

AN EDGE CLUSTERED SEGMENTATION BASED MODEL FOR PRECISE IMAGE RETRIEVAL

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Abstract

The modern era necessitates efficient smart image retrieval from various image collections. Image retrieval relies heavily on primitive image signatures and their internal features. Image retrieval relies heavily on deep metric learning, which aims to identify semantic similarities between data points in the image for accurate image retrieval procedures. The image shape feature representation was generated using a histogram image processing model. To limit the search space, the image pixel shape-based retrieval procedures are effectively used for image retrieval. The dominant colour, edge and shape descriptor has become a common feature in image processing applications. Because of lighting and other variables, colour in nature can shift slightly. A consistent region of an image is detected and extracted from this consistent zone for an accurate image retrieval strategy by performing image segmentation. The proposed model implements a Related Edge Clustered Pixel Extraction Model with Weighted Feature Vector Set (RECPE-WFVS) for extracting the image content set for searching with the query image for an accurate image retrieval procedure. The proposed model is compared with the traditional Remote Sensing Image Retrieval approach based on Fully Convolutional Network (RSIR-FCN) and Classification Using High-Resolution Remote Sensing Images (CHR-RSI), and the results represent that the proposed model's performance is high.

Keywords: Image Retrieval, Feature Vector, Clustering, Image Processing, Edge Detection, Pixel Extraction.

1. Introduction

In today's digital age, the image retrieval method is used extensively on the internet because of digital image approaches. The features extraction system gets images from the internet and stores them in a database with distinct labels and captions for each image. It is referred to as Content-based Image Retrieval (CBIR) [Yuan et al. (2019)] when the content of an image is used as the identifier for browsing. Color, shape, and texture [Yu et al. (2018)] are just a few details gleaned from an image using the CBIR approach. The research community-contributed image characteristics, relevance feedback, fuzzy color, and texture histograms to CBIR. Color histograms, based on relevant feature extraction, use low-level factors [Wei et al. (2017)], such as the physical attributes of the objects in the image, for image retrieval [Raza et al. (2018)]. It's possible, though, that these visual cues don't accurately transmit the image's underlying meaning. Photographs may lead to erroneous findings when these techniques are applied to a large content database.

All image retrieval algorithms aim to recover the image as quickly and correctly as possible. The image can be retrieved with more accuracy [Liu et al. (2017)]. Intensity differences often influence images. To avoid any distortion, the histogram distributions of the images must match exactly, using the edges and intensities of the photos as a starting point [Liu et al. (2019)]. Large-scale datasets are required to verify the accuracy of the similarities between the photographs today. A comparable retrieval capability was provided earlier by computational visual attention [Hua et al. (2019)].

To make a more accurate retrieval model, users need to add more features in the future. Several studies examine image retrieval methods to retrieve data efficiently [Nawaz et al. (2018)]. Extracting the color spaces from distinguishing the texture and spatial information is done using this method. CBIR and TBIR (Text-Based Image Retrieval) are two of the most commonly used image retrieval technologies. An image search strategy in CBIR is comparable to a search done by recognizing the pattern in the compared images. It is possible to create this pattern by extracting color features, texture, margins, etc. However, this technique is more

appropriate when used for object detection [Zhou et al. (2018)]. In CBIR, the resemblance of patterns is just an absolute requirement that must be met to claim that the three images share similarities [Chadha et al. (2018)]. Images can be retrieved using different query images, making terms unsuitable for image retrieval. It is also possible to search for another image using the same query [Varish et al. (2018)]. A typical a gray scale image furnished as Figure 1.

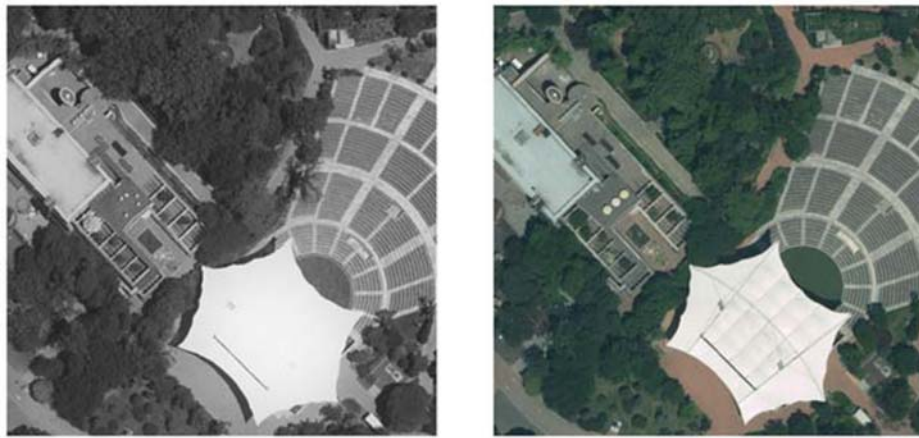


Fig. 1. Image to Grayscale Conversion

A Content-Based Information Extraction System was created and introduced to solve the disadvantages of text-based retrieval systems. A picture can be extracted from a big database using these features, which are used to match image features taken from a query with the available database images. Images are retrieved from the source by resemblance in characteristics [Zeng et al. (2016)] to evaluate query conditions relevant to the picture stored in the database to identify which image best fits known attributes. More recent CBIR applications use pattern recognition or image comparison to identify and compare images. The image retrieval architecture of the system is depicted in Figure 2.

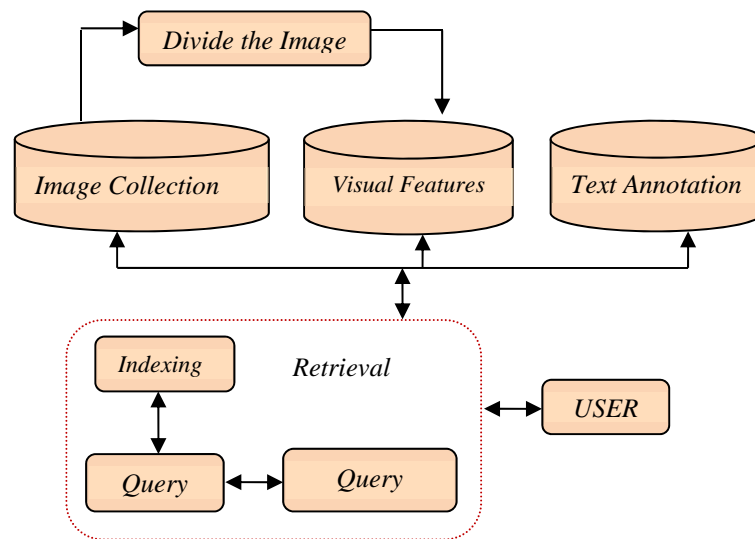


Fig. 2. CBIR Architecture

The image must first be taken using a suitable camera [Liu et al. (2018)]. A picture must be preprocessed so that it may be cleaned up of distortions and other undesirable aspects before processing can begin. It is done to ensure the image is only left with the relevant portions [Alkhwilani et al. (2015)] needed for image retrieval analysis utilizing various algorithms. During preprocessing [Kaur et al. (2015)], undesired elements are removed, the image is resized, boundary detection is performed, and normalized the results. The query image extraction process is shown in Figure 3.

