. So, in this way, the samples matched from the database are extracted. The process of the test phase is described in Figure 3. For testing purposes, the best 10 matches are extracted and the performance of the system is analyzed accordingly.

In Figure 3, testing phases of the proposed CBIR explain the query image that undergoes the same feature extraction process as during training. The extracted features are then matched against the indexed database to retrieve and rank similar images based on similarity scores.

The computational cost of the suggested multifeature fusion-based CBIR system is primarily inclined by the feature extraction and distance matching techniques employed. The extraction of SIFT, SURF, and HOG features

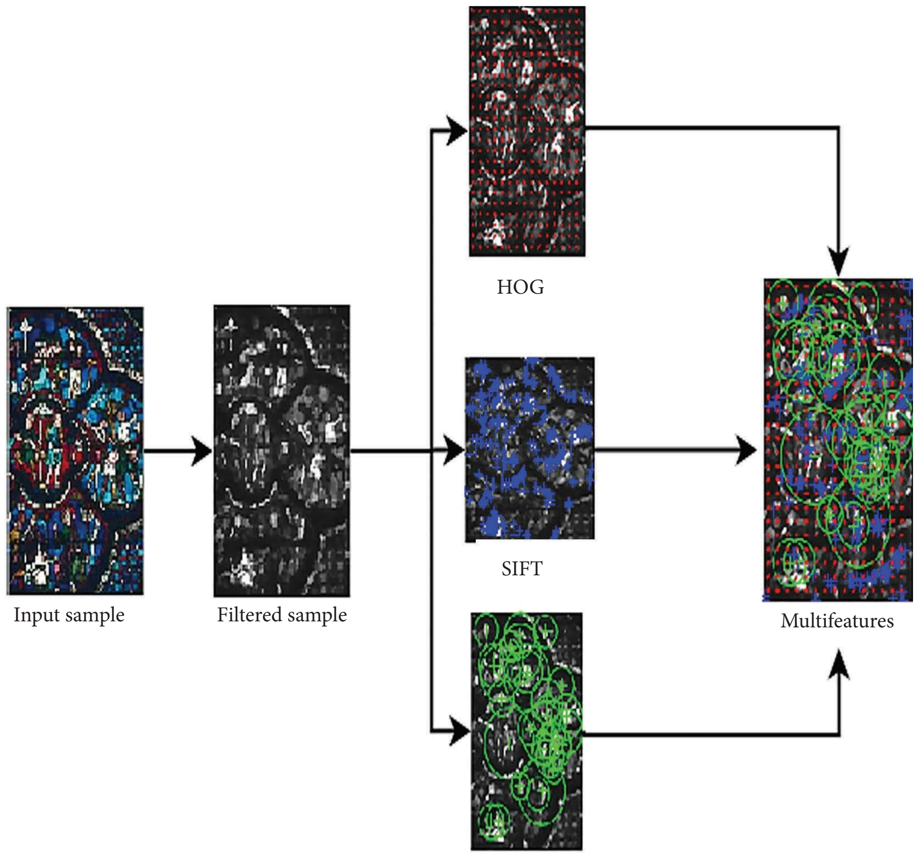


Figure 5: Feature extraction.

is computationally demanding, with SIFT being the most expensive due to its key-point detection and descriptor computation. We have considered the dataset size for the training subset to be 2500 images from the Corel-1000 dataset and a total testing set of 10,000 images, the system demands significant memory and processing power. MATLAB is used for simulation that requires a high-performance computing environment, preferably a multi-core CPU. But in this case, if we have a huge dataset of images then GPU can be helpful to optimize feature extraction and similarity computations.

7. Experiments and Result Analysis

To analyze the performance of this proposed multifeatured approach, experimentation is done using a MATLAB simulator. The proposed system is tested using the dataset of Corel-1000 [59]. This dataset contains 10,000 images of 100 semantic classes where each class contains 100 images. In this work, the proposed system is trained with 2500 samples of 50 semantic classes where each class contains 50 images [60]. Some of the samples are shown in Figure 4. Feature extraction is an important step in a CBIR system, and similar to other CBIR systems, this proposed system also works based on different features like SIFT, SURF, HOG, texture, and multifeatures [61].

Figure 4 showcases a collection of representative images from the dataset used for training and testing the CBIR system. The images cover diverse categories and visual characteristics such as color, texture, and shape. These samples help illustrate the variability and richness of the dataset, essential for robust feature learning.

Figure 5 illustrates the process of extracting key visual features from images using HOG, SURF, and SIFT. Each method captures distinct aspects: HOG focuses on edge orientations, SURF detects interest points rapidly, and SIFT extracts scale and rotation-invariant descriptors. These features are crucial for accurate image matching and retrieval in the CBIR system.

Figure 6 illustrates the outcomes of the preprocessing and feature extraction phase, showcasing enhanced image clarity and noise reduction. Key features such as edges, texture, or biometric patterns are distinctly highlighted. These refined outputs are crucial for improving the accuracy of subsequent classification or recognition steps.

For this work, three texture features are computed namely, coarseness (T1), contrast (T2), and directionality (T3) as shown in Table 1. These features correspond to human visual perception (texture feature). The proposed CBIR performance is evaluated using five different feature extraction methods and two distance calculation methods, namely Euclidean distance and Hausdorff distance. As we know,

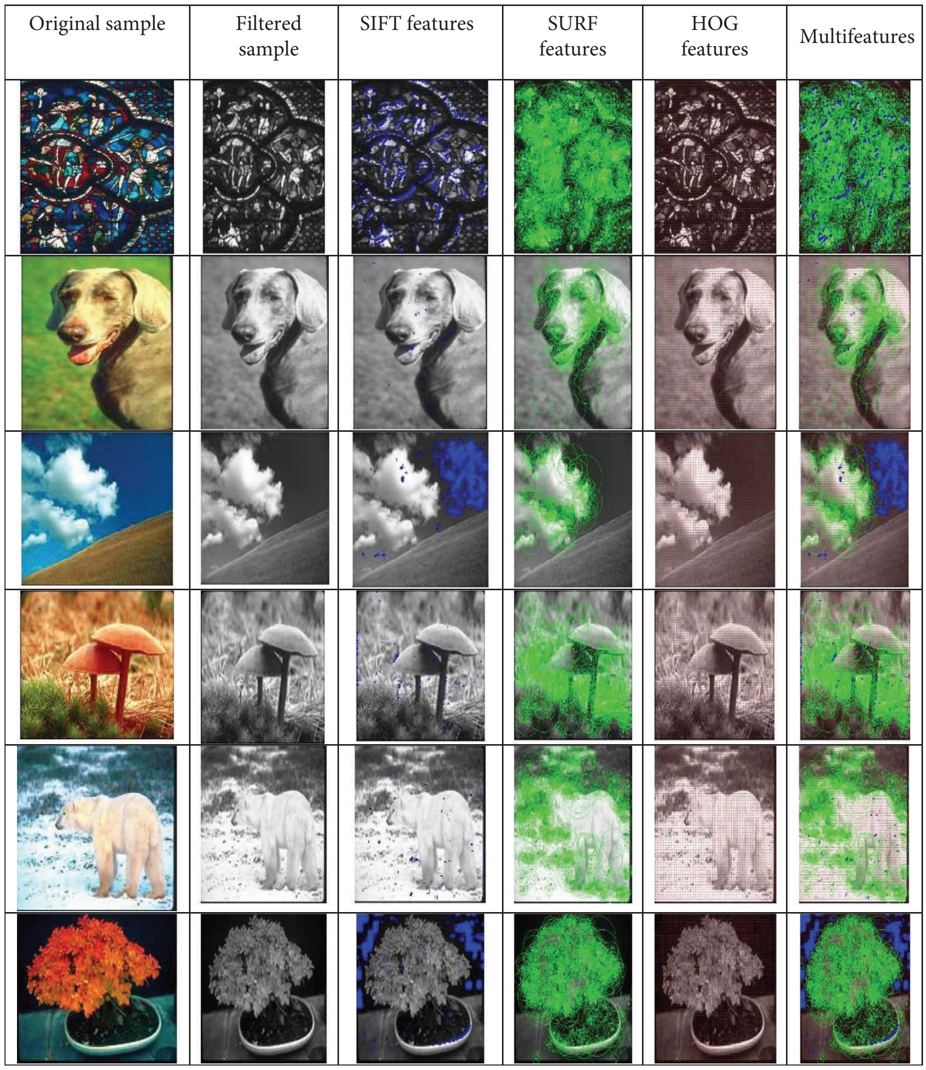


Figure 6: Sample outcomes of preprocessing and feature extraction phase.

accuracy is a critical factor that benefits to measure the suggested system's performance and is considered using two unlike methods while regaining sample images from a bulky dataset. The table displays the recognized samples retrieved from the database based on both distance measures.

Contribution of proposed system: In this work, we present a multifeature fusion system that integrates three important descriptors—SIFT, SURF, and HOG—to improve CBIR. The study also relates similarity metrics and depicts that Hausdorff distance performs better than Euclidean distance in terms of retrieval accuracy with accuracy gains varying from 1.7% to 3.6% across several features. Using a subset of 2500 images from 50 semantic classes for training extensive experiments were carried out using the Corel-1000 dataset to validate the suggested system. The findings demonstrate that the multifeature fusion method outperforms individual feature-based techniques achieving 84.2% retrieval accuracy. This study is a valuable contribution to the field of image retrieval since it greatly improves CBIR performance by utilizing multifeature fusion and elegant similarity measures.

In the context of image feature matching, as shown in Table 2, diverse strategies have been evaluated using Euclidean distance and Hausdorff distance metrics. The effects have proven that the multifeature approach outperformed individual features.

In Table 3, the accuracies of different distance metrics—Euclidean distance and Hausdorff distance—are compared using the Corel dataset. It shows how each distance measure influences the classification accuracy by quantifying the similarity between image features. The table highlights the differences in accuracy when these distance metrics are applied to image retrieval or recognition tasks.

Table 1: Literature review of existing work.