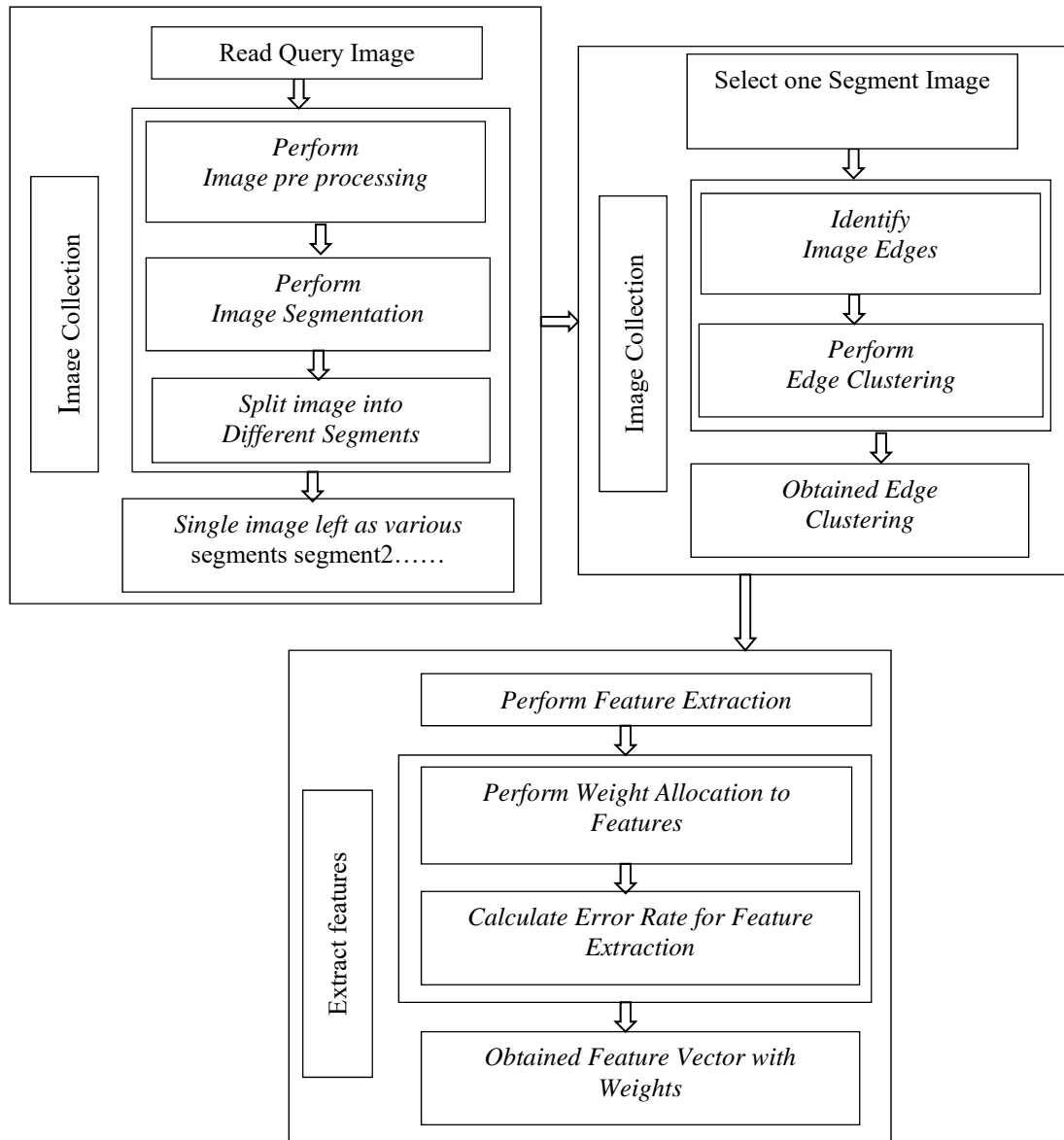


Fig. 3. Query Image Extraction using feature Vector.

Using imagesegmentation [Dubey et al. (2015)], users can separate individual images from the rest of the image. Segmentation is how an image is broken down into smaller parts. Image segmentation groups pixels that collectively represent a specific part of the current picture [Feng et al. (2015)]. The goal of separating an image is to reduce its size by slicing it into smaller images or objects for better analysis. It also aids in locating the objects and determining their boundaries inside the image [Zeng et al. (2016)]. As a result, similar labels and visual characteristics might be derived from the same pixels in the image. Images can be gathered into a whole image or a collection of regions taken from the image after the image separation process is completed. Image segmentation is the initial step in the analysis of images since it represents the image as a meaningful and analyzable form [Douik et al. (2016)]. The terms Local Segmentation and Global Segmentation describe the two primary image segmentation approaches. Various Image segmentation models are shown in Figure 4.

An image's intensity data provides only a limited amount of information about its edges. Edge detection is locating a pixel on the edge of a region. Images can be segmented using this method, which identifies the boundaries of pixels among areas with a rapid change in intensity and links them to construct closed object borders. A binary image is generated. Better image quality is needed for edge detection; therefore, noise must be reduced or eliminated. The proposed model implements a Related Edge Clustered Pixel Extraction Model with Weighted Feature Vector Set to extract the image content set for searching with the query image for an accurate image retrieval procedure. The image pixels are extracted for further analysis to extract authentic images based on the query image.

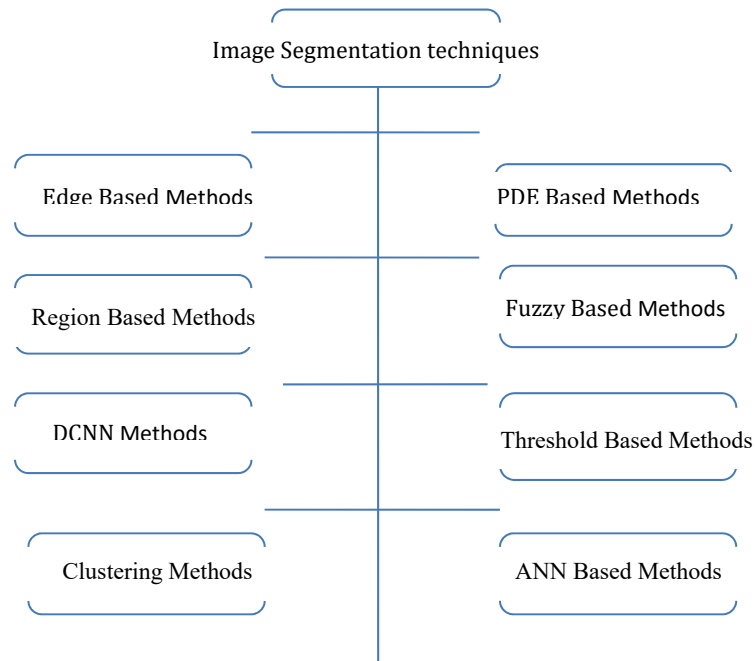


Fig. 4. Image Segmentation Techniques

2. Literature Review

An image's high-dimensional feature vector can be obtained using a local descriptor developed by Yuan et al. [Yuan et al. (2019)], an approach that combines SIFT and LBP. For feature fusion, two models, patch-level or image-level, are used. A k-means clustering technique is employed to generate a dictionary for the concise representation of more outstanding feature vectors. Image retrieval is done using the lexical category of the enquiry image and a similarity measure to rank relevant photos in order of relevance. The methodology proposed by Yu et al. [Yu et al. (2018)] uses HOG & SIFT with LBP to integrate features. It is used to cluster the data using the k-means clustering approach. The new features didn't rely on image segmentation and instead found exciting areas of an image on their own. SIFT and an LBP feature combination have increased picture retrieval performance in experiments. Gabor filter and multiple 3Dcolorhistogram can adequately characterize the attributes of the mage. Still, incorporating many features may result in computational complexity, which in turn increases the calculation time and cost during the image retrieval.

Raza et al. [Raza et al. (2018)] proposed a feature selection strategy to extract just the essential features from the data set. This method uses two methods: a Gabor filter and a three-dimensional color histogram. A genetic algorithm is used to find the best way to partition features. A feature selection method employing preliminary and profound reduction extracts the most relevant features. Using this strategy, users can get precise results in a short period. Improved LBP was developed by Liu et al. [Liu et al. (2017)] and a new texture feature descriptor called MLSBPs was created for CBIR because of the lack of spatial texture features in LBP. The feature vector is formed by computing LBP at multiple sizes and directions. MLSBP outperforms conventional CBIR approaches, according to the results of the research.

G.H. Liu et al. [Liu et al. (2019)] suggested a hybrid approach to retrieving images. The image's local characteristics are combined in this approach. The Angular Radial Convert (ART) And Color Distinction Histogram (CDH) methods extract the image's shape, texture, and color attributes. Hybrid aspects in the basic CDH technique have been modified to make the proposed system work. According to Hua et al. [Hua et al. (2019)], an edge orientation disparity histogram (EODH) descriptor can be used to demonstrate features. To determine the primary orientation of each edge pixel, the researcher utilized a steerable filter and a vector sum. The EODH and color-SIFT descriptors are then combined to obtain a balanced word distribution. The CBIR technique proposed by J.X. Zhou et al. [Zhou et al. (2018)] used a BoW layout and incorporated feature points (SIFT and SURF). The k-means clustering technique is utilized to create a codebook for compact feature extraction, and the SVM is used to classify semantic categories.

Varish et al. [Varish et al. (2018)] offered an upgraded SURF descriptor, SVM classifier, and a neuronal network for image retrieval. The SURF descriptors are used to extract image features, and SVM and neural networks are combined to improve retrieval accuracy. To speed up image retrieval, Pavithra et al. [Pavithra et al. (2016)] offered a hybrid input model that gets rotations and scale-invariant. Color data is extracted using RGB quantization, whereas texture data is generated using patterns produced by spatially organizing elements. The

Rotation And Extent Hybrid Descriptor is created by cograymbining colour and texture data (RSHD). RSHD descriptions can be rotated and scaled without losing any of their functionality. Using an innovative application proposed by Ahmad et al. [Ahmad et al. (2017)], users can extract the image's colour and texture. The term Global Correlation Descriptor (GCD) refers to this descriptor. GCV is used to characterize the color feature, whereas directional GCV indicates the texture feature (DGCV).

The GCD surpasses previous CBIR approaches, according to the findings of the experiments. Picture moment invariants are used as feature descriptors for image retrieval by Pradhan et al. [Pradhan et al. (2018)]. In the BoW model, the moments are used to generate feature vectors. It is the first time that SURF feature descriptor has been utilized to extract affine moment invariants as local features. SGO and APSO [Gupta et al. (2021)] were used to extract data from images without errors, and a programme was provided to improve image quality. They built an automated method utilizing the DL Algorithm [Shankar et al. (2020)] to colorize grayscale images using RGB Format on various fields and visuals of CCTV monitoring. Blur image sharpening in multiple fields has a more significant influence, and LSTM is utilized to enhance an image [Shankar et al. (2020)]. An Image Extractor technique based on a genetic algorithm [Shankar et al. (2017)] was used to increase picture retrieval performance. They used NN-based Decision Trees with 80% accuracy to retrieve face expressions using emotions by drawing Beizer curves [Babu et al. (2017)]. They used XML terms to acquire diverse responses from query keywords within the data to extract information [Rajanikanth et al. (2016)]. They employed a vector median filter on PGM pictures with fuzzy membership functions to reduce the noise content [Shankar et al. (2012)].