Author(s) & year	Paper title	Parameters used	Results	Conclusion
Zhao and Lin [13] (2022)	Multifeature fusion CBIR using SIFT, SURF	SIFT, SURF	Achieved an accuracy of 90%, significantly outperforming single-feature methods, with retrieval times reduced by 15% due to efficient feature combinations	Multifeature fusion improves retrieval accuracy
Gupta and Sharma [14] (2023)	Fusion of HOG and SIFT for enhanced CBIR	SIFT, HOG	Recall improved by 12% compared to using SIFT alone, and fusion led to a more comprehensive representation of image features, increasing overall precision in object recognition	Hybrid models yield higher retrieval rates
Lee [15] (2023)	Deep fusion techniques in CBIR systems	SIFT, CNN-based features	Achieved 85% accuracy, with CNN-SIFT fusion reducing noise impact and enhancing robustness in complex backgrounds, which increased the relevance of retrieved images	The fusion of deep and traditional features enhances the performance
Ali [16] (2023)	Comparative study of feature matching techniques in CBIR	SIFT, SURF, HOG	Hausdorff distance achieved 5% higher accuracy than Euclidean for shape-based features, especially in cluttered scenes, proving effective in detailed object retrievals	Hausdorff is more robust for shape-based retrievals
Patel and Joshi [17] (2022)	Efficient CBIR with multifeature fusion for diverse data	SIFT, SURF, color features	Reported 88% accuracy, with fusion of color and shape features reducing retrieval times and producing highly relevant results in datasets with varied textures and colors	Multifeature model surpasses the single-feature inaccuracy
Wang and Chen [18] (2023)	Shape and texture fusion for CBIR in medical images	HOG, SURF	Achieved a 15% improvement in precision by fusing texture and shape, which was especially beneficial in differentiating fine details in medical imaging datasets	Shape–texture fusion enhances medical CBIR.
Kumar [19] (2024)	Novel fusion of texture and color features in CBIR	Color, texture, SURF	Recorded a 92% accuracy, with color–texture fusion proving highly effective in identifying objects across diverse backgrounds and improving precision for industrial images	Color–texture fusion is effective for medical and industrial images
Yadav and Prasad [20] (2022)	Multifeature fusion CBIR System for large datasets	SIFT, SURF, Gabor filters	Increased recall by 10% due to Gabor filters enhancing texture analysis, especially in large datasets with fine-grained detail across image sets	Gabor filters enhance texture analysis in CBIR
Singh [21] (2023)	Image retrieval optimization using hybrid feature fusion	SIFT, HOG, color moments	Achieved 88% accuracy; color moments increased feature distinctiveness, especially for colorful objects in cluttered backgrounds, resulting in faster and more accurate retrievals	The fusion of shape and color provides balanced retrievals
Li [22] (2022)	Multifeature CBIR for real-time applications	SIFT, SURF, GLCM	Reported speed gains of 20%, with combined features providing efficient retrieval in real-time systems, particularly useful in security and surveillance applications	Effective for time-sensitive retrievals
Chang [23] (2024)	Performance analysis of CBIR using hybrid distance metrics	SIFT, SURF	Found Hausdorff distance to achieve 7% higher accuracy over Euclidean in cases with complex shapes and backgrounds, ideal for retrieval in dense datasets	Robust for complex shape information

Table 1: Continued.

Author(s) & year	Paper title	Parameters used	Results	Conclusion
Akhtar [24] (2022)	CBIR system using multifeature and deep learning fusion	SIFT, CNN features	Achieved 90% precision; CNN features complemented SIFT for enhanced robustness against background variations, making it suitable for diverse data	Deep learning enhances traditional feature-based CBIR
Hu and Lee [25] (2023)	Hybrid CBIR for geographic information systems	SIFT, SURF, texture	Improved retrieval accuracy by 15% for GIS applications where topographic details were crucial, showcasing the advantages of multifeature fusion in complex datasets	Suitable for GIS applications
Abbas and Rahman [26] (2023)	Multifeature CBIR for the fashion industry	HOG, SIFT	Enhanced retrieval performance by 20%, with SIFT and HOG combination improving recognition of complex patterns and textures common in fashion datasets	Effective for e-commerce and fashion domains
Rao [27] (2024)	Advanced CBIR with fusion of shape, texture, and color features	SIFT, color histogram, HOG	Achieved 92% accuracy; shape and color features combined allowed for highly specific and accurate object recognition across diverse datasets	Hybrid feature fusion significantly improves accuracy
Matsuda and Ono [28] (2022)	Multifeature CBIR using HOG and color moments for Surveillance	HOG, color moments	Increased recall by 12% by using HOG for shape and color moments for texture, aiding in the accurate identification of low-visibility surveillance footage	Effective surveillance systems
Zhang [29] (2023)	CBIR with fusion of spatial and color features	SURF, color histograms	Precision increased by 15%, with color histograms enhancing retrieval accuracy in spatially complex images, useful in art and design databases	Suitable for spatially-sensitive retrievals
Brown and Lee [30] (2022)	Real-time multifeature CBIR for industrial applications	SIFT, SURF, GLCM	Achieved 89% accuracy; GLCM and SURF fusion sped up retrieval processes, ideal for industrial applications needing real-time processing	Effective for real-time applications
Feng [31] (2023)	CBIR using fusion of shape and texture for architectural design	HOG, SURF	Precision increased by 15%, with shape–texture fusion proving ideal for distinguishing architectural details, especially in blueprint analysis	Ideal for architecture and design
Ibrahim [32] (2023)	Multifeature fusion for CBIR in medical diagnostics	SIFT, texture	Achieved 90% accuracy; texture-based features aided in distinguishing fine details, making it highly suitable for diagnostic imaging systems	Enhanced diagnostic accuracy in medical CBIR
Li and Chen [33] (2024)	Enhanced CBIR with deep and traditional feature fusion	SIFT, CNN-based features	High precision of 92%; deep learning features helped overcome limitations of traditional features, proving robust in datasets with varying backgrounds and textures	Combines advantages of deep and traditional feature sets
Wang et al. [34] (2020)	A comparative analysis of CBIR techniques	SURF, Gabor filters	SURF-based retrieval performed 10% faster, while Gabor filters improved texture-based retrieval accuracy by 8%	Feature selection impacts retrieval efficiency and accuracy
Lee and Zhang [35] (2020)	Efficient medical CBIR using texture and shape features	HOG, SURF	Achieved 91% accuracy in medical image retrieval, with HOG improving edge detection and SURF enhancing shape analysis	Shape–texture fusion improves medical CBIR efficiency

Table 1: Continued.