Gaussian Mixture Models (GMMs) can be used to describe an image as a spectrogram, according to Wu et al. [Wu et al. (2017)]. The quantized colour space is determined using the trained data set and the Expectation-Maximization (EM) approach. When it comes to Gaussian components, the Bayesian criterion defines colour bins. The spatialogram is subjected to a quantized Finite mixing colour model. After comparing two spectrograms, a novel measurement method called Andersen divergence was proposed to improve image retrieval. The Multi-Trend Structure Descriptor (MTSD), presented by Liu et al. [Liu et al. (2018)], is a feature representation descriptor based on local and inter structure. This descriptor combines elements such as color, edge orientation, shape, and intensity information for a robust representation of a picture. To extract picture features, it also represents local spatial structure information. MTSD delivered discriminative outcomes for effective CBIR, as indicated by the experiment results. Incorporating both local and global variables, Zhao et al. [Zhao et al. (2016)] provided a hybrid approach. The SIFT descriptor is used to extract local features, whereas the upper-lower LBP (UL-LBP) description based on LBP extracts global features. Then, features are quantified into the BoW model to increase the performance of picture retrieval. Even though LBP is not ideal for color photos, it is not appropriate for capturing similarities between color photos. Only textual information is retrieved from images via LBP.

Douik et al. suggested a model by providing a descriptor that included an additional color feature termed the Color Information Feature (CIF) for picture retrieval [Douik et al. (2016)]. According to the experiments, combining these two aspects resulted in an effective retrieval system. LBP and wavelet transform are incorporated in the model proposed by Liu et al. [Liu et al. (2017)]. These features are retrieved by calculating LBP codes with the parameters of wavelet transform (DWT) coefficients. Using these LBP codes, form features are retrieved from texture features to build a feature vector by computing Legendre seconds. The results of the experiments demonstrate that tiny picture databases perform better than large ones. For image retrieval, Ng et al. [Ng et al. (2020)] recently estimated the second-order similarity (SOS) loss across the attention-based selected regions of the input image. Cross-modal retrieval and fine-grained sketch-based image retrieval are two applications for the seven attention-based models. Deep hashing based on a gradient attention network (GEN) enforces the CNN binary properties to reduce the distances between them, regardless of their signs or directions. Gao et al. (2020) used a multiview discrimination and pairwise CNN (MDPCNN) [Gao et al. (2020)] network to achieve 3D object retrieval.

3. Methodology

The proposed model implements a Related Edge Clustered Pixel Extraction Model with Weighted Feature Vector Set (RECPE-WFVS) for extracting the image content set for searching with the query image for an accurate image retrieval procedure. Image processing, database applications, and multimedia databases rely heavily on images for sorting. As a result, this knowledge area is called image recovery when returned data is an image set. This data is used to search for images. Today, photographs are widely employed in various sectors, from corporations to architecture and advertising to policing and the study of fashion and history. A database of these photos is referred to as a collection. Image retrieval is one of the essential computer systems for seeing and storing photographs in a wide-ranging database.

A grayscale intensity image is used for image retrieval in the proposed approach, comparable to the Colour Weighted Average Method (CWAM). Unlike a colour image, which assigns an eight-bit number to each red,

green, and blue plane independently, a grayscale image generates distinct shades of the pixel with an eight-bit value ranging from 0 – 255.

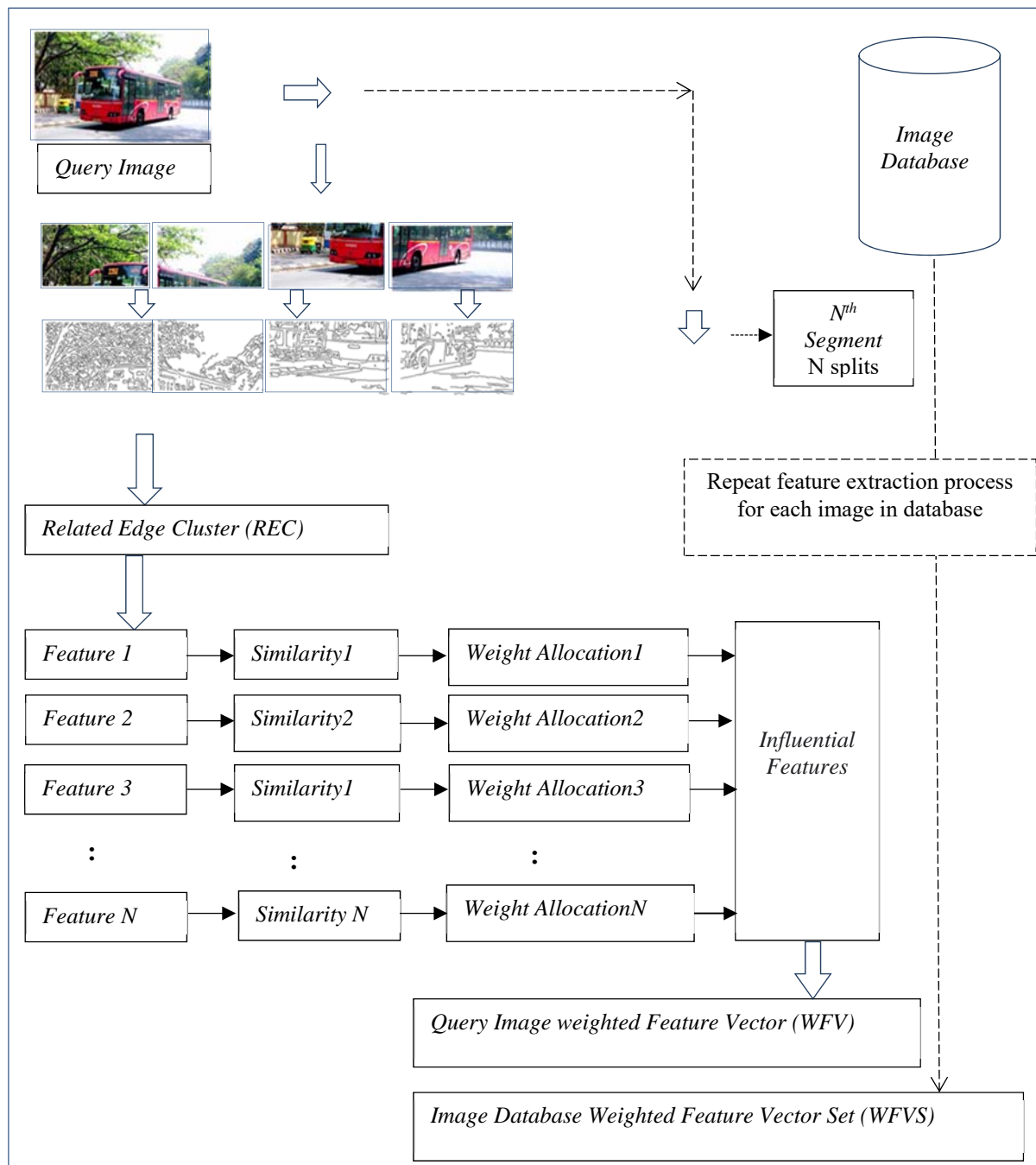


Fig. 5. Proposed Model Framework

The values 0–255 are unique to each plane in the same way. Grayscale intensity images can reduce the amount of information they contain and occupy less memory space than three-dimensional colour images. Edges, areas, blobs, and other image details are preserved on a gray scale. Extracting meaningful information from raw pixel values is the process of feature extraction, which can be employed in different approaches like machine learning. This method is helpful for huge image sizes, such as image matching, to speed up the process. A reduction in the number of objects is used. Extraction of the most valuable information from raw data is done using this method. During image processing, a characteristic known as extraction is used to build non-redundant and valuable values from the initial measured data collection. The dimensionality reduction is linked to the selection of features. It is possible to reduce an algorithm's input data to a smaller group of features when the data is too vast to process.

In developing any categorization of patterns, feature extraction is a crucial stage in extracting useful information that distinguishes each class. Feature vectors are formed by removing the relevant features from

images. The image features are taken into account to a detectable level when doing feature extraction. The image's testable properties can be gleaned using Average RGB, Color Moments, Co-occurrence, Local Color Histogram, Global Color Histogram, and Geometric Moments. Comparing extracted features to obtain visual similarity results is known as feature matching.

Edge detection is a computer vision technique used to determine an image boundary in digital image processing. An algorithm is used to look for pixel brightness inconsistencies in a grayscale image. The edges of an image are the curved line segments where the intensity changes abruptly. Edges of an image have a high contrast intensity, and a sudden shift in intensity from one pixel to the next can significantly impact the image's quality. Using edge image detection, users may reduce the amount of data they are working with while still keeping the entire critical image attributes. The size of the edge determines what kind of edge it has; however, at a certain point, the edge will have no width. The images' edges may be used to properly quantify the basic properties of each item, such as area, perimeter, and form. As a result, the edges of the scene are used to determine its boundaries and segments. The edge detection function is used to find the object's border, and then the edge information is used to extract the limit. Because of the unpredictable difference in levels between pixels, it isn't easy to distinguish the edges. As a result, real-world photographs rarely contain perfect edges. The proposed model implements a Related Edge Clustered Pixel Extraction Model with Weighted Feature Vector Set to extract the image content set for searching with the query image for an accurate image retrieval procedure. The proposed model framework is shown in Figure 5.

Initially, an image dataset is considered for applying the proposed model. From the dataset, an image is loaded, and Segmentation is used on it that divides the image into Nth segments as N multiple partitions. After Image segmentation, on each segment, edge detection is performed to accurately identify the edges of the segment so that the pixels can be extracted only within the edges range. All the identified edges are clustered as a related edge cluster (REC) forms the image outline and performs the feature extraction. For the extracted features, weights are allocated based on the usage of those features in query execution. The final feature vector set as influential features is called Query Image weighted Feature Vector (WFV). This exact procedure is applied to all the images in the database and created as Image Database Weighted Feature Vector Set (WFVS) represented that further used for accurate image retrieval. Here, PatternNet [Zhou et al. (2018)] data set is used for this simulation. It is a large-scale, high-resolution remote sensing dataset compiled for image retrieval from remote sensing. There are 38 classes, and each class includes 800 photos at a resolution of 256X256 pixels. PatternNet photos are derived from Google Earth imagery or, in the case of select US cities, from the Google Map API. The classes and spatial resolutions are shown in the Figure 6 below. The diagram depicts several examples of photos from each class.



Fig. 6. PatternNet data set with 38 classes[Zhou et al. (2018)]

3.1. PROPOSED ALGORITHM

ALGORITHM 1 RECPE-WFVS

Step 1: Select an Image from Dataset and perform Segmentation on the Operational Set.

$$\text{Opset}(\text{Img}(i)) = \sum_{i=1}^N \text{IMGDS}(\text{Img}(i)) \varepsilon \text{IMG} - \text{DS}\{I \dots N\}$$

Step 2: Compute Image Segmentation to Extract Image Pixels Accurately.

$$\begin{aligned} \text{Img} - \text{Seg}(\text{Img}(i, j)) \\ = \sqrt{\frac{\sum_{i=1}^M (\text{Img}(i)_i - \lambda)^T + ((i + j)_N)^\delta}{(j + 1) + \theta}} \\ + \sum_{i=1}^N \text{get int ensity}(\text{Img}(i)) + \max(\text{int ensity}(\text{Img}(i))) \end{aligned}$$

Step 3: Compute Edge Detection to avoid Noisy Pixels from Extraction.

$$\text{Edset}(\text{Img}(i)) = \frac{\text{getrange}(\text{Img}(i)) + \alpha}{\max(\sum_i \text{Img} - \text{Seg}(\text{Img}(i)))} + \sum_{i=1}^N \left\{ \frac{\|\max(\text{pixel}(\text{Img} - \text{Seg}(i, j)))\|}{\text{size}(\text{IMGDS})} \right\}^N + Th$$

Step 4: Perform Edge Clustering to similar group Edges to form an accurate Image Shape.

$$\begin{aligned} \text{Cluster_Set}(\text{EdSet}(\text{Img}(i))) \\ = \sum_{i=1}^N \text{getgreyrange}(\text{Img}(i, j)) + \max(\text{greyrange}(i, j))_\lambda + \max(\text{Img} - \text{Seg}(i)) \end{aligned}$$

Step 5: Generate a feature vector to form the Cluster Set.

$$\text{pix} - \text{set}[N(i)] = \frac{\sum_{i=1}^N \max(\text{Pixel range}(i, j) + \lambda + \max(\text{Img_Filter}(i, j)))}{\text{size of}(\text{cluster}_{\text{set}})}$$

$$\begin{aligned} \text{Fvectorset}(i, j, I) \\ = \text{pix} - \text{set}[i]^\delta(i, j) + \sum_{i=1}^N \min(\text{Img} - \text{Filter}(i, j)) + \frac{Th}{\text{sizeof}(\text{Edset})} \\ + \sum_{i=1}^M \minrange(\text{Clusterset}(\text{Img}(i, i + 1)))_N \end{aligned}$$