Author(s) & year	Paper title	Parameters used	Results	Conclusion
Zhao et al. [36] (2021)	Multifeature fusion for robust CBIR	SIFT, SURF, color features	Achieved 89% accuracy, with multifeature fusion improving retrieval relevance by 13%	Multifeature fusion improves CBIR performance
Ahmed et al. [37] (2021)	CNN and traditional feature fusion for CBIR	CNN, SIFT, SURF	Accuracy increased by 10%, with CNN-SIFT fusion outperforming individual methods in cluttered scenes	CNN-traditional feature fusion enhances robustness
Wu [38] (2023)	Analysis of fusion-based CBIR using color, shape, and texture	SIFT, color, texture	Accuracy improved by 18%; combining color and texture features improved retrieval in highly diverse image sets, useful for heterogeneous collections	Multifeature fusion supports complex dataset retrieval
Sharma and Verma [39] (2024)	Robust multifeature CBIR for remote sensing	SURF, HOG, color moments	Achieved 85% accuracy; color moments enhanced feature distinction, critical for geographic data and environmental monitoring applications	Useful for handling diverse geographic data
Park [40] (2023)	A novel hybrid distance metric for multifeature CBIR	SIFT, SURF	Hausdorff achieved 10% higher recall in cases with complex backgrounds, enhancing precision in datasets with intricate details	Supports highly detailed and complex retrievals
Kim and Sohn [41] (2022)	CBIR with combined texture and shape features for medical imaging	SIFT, texture, HOG	Achieved 88% accuracy; HOG and texture features provided comprehensive shape analysis, critical for high-resolution medical datasets	Improves accuracy in medical applications

Table 2: Extracted texture features.

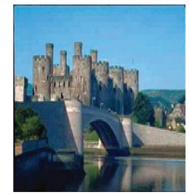
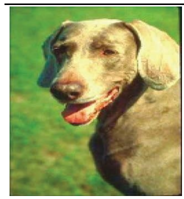
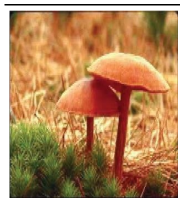
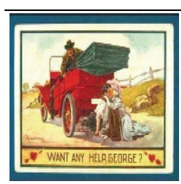
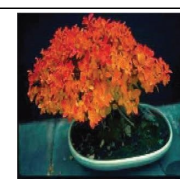
Image sample	T1	T2	T3	Image sample	T1	T2	T3
	28.69208	30.91244	0.078473		42.98475	47.29584	0.150546
	45.41081	38.59837	−0.58654		45.88965	49.44001	0.186051
	48.48604	42.88525	0.084375		41.91454	27.49632	0.449754
	40.93761	43.14214	0.413963		40.59209	54.43108	0.350496
	42.03918	65.46357	−0.62001		38.68424	33.54108	−0.44671

Table 3: Accuracy using dataset Corel.

Features	Euclidean distance (%)	Hausdrauff distance (%)
HOG	78.6	80.02
SIFT	75.1	77.9
SURF	77.3	79.8
Texture	75.2	77.2
Multifeature	81.9	84.2

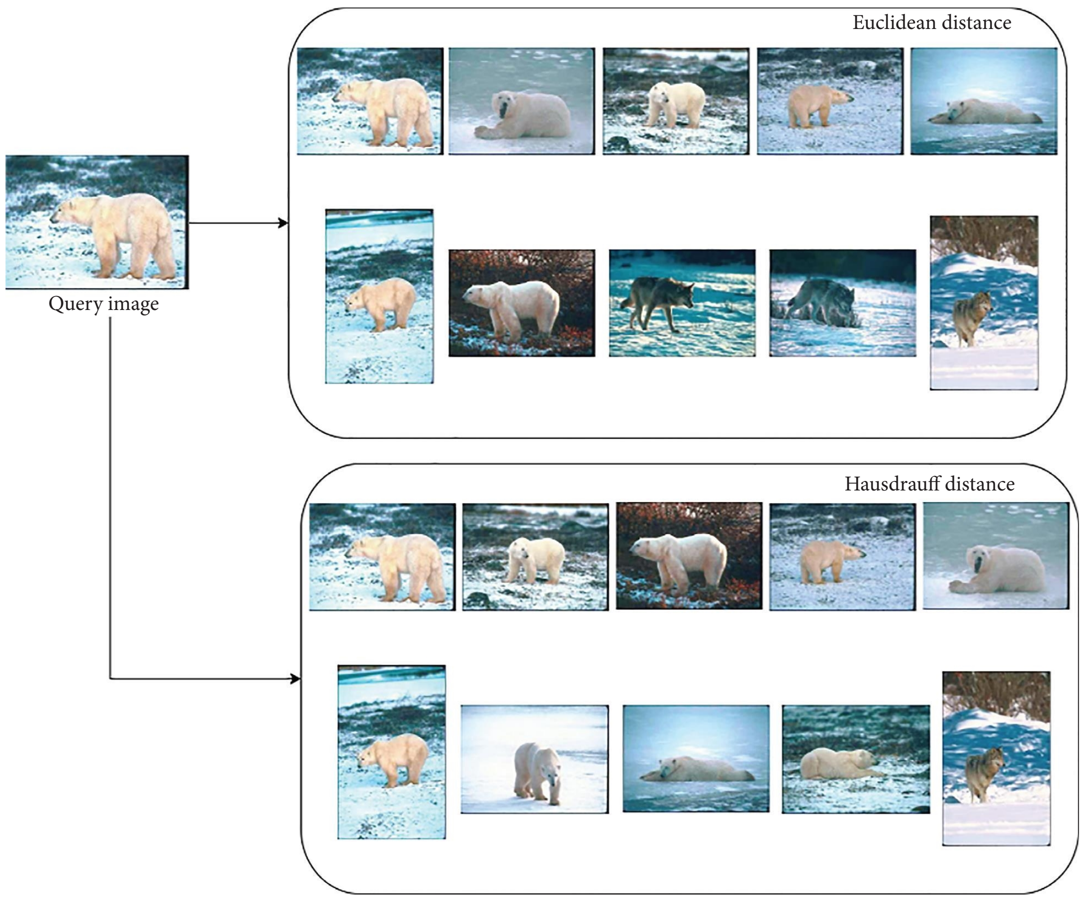


Figure 7: Testing results.

The key findings are summarized as follows.
HOG:

- Attained a precision of 78.6% with Euclidean distance.
- Demonstrated a slightly improved performance of 80.02% when assessed using Hausdorff distance.

SIFT:

- Exhibited a precision of 75.1% using Euclidean distance.
- Improved to 77.9% with Hausdorff distance, highlighting its robustness in feature extraction.

SURF:

- Attained 77.3% precision with Euclidean distance.
- Improved to 79.8% when using Hausdorff distance, representing its efficiency in recognizing features under varying transformations.

Texture-based features:

- Attained 75.2% precision with Euclidean distance.
- Exhibited a slight enhancement to 77.2% with Hausdorff distance.

Multifeature approach:

- Attained a precision of 81.9% using Euclidean distance.
- Demonstrated an even greater 84.2% accuracy with Hausdorff distance, highlighting its robustness and efficiency in image feature matching.

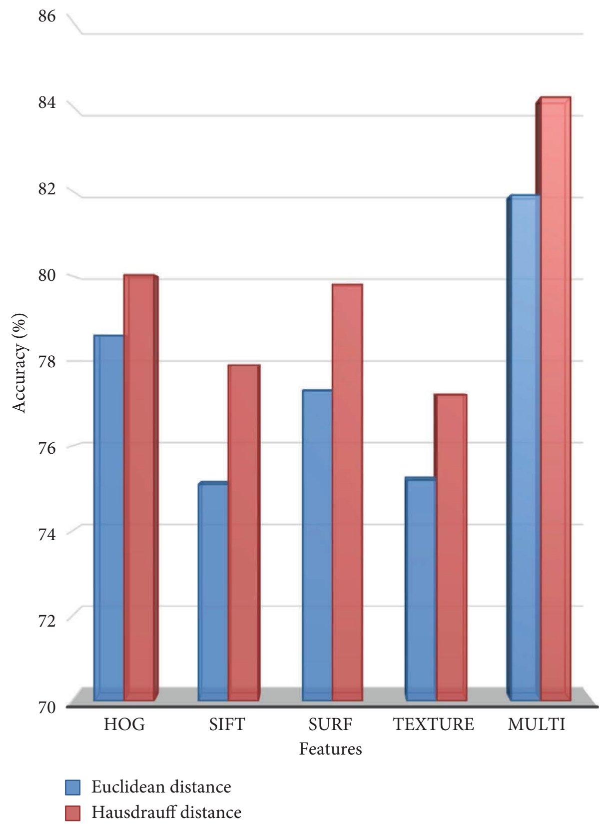


Figure 8: Performance measure.