Step 6: Calculate the weight allocation for accurate Image Retrieval.

$$\begin{aligned} \text{Walloc}(\text{Fvectorset}(\text{Img}(i))) \\ = \sum_{i=1}^M \frac{\max(\text{Edset}(\text{Img}(i, j))) + \sum_{i=1}^N \minrange(\text{Clusterset}(i, j)) + \maxrange(\text{Fvectorset}(i, j))^\delta}{\text{sizeof}(\text{Fvectorset}(i, j))} \end{aligned}$$

Step 7: Calculate the Error Rate of Feature Extraction as

$$\begin{aligned} \text{MSE} = \frac{1}{\text{size of}(\text{F vector set})} \sum_{i=1}^N \left(\text{Walloc}(\text{pix} - \text{Set}(\text{Img}(i)))_{i, j} + \text{Fvectorset}(i) - \min(\text{Cluster_Set}(i, i \right. \\ \left. + 1)) \right)^\lambda \end{aligned}$$

Step 8: Now display Feature Vector Set for Image Retrieval.

3.2. ALGORITHM EXPLANATION

Initially, Load an image from respective class from the patternetdataset IMG-DS{I1, I2,...,IN } and consider the image loaded into the operational set for performing Segmentation as a Step 1 by evaluating Eq. (1).

$$\text{Opset}(\text{Img}(i)) = \sum_{i=1}^N \text{IMGDS}(\text{Img}(i)) \varepsilon_{\text{IMG} - \text{DS}\{I \dots N\}} \quad (1)$$

In Step 2, the loaded images undergo Segmentation, where the image will be divided into smaller partitions so that the image pixels can be extracted accurately. The image segmentation is performed as Eq. (2).

$$\begin{aligned} \text{Img} - \text{Seg}(\text{Img}(i, j)) \\ = \sqrt{\frac{\sum_{i=1}^M (\text{Img}(i)_i - \lambda)^T + ((i + j)_N)^\delta}{(j + 1) + \theta}} + \sum_{i=1}^N \text{get int ensity}(\text{Img}(i)) + \max(\text{int ensity}(\text{Img}(i))) \end{aligned} \quad (2)$$

Where λ is the default intensity range of a pixel in a standard image and δ represents the maximum pixel range in a snap. The idea is divided into multiple segments with I, j as adjacent pixels.

In Step 3, edge detection is applied on each segment so that accurate image pixels can be extracted and noisy pixels are avoided from extraction. The edge detection is performed as Eq. (3).

$$\text{Edset}(\text{Img}(i)) = \frac{\text{getrange}(\text{Img}(i)) + \alpha}{\max(\sum_i \text{Img} - \text{Seg}((\text{Img}(i))))} + \sum_{i=1}^N \left\{ \frac{\|\max(\text{pixel}(\text{Img} - \text{Seg}(i, j)))\|}{\text{size}(\text{IMGDS})} \right\}^N + Th \quad (3)$$

Here Th is the threshold range of the image gray levels that need to be extracted.

In Step 4, the edge clustering is applied to group a similar edge that forms the proper image shape. The clustering is applied to the similarity values of the linked pixels to create the exactcondition of the original image where pixels need to be extracted. The edge clustering is performed as Eq. (4).

$$\text{Cluster_Set}(\text{EdSet}(\text{Img}(i))) = \sum_{i=1}^N \text{getgreyrange}(\text{Img}(i, j)) + \max(\text{greyrange}(i, j))_\lambda + \max(\text{Img} - \text{Seg}(i)) \quad (4)$$

In Step-5, the feature extraction process from the cluster set is performed to consider the image values for accurate image extraction by generating the feature vector set as Eq. (5).

$$\begin{aligned} \text{pix} - \text{set}[N(i)] &= \frac{\sum_{i=1}^N \max(\text{Pixel range}(i, j) + \lambda + \max(\text{Img_Filter}(i, j)))}{\text{size of}(\text{cluster_set})} \\ \text{Fvectorset}(i, j, I) &= \text{pix} - \text{set}[i]^\delta(i, j) + \sum_{i=1}^N \min(\text{Img} - \text{Filter}(i, j)) + \frac{Th}{\text{sizeof}(\text{Edset})} + \\ &\sum_{i=1}^M \minrange(\text{Clusterset}(\text{Img}(i, i + 1))) \end{aligned} \quad (5)$$

In Step 6, the weights are allocated for the features extracted and based on these weights, the features are considered for training the model for accurate image retrieval. The weight allocation is performed as Eq. (6).

$$\begin{aligned} \text{Walloc}(\text{Fvectorset}(\text{Img}(i))) \\ = \sum_{i=1}^M \frac{\max(\text{Edset}(\text{Img}(i, j))) + \sum_{i=1}^N \minrange(\text{Clusterset}(i, j)) + \maxrange(\text{Fvectorset}(i, j))^\delta}{\text{sizeof}(\text{Fvectorset}(i, j))} \end{aligned} \quad (6)$$

In Step-7, calculate the error rate of feature extraction as Eq. (7).

$$\text{MSE} = \frac{1}{\text{size of}(\text{F vector set})} \sum_{i=1}^N \left(\text{Walloc}(\text{pix} - \text{Set}(\text{Img}(i)))_{i, j} + \text{Fvectorset}(i) - \min(\text{Cluster_Set}(i, i + 1)) \right)^\lambda \quad (7)$$

After evaluating Step 1 to Step 7, the Feature Vector Set for further image retrieval procedure has been displayed as a Step 8.

4. Results

The major purpose of the suggested system is to produce a precise outcome with minimal processing time. The suggested model is written in Python and runs on Google Colab environment. The imagePatternNetdataset [Zhou et al. (2018)] is considered for this model execution. The term Content-based image retrieval (CBIR) is extensively used to describe finding needed images from a vast database based on attributes that can be automatically retrieved from the images themselves. Earlier CBIR approaches were based on extracting the image's low-level properties such as shape, colour, texture, etc. But such systems lacked effectiveness since the picture concepts were not appropriately detected. The suggested model uses a Related Edge Clustered Pixel

Extraction Model with Weighted Feature Vector Set (RECPE-WFVS) to extract the image content set for searching with the query image to achieve accurate image retrieval. The suggested RECPE-WFVS is compared to the standard Remote Sensing Image Retrieval (RSIR-FCN) and Classification Using High-Resolution Remote Sensing Images approaches (CHR-RSI). Image Segmentation Accuracy Levels, Image Segmentation Timed Levels, Image Edge Detection Accuracy Levels, Image Pixel Extraction Accuracy Levels, Pixel Extraction from Edge Time Levels, Feature Extraction Accuracy Levels, Feature Weight Allocation Accuracy Levels and Error Rate are the metrics used to assess the results.