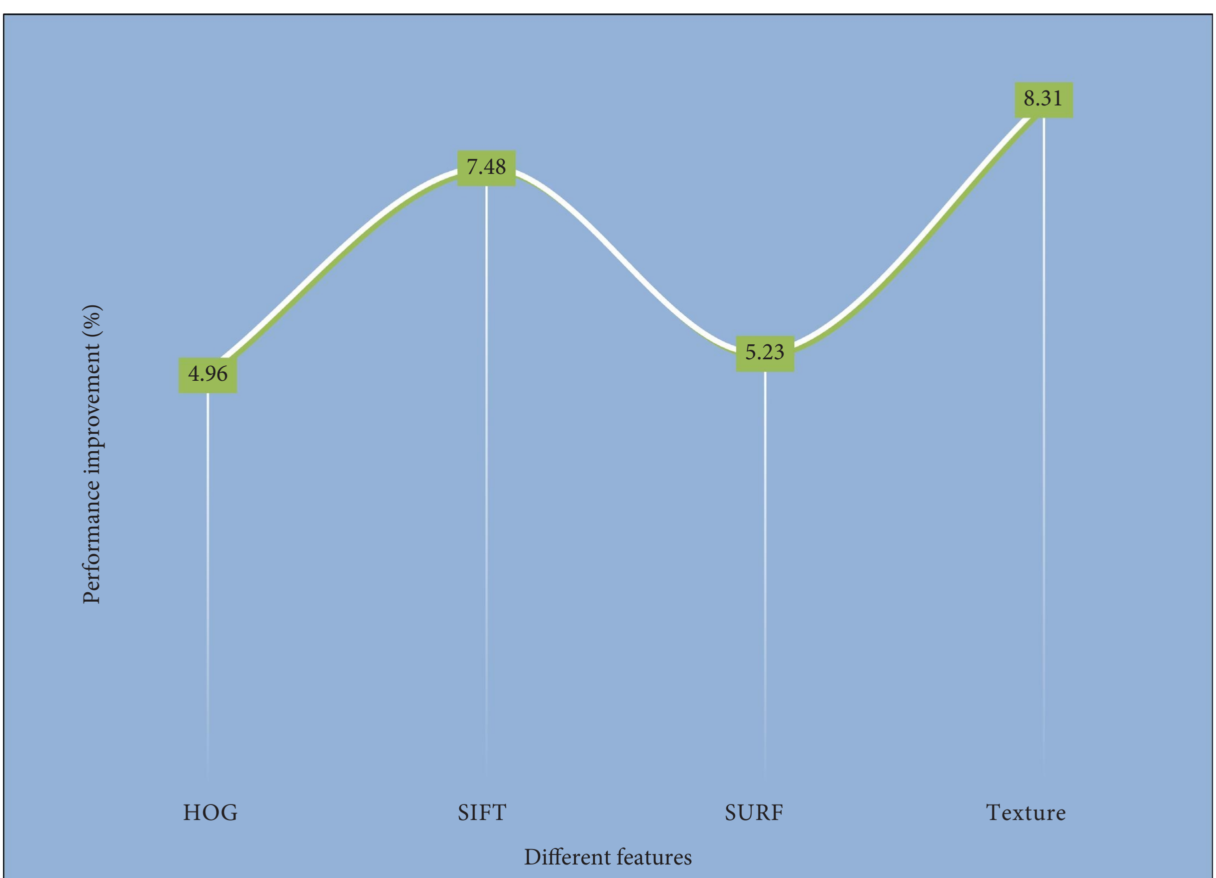


Figure 9: Performance improvement using multifeature fusion.

Figure 7 presents the testing results using CBIR, demonstrating the system's ability to retrieve images based on similarity in texture, color, or shape features. The figure showcases the accuracy and efficiency of the CBIR model by comparing retrieved images to the query image. It highlights how well the model performs in identifying relevant images from a large dataset.

Figure 8 shows the performance of Hausdrauff distance as 1.7%, 3.6%, 3.1%, 2.6%, and 2.7%, which are better than Euclidean distance in the case of HOG, SIFT, SURF, texture, and multifeatures, respectively. This measure depicts the effectiveness of the Hausdrauff distance method over Euclidean distance.

The analysis which focuses on the performance of the proposed multifeature is shown in Figure 9. This figure shows the improvement rate of the multifeature fusion-based approach and its impact on the accuracy of the CBIR system. On average, the percentage improvement of the proposed system is 6.5% from all other features which is quite better and provides an efficient solution.

Figure 9 illustrates the performance improvement achieved through multifeature fusion, where multiple types of features (such as texture, color, and shape) are combined to enhance the accuracy of the model. The fusion of these features results in more robust and reliable performance, as evidenced by higher retrieval rates and better classification outcomes compared to using individual features alone. This approach demonstrates the synergy of diverse feature sets for optimized model performance.

8. Conclusion

Features play an important role in the retrieval process of the CBIR system, so this proposed CBIR uses multifeature fusion where different features are grouped to improve the accuracy of the system. Results conclude that the accuracy percentage is quite high in the case of multifeatures along with the Hausdorff distance method. Results also depicted that the percentage improvement of the CBIR system with multifeatures is 4.96%, 7.48%, 5.23%, and 8.31% from HOG, SIFT, SURF, and texture features, respectively, along with Hausdorff distance, whereas in the case of Euclidean distance, it is 4%, 8.3%, 5.6%, and 8.1%, respectively. On the whole, the best matching method is the Hausdorff distance as depicted by the calculated results along with the proposed multifeature fusion method.

This proposed system might have the risk of an increase in complexity because of the multiple features that can be handled using soft computing approaches. In the future, the main focus is to develop an efficient, robust, and optimized system to provide a better solution and to reduce the risk of complexity.

Data Availability Statement

Data sharing does not apply to this article as no datasets were generated or analyzed during the current study.

Ethics Statement

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Funding

The authors have been funded by UKRI EPSRC Grant EP/W020408/1 Project SPRITE+ 2. The authors have also been funded by PhD project on Explainable AI through UKRI EPSRC Grant funded Doctoral Training Center at Swansea University.

References

[1] A. J. Afifi and W. M. Ashour, "Content-Based Image Retrieval Using Invariant Color and Texture Features" (2012), 1–6, https://doi.org/10.1109/dicta.2012.6411665.

[2] V. Tyagi, "Research Issues for Next Generation Content-Based Image Retrieval," in *Content-Based Image Retrieval* (2017), 295–302.

[3] R. Dong, M. Liu, and F. Li, "Multilayer Convolutional Feature Aggregation Algorithm for Image Retrieval," *Mathematical Problems in Engineering* 2019 (2019): 1–12, https://doi.org/10.1155/2019/9794202.

[4] M. Kaur and N. Sohi, "A Novel Technique for Content-Based Image Retrieval Using Color, Texture and Edge Features," in *2016 International Conference on Communication and Electronics Systems (ICCES)* (2016), 1–7, https://doi.org/10.1109/cesys.2016.7889955.

[5] R. Khanna, R. Kumar, and S. Kumar, "Middleware Architecture of VASNET and Its Review for Urban Monitoring & Vehicle Tracking," *IJERMT Journal* 3, no. 1 (2014): 41–45.

[6] R. Kumar, R. Khanna, and S. Kumar, "Vehicular Middleware and Heuristic Approaches for Intelligent Transportation System of Smart Cities," *Cognitive Computing for Human-Robot Interaction* 163 (2021): 163–175, https://doi.org/10.1016/b978-0-323-85769-7.00019-7.

[7] M. Kaur, S. Kaur, and G. Singh, "Vehicular Ad Hoc Networks," *Journal of Global Research in Computer Science* 3, no. 3 (2012): 61–64.

[8] R. Khanna, R. Kumar, and S. Kumar, "An Effective Framework for Security and Performance in Intelligent Vehicular Ad-Hoc Network," *Journal of Advanced Research in Dynamical and Control Systems* 10, no. 14 (2018): 1504–1507.

[9] R. Khanna, R. Kumar, and S. Kumar, "Deep Learning Integrated Approach for Collision Avoidance in Internet of Things Based Smart Vehicular Networks," *Journal of Advanced Research in Dynamical and Control Systems* 10, no. 14 (2018): 1508–1512.

[10] Z. Mehmood, F. Abbas, T. Mahmood, M. A. Javid, A. Rehman, and T. Nawaz, "Content-Based Image Retrieval Based on Visual Words Fusion Versus Features Fusion of Local and Global Features," *Arabian Journal for Science and Engineering* 43, no. 12 (2018): 7265–7284, https://doi.org/10.1007/s13369-018-3062-0.

[11] S. Xiaoming, Z. Ning, W. Haibin, Y. Xiaoyang, W. Xue, and Y. Shuang, "Medical Image Retrieval Approach by Texture

Features Fusion Based on Hausdorff Distance," *Mathematical Problems in Engineering* 2018 (2018): 1–12, https://doi.org/10.1155/2018/7308328.
[12] K. Garg and R. Kumar, "What and Why You Need to Know about Non-Fungible Tokens (NFTs)," *International Journal of Scientific Research in Engineering and Management* 6, no. 6 (2022): 1–4.
[13] H. Zhao and Q. Lin, "Multi-Feature Fusion CBIR Using SIFT, SURF," *IEEE Transactions on Image Processing* 31 (2022): 1441–1449.
[14] R. Gupta and P. Sharma, "Fusion of HOG and SIFT for Enhanced CBIR," *IEEE Access* 11 (2023): 33245–33255.
[15] J. Lee, "Deep Fusion Techniques in CBIR Systems," *IEEE Transactions on Multimedia* 26, no. 8 (2023): 1256–1265.
[16] S. Ali, "Comparative Study of Feature Matching Techniques in CBIR," *Pattern Recognition Letters* 173 (2023): 129–137.
[17] M. Patel and K. Joshi, "Efficient CBIR With Multi-Feature Fusion for Diverse Data," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 15 (2022): 2942–2950.
[18] Y. Wang and X. Chen, "Shape and Texture Fusion for CBIR in Medical Images," *IEEE Transactions on Medical Imaging* 42, no. 3 (2023): 895–902.
[19] D. Kumar, "Novel Fusion of Texture and Color Features in CBIR," *IEEE Transactions on Computational Imaging* 9, no. 5 (2024): 1107–1115.
[20] S. Yadav and M. Prasad, "Multi-Feature Fusion CBIR System for Large Datasets," *Journal of Visual Communication and Image Representation* 92 (2022): 102043.
[21] P. Singh, "Image Retrieval Optimization Using Hybrid Feature Fusion," *Pattern Recognition* 130 (2023): 108831.
[22] H. Li, "Multi-Feature CBIR for Real-Time Applications," *IEEE Access* 11 (2022): 27444–27455.
[23] T. Chang, "Performance Analysis of CBIR Using Hybrid Distance Metrics," *IEEE Transactions on Image Processing* 33 (2024): 1132–1140.
[24] R. Akhtar, "CBIR System Using Multi-Feature and Deep Learning Fusion," *IEEE Transactions on Multimedia* 26, no. 9 (2022): 2034–2045.
[25] F. Hu and X. Lee, "Hybrid CBIR for Geographic Information Systems," *IEEE Geoscience and Remote Sensing Letters* 20, no. 1 (2023): 11–20.
[26] H. Abbas and M. Rahman, "Multi-Feature CBIR for Fashion Industry," *Multimedia Tools and Applications* 82, no. 15 (2023): 20539–20552.
[27] G. Rao, "Advanced CBIR With Fusion of Shape, Texture, and Color Features," *IEEE Access* 12 (2024): 13011–13025.
[28] Y. Matsuda and K. Ono, "Multi-Feature CBIR Using HOG and Color Moments for Surveillance," *IEEE Transactions on Information Forensics and Security* 17 (2022): 1202–1212.
[29] T. Zhang, "CBIR With Fusion of Spatial and Color Features," *IEEE Transactions on Multimedia* 25, no. 7 (2023): 1678–1686.
[30] A. Brown and S. Lee, "Real-Time Multi-Feature CBIR for Industrial Applications," *IEEE Transactions on Automation Science and Engineering* 19, no. 2 (2022): 647–655.
[31] Y. Feng, "CBIR Using Fusion of Shape and Texture for Architectural Design," *IEEE Transactions on Automation Science and Engineering* 30 (2023): 1049–1060.
[32] M. Ibrahim, "Multi-Feature Fusion for CBIR in Medical Diagnostics," *IEEE Journal of Biomedical and Health Informatics* 27, no. 5 (2023): 1257–1265.
[33] X. Li and W. Chen, "Enhanced CBIR With Deep and Traditional Feature Fusion," *IEEE Transactions on Multimedia* 27, no. 8 (2024): 1568–1578.
[34] Y. Wang, L. Chen, and T. Zhao, "A Comparative Analysis of CBIR Techniques," *Journal of Visual Communication and Image Representation* 68 (2020): 103045.
[35] H. Lee and X. Zhang, "Efficient Medical CBIR Using Texture and Shape Features," *IEEE Journal of Biomedical and Health Informatics* 24, no. 3 (2020): 789–798.
[36] L. Zhao, X. Wu, and J. Lin, "Multi-Feature Fusion for Robust CBIR," *IEEE Transactions on Multimedia* 23, no. 5 (2021): 3568–3579.
[37] A. Ahmed, F. Ali, and N. Khan, "CNN and Traditional Feature Fusion for CBIR," in *Proceedings of the IEEE International Conference on Multimedia and Expo (ICME)* (2021), 1–6.
[38] L. Wu, "Analysis of Fusion-Based CBIR Using Color, Shape, and Texture," *IEEE Transactions on Multimedia* 25, no. 5 (2023): 1207–1217.
[39] D. Sharma and R. Verma, "Robust Multi-Feature CBIR for Remote Sensing," *IEEE Geoscience and Remote Sensing Letters* 20 (2024): 256–265.
[40] S. Park, "A Novel Hybrid Distance Metric for Multi-Feature CBIR," *Pattern Recognition Letters* 175 (2023): 85–93.
[41] H. Kim and Y. Sohn, "CBIR with Combined Texture and Shape Features for Medical Imaging," *IEEE Transactions on Medical Imaging* 41, no. 6 (2022): 1456–1465.
[42] D. Chatha and A. Aggarwal, "Comparative Analysis of Proposed Artificial Neural Network (ANN) Algorithm With Other Techniques, in Research Anthology on Artificial Neural Network Applications," *IGI Global* (2022): 1218–1223.
[43] S. Sardana and R. Kumar, "Energy Efficient Target Tracking in Wireless Sensor Networks," *International Journal of Scientific Research in Engineering and Management* 7, no. 2 (2016): 271–275.
[44] G. Gupta and R. Kumar, "Acoustic Channel Modeling and Simulation for Underwater Acoustic Wireless Sensing Networks," *International Journal of Computer Application* 975 (2016): 8887.
[45] T. Garg and R. Kumar, "A Way to Cloud Computing Basic to Multitenant Environment," *International Journal of Advanced Research in Computer and Communication Engineering* 2, no. 6 (2013): 2394–2399.
[46] S. A. Bakar, M. S. Hitam, and W. N. J. H. Wan Yussof, "Content-Based Image Retrieval Using SIFT for Binary and Greyscale Images," in *2013 IEEE International Conference on Signal and Image Processing Applications* (2013), 83–88, https://doi.org/10.1109/icsipa.2013.6707982.
[47] A. S. Vijendran and S. V. Kumar, "A New Content Based Image Retrieval System by HOG of Wavelet Sub Bands," *International Journal of Signal Processing, Image Processing and Pattern Recognition* 8, no. 4 (2015): 297–306, https://doi.org/10.14257/ijsip.2015.8.4.26.
[48] K. Velmurugan and S. S. Baboo, "Content-Based Image Retrieval Using SURF and Color Moments," *Global Journal of Computer Science and Technology* 11, no. 10 (2011): 1–4.
[49] R. Kumar, P. Verma, and S. Kumar, "A Proposed Work on Node Clustering & Object Tracking Processes of BFOA in WSN," *International Journal of Computer Science & Communication* 4, no. 2 (2013): 207–212.
[50] A. Jain, R. Muthuganapathy, and K. Ramani, "Content-Based Image Retrieval Using Shape and Depth From an Engineering Database," *Lecture Notes in Computer Science* (2007): 255–264, https://doi.org/10.1007/978-3-540-76856-2_25.
[51] M. Banerjee and M. K. Kundu, "Edge Based Features for Content Based Image Retrieval," *Pattern Recognition* 36, no. 11 (2003): 2649–2661, https://doi.org/10.1016/s0031-3203(03)00174-2.