Model Images	RECPE- WFVS	RSIR- FCN	CHR- RSI
100	76	55	25
200	80	58	30
300	82	60	35
400	85	65	42
500	90	70	50
600	95	75	55
700	98	78	62

Table 1. Image Segmentation Accuracy Levels

Model Images	CHR-RSI	RSIR- FCN	RECPE- WFVS
100	13	10	7
200	15	12	8
300	17	13	10
400	19	15	11
500	21	17	13
600	23	18	14
700	25	19	16

Table 2. Image Segmentation Time Levels

An image is segmented into smaller subsets called Image segments, which simplifies further analysis or evaluation of the image by lowering its overall complexity. Simply explained, segmentation refers to the process of labelling individual pixels. Alternatively, the percentage of correctly categorized pixels in a picture can be used as a statistic for evaluating Semantic Segmentation. As well as for individual classes, the pixel precision is also typically stated as a whole across all image classes. The proposed and traditional models of accuracy levels for image segmentation graph is furnished in Figure 7, by measuring the accuracy level respective to percentage with number of images and models as show in Table 1.

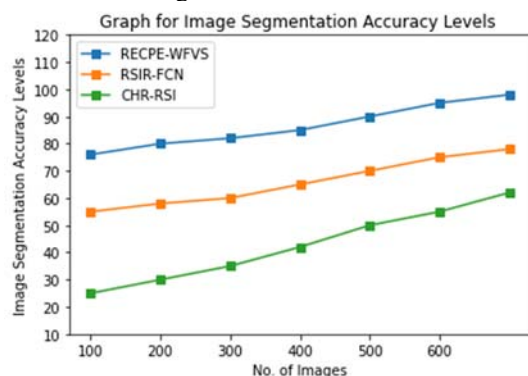


Fig.7. Image Segmentation Accuracy Levels

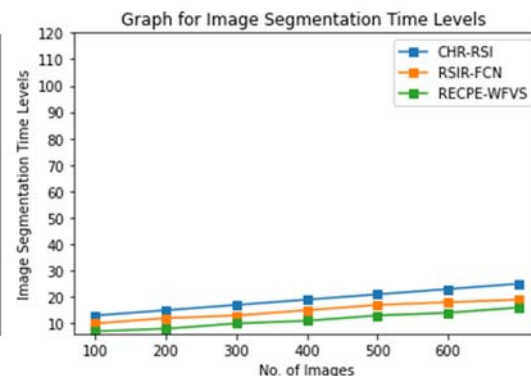


Fig. 8. Image Segmentation Time Levels

As a part of the image identification system, Segmentation is critical to extracting certain items for subsequent processing, such as labelling or recognizing them. It is feasible to separate the object of interest from the remainder of the image using segmentation techniques. The proposed model consumes the less time to finish the segmentation process. The image segmentation time levels of the traditional and proposed models are shown in Figure 8, by measuring the time level in milliseconds (ms) respective to number of images and models as show in Table 2.

Model Images	RECPE- WFVS	RSIR- FCN	CHR- RSI
100	70	60	50
200	72	62	52
300	78	68	58
400	82	72	60
500	90	74	62
600	92	78	64
700	95	82	67

Table 3. Image edge detection Accuracy Levels

Model Images	RECPE- WFVS	RSIR- FCN	CHR- RSI
100	76	56	42
200	85	62	44
300	88	70	50
400	92	75	55
500	96	78	58
600	98	80	62
700	99	82	63

Table 4. Image Pixel Extraction Accuracy Levels

Edge detection is a common image processing technique that detects the edges of image. Detection of brightness discontinuities locations is how it does it. Image analysis, and machine learning all use edge detection

to segment and extract data from images. The image edge detection helps in extracting accurate pixels in the range. Figure 9, depicts the image edge detection accuracy levels of the proposed and traditional approaches by measuring the edge detection accuracy level respective to percentage with number of images and models as show in Table 3.

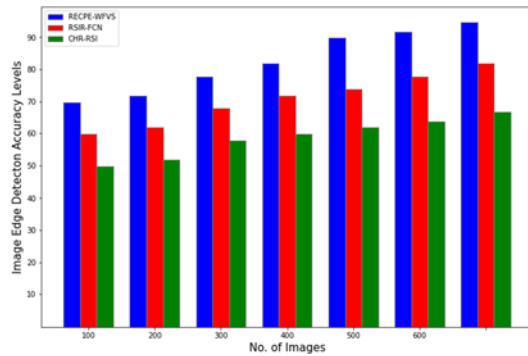


Fig. 9. Image Edge Detection Accuracy Levels

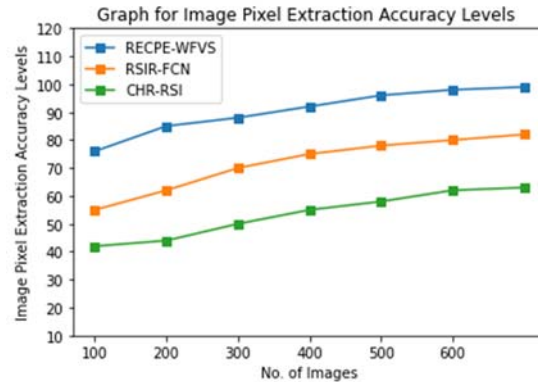


Fig. 10. Image Pixel Extraction Accuracy Levels

Pixel Extraction is a component of the dimensional reduction process in which raw data is separated and reduced into more understandable categories. As a result, it will be easier for users to utilize the data. The abundance of variables in these massive datasets is their most unique characteristic of pixels that contain useful information. The graph for image pixel extraction accuracy levels of the proposed and traditional models are shown in Figure 10, by using the accuracy level respective to number of images and models as show in Table4.

The proposed model extracts the pixels with the region of edges identified. The proposed model considers these features to identify accurate images from the dataset. The proposed model, in less time, extracts the pixels for consideration of an image. The graph for the pixel extraction from edges time levels of the traditional and proposed models is shown in Figure 11, by using the data shown in Table 5.

Model \ Images	CHR-RSI	RSIR-FCN	RECPE-WFVS
100	32	23	12
200	34	25	14
300	36	28	16
400	42	30	18
500	44	32	20
600	46	34	22
700	49	37	25

Table 5. Image pixel extraction from edges time levels

Model \ Images	RECPE-WFVS	RSIR-FCN	CHR-RSI
100	86	72	52
200	88	76	54
300	90	78	56
400	94	80	60
500	98	82	62
600	99	84	63
700	102	86	66

Table 6. Image Feature Extraction Accuracy Levels

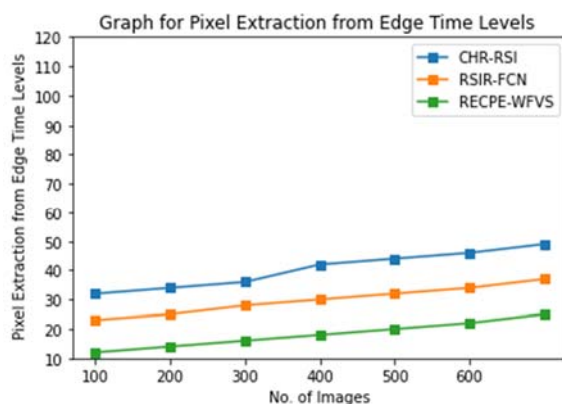


Fig. 11. Pixel Extraction from Edge Time Levels

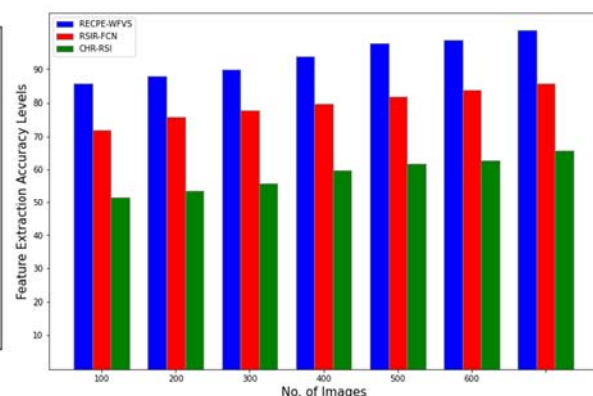


Fig. 12. Feature Extraction Accuracy Levels

Feature Extraction is translating raw data into numerical characteristics that may be handled while retaining the original data set's information. It's more effective than using raw data to train a machine learning model.

Figure 12 depicts the graph for feature extraction accuracy levels of the proposed model with the standard models with respective to data as shown in Table 6. The proposed model allocates weights to the extracted features.

The weight allocation process considers the features that are more relevant in image identification from a database. Figure 13 depicts the graph for feature weight allocation accuracy levels of the proposed and traditional models by using data shown in Table 7.

Model Images	RECPE- WFVS	RSIR- FCN	CHR- RSI
100	75	55	25
200	78	58	38
300	85	64	42
400	92	66	45
500	96	68	48
600	98	78	55
700	99	80	59

Table 7. Image Feature Weight Allocation Accuracy Levels

Model Images	CHR- RSI	RSIR- FCN	RECPE- WFVS
100	22	12	2
200	24	15	4
300	26	17	7
400	28	19	9
500	30	20	10
600	32	22	12
700	34	24	14

Table 8. Error Rate

Model	Feature Extraction Accuracy Levels	Weight Allocation Accuracy	Error Rate
RECPE-WFVS	97%	96%	12%
RSIR-FCN	84%	80%	24%
CHR-RSI	68%	55%	33%

Table 9. Parameters Evaluated

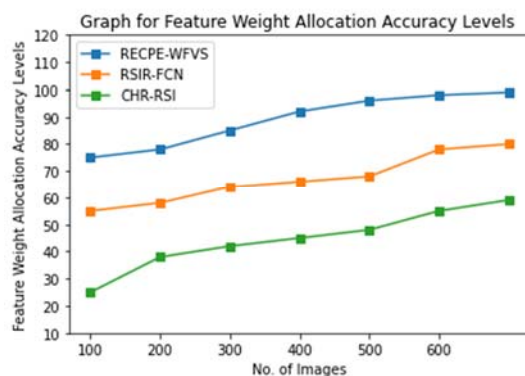


Fig. 13. Feature Weight Allocation Accuracy Levels

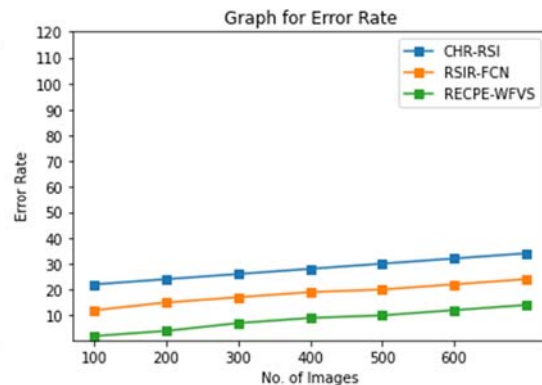


Fig. 14. Error Rate

The error rate represents the wrongly extracted pixels and features from an image. The error rate of the proposed model is less than the traditional methods. The error rate levels are shown in Figure 14, with respective to Table 8 and parameters evaluated and shown in Table 9.

5. Conclusion

CBIR is one of the most significant fields of study in image processing. There is a problem with finding digital photographs comparable throughout an extensive collection called the CBIR, or inquiry by image content. The suggested method uses colour photos as input. In the beginning, the median filter is utilized. The suggested method extracts information such as colour, texture, brightness distribution, and Euclidean distance from the images. The proposed mechanism for image segmentation for image retrieval can be applied by fine-tuning the picture intensity level of the feature parameter. Changing the estimation parameter for the feature extraction database improves results for the suggested approach. Color and gray level information is extracted from images as part of feature extraction. Standard equations, rather than more complex ones, are employed to speed up the calculation process and improve the correctness of the system. By utilizing the attributes of the image as input, the suggested model can find an exact match to the query photo via other image searches. Accuracy in weight allocation and feature extraction is 97% observed with the model proposed. In the future, the number of extracted features can be lowered to reduce the model's training time and the system's time complexity, and the feature vector model can be used for image retrieval from an extensive database.

6. Conflicts of Interest

The authors declare no conflict of interest.

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