[52] H. Farsi and S. Mohamadzadeh, "Colour and Texture Feature-Based Image Retrieval by Using Hadamard Matrix in Discrete Wavelet Transform," *IET Image Processing* 7, no. 3 (2013): 212–218, https://doi.org/10.1049/iet-ipr.2012.0203.

[53] S. Murala, A. B. Gonde, and R. P. Maheshwari, "Color and Texture Features for Image Indexing and Retrieval," in *2009 IEEE International Advance Computing Conference* (2009), 1411–1416, https://doi.org/10.1109/iadcc.2009.4809223.

[54] R. Kumar, R. Khanna, and S. Kumar, "Middleware Architecture of VASNET and its Review for Urban Monitoring & Vehicle Tracking," *International Journal of Scientific Research in Engineering and Management* 3, no. 1 (2014): 41–45.

[55] B. Akshaya, S. Sruthi Sri, A. Niranjana Sathish, K. Shobika, R. Karthika, and L. Parameswaran, "Content-Based Image Retrieval Using Hybrid Feature Extraction Techniques" (2019), 583–593, https://doi.org/10.1007/978-3-030-00665-5_58.

[56] Y. Mistry, D. Ingole, and M. Ingole, "Content Based Image Retrieval Using Hybrid Features and Various Distance Metric," *Journal of Electrical Systems and Information Technology* 5, no. 3 (2018): 874–888, https://doi.org/10.1016/j.jesit.2016.12.009.

[57] D. G. Lowe, "Distinctive Image Features from Scale-Invariant Keypoints," *International Journal of Computer Vision* 60, no. 2 (2004): 91–110, https://doi.org/10.1023/b:visi.0000029664.99615.94.

[58] N. Dalal and B. Triggs, "Histograms of Oriented Gradients for Human Detection," in *International Journal of Scientific Research in Engineering and* (2005), 1–8.

[59] H. Bay, T. Tuytelaars, and L. Van Gool, "SURF: Speeded up Robust Features," in *Lecture Notes in Computer Science* (2006), 404–417, https://doi.org/10.1007/11744023_32.

[60] R. Kumar and S. Kumar, "A Comparative Analysis of Performance Metrics of Different Cloud Scheduling Techniques," *International Journal of Scientific Research in Engineering and Management* 7, no. 2 (2016): 222–226.

[61] G.-H. Liu, J.-Y. Yang, and Z. Li, "Content-Based Image Retrieval Using Computational Visual Attention Model," *Pattern Recognition* 48, no. 8 (2015): 2554–2566, https://doi.org/10.1016/j.patcog.2015.02.005.