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INTERLINKED FEATURE QUERY-BASED IMAGE RETRIEVAL MODEL FOR CONTENT-BASED IMAGE RETRIEVAL

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Abstract

Visual data retrieval and management have become significant research areas due to the rapid expansion of image data on the internet and the rise of multimedia technologies. Many professional organizations, such as journalists, engineers, agriculture, urban planning to meteorology and art historians, have a shared requirement to discover a particular image in an extensive collection. Researchers were inspired by their difficulties with text-based picture retrieval to create new ways to encode visual index input. Researchers are focused on Content-Based Image Retrieval (CBIR) to overcome these issues and improve the performance of image retrieval models. Using the optical characteristics of an image, such as colour, body, and texture, CBIR searches massive databases for user-requested photos with a query image. An image's visual features are extracted using CBIR's feature extraction method, which is done automatically, without human intervention. The extraction of crucial points in a picture is done using the feature extraction algorithm in this research. It is possible to think of a CBIR system's design as a group of modules that work together to get database images in response to a specific query. This research proposes an Interlinked Feature Query-based Image Retrieval Model (IFQ-IRM) for accurate image extraction from the image database. Image queries are transformed into feature vectors by the system. The extracted features of the query instance and the photos in the databases are then compared, and an indexing strategy is used to retrieve the images. The proposed model results show that image extraction accuracy is better than traditional models.

Keywords: Image Retrieval, Image Features, Query Image, Interlinked Features, Image Classification, Feature Comparisons, Content Based Image Retrieval (CBIR), Interlinked Feature Query-based Image Retrieval Model (IFQ-IRM)

1. Introduction

In today's world, digital image collections are available in nearly every field, from health to astronomy to remote sensing and education to multimedia [Brogan et al. (2021)]. As our daily lives become increasingly reliant on the use of vast digital image collections, the primary goal of an image retrieval system is to make it easier and faster to find relevant photos [Johnson et al. (2021)]. For the most part, images are searched for using keywords or visual content or high-level semantics [Cao et al. (2020)]. Because of the difficulty in keyword annotating images with rich content and the shortage of specific discriminatory language, this method has drawbacks, such as the inability to handle large quantities of digital images [Wang et al. (2020)]. A large and diversified digital image collection requires many labours for the annotation task. The interpretation of keywords varies from work to the next, resulting in incorrect labelling of images [Amelio et al. (2018)]. Another area that has drawn interest for over a decade is mapping low-level visual material to high-level semantics [Susan et al. (2019)]. It is difficult, however, to close the semantic gap between an image's low-level qualities and its high-level meaning because of semantic labels that don't adequately describe an image's visual properties [Dai et al. (2018)].

Annotating images in a database is necessary for text-based image retrieval systems. Content-based Image Retrieval (CBIR) [Tekeste et al. (2018)], a method that does not suffer from this shortcoming, is an alternative to traditional image retrieval methods. Users can utilize this method to find what they're looking for by selecting an appropriate query image [Chaudhuri et al. (2018)]. In this way, the database's contents can be gleaned from the query results. In the last decade, several CBIR techniques and CBIR implementations have been published in the literature. These CBIR systems use low-level feature descriptors to characterize the visual features of an image. The image's colour, texture, and shape may all be described using these descriptors [Boualleg et al. (2018)]. Images may be quantitatively compared using these low-level features, which convert the visual content of an image to numerical vectors [Ye et al. (2018)].

Many visual characteristics have been suggested in the literature. Generic and application-specific descriptors are both included. The semantic interest of the user and a visual feature descriptor extracted do not match up perfectly [Li et al. (2018)]. For example, if the CBIR system accepts an image of an apple that is red, it can return visuals that include a red rose, a red balloon, or a green apple. There have been recent developments in multiple query retrieval systems, which aim to address this shortcoming and connect low-level picture information to semantics [Roy et al. (2018)]. These systems rely on a set of query photos that the user submits. The user's high-level interest in the retrieval system is conveyed this way. Feature extraction from images can be done in one of two ways: locally or globally. Two picture features describe the overall image and represent individual objects or regions [Qin et al. (2019)]. Distinctive feature discrimination ability heavily depends on the type of features employed in the system, regardless of whether they are global or local [Huang et al. (2019)]. In contrast, local image features, which are more tolerant to light fluctuations, occlusions, distortion, and picture alterations, have received more attention.

Automated computation of an alphanumeric or numeric compact representation of the property in digital images is known as feature extraction for content-based image retrieval. Dimensionality reduction may be seen to be at work here. In addition to visual quality, an attribute can also be linked to an interpretative reaction [Xia et al. (2019)] to an image or an emotional, spatial, symbolic, or linguistic trait [Li et al. (2017)]. A feature might represent a single feature or combine several different qualities in one package [Xia et al. (2018)]. It is possible to classify features as either universal or domain specific. In contrast to the domain-specific features [Xia et al. (2016)], the general-purpose characteristics can be used for any situation. All components are linked to the type of data they can collect. The process of image retrieval based on a query image is shown in Figure 1.

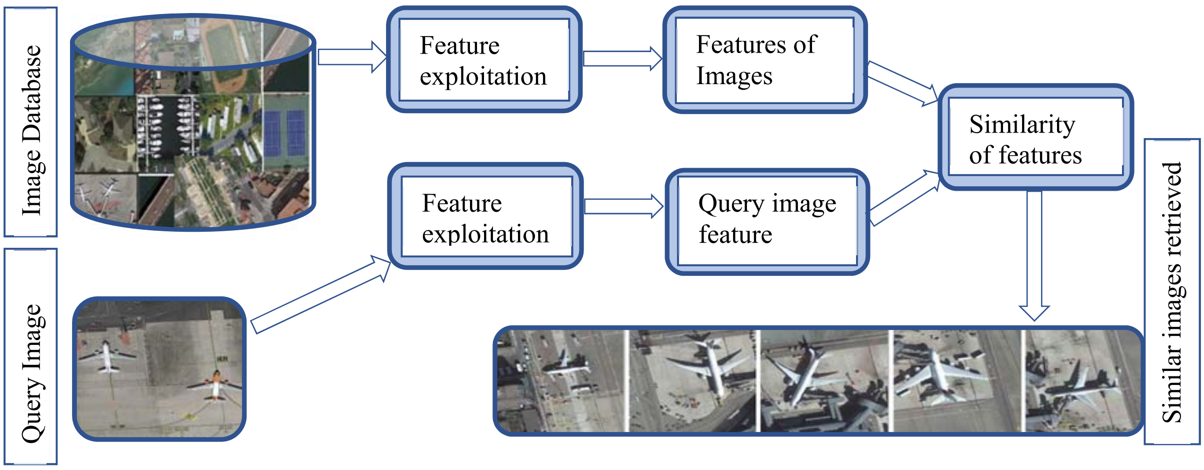

Fig. 1. Query-based Image Retrieval

Image retrieval systems must also include a representation of discriminative feature information. There must be a high computational cost to get more accurate findings to make the feature robust and distinctive representation fusion of low-level visual features [Johnson et al. (2021)]. However, an image retrieval model's performance might be adversely affected by the incorrect selection of features. By training and testing models, the image feature vectors have been used as a source for machine learning techniques to improve CBIR's performance [Xu et al. (2017)]. Supervised and unsupervised training-testing frameworks can implement machine learning algorithms [Xia et al. (2019)]. This research proposes an Interlinked Feature Query-based Image Retrieval Model for accurate image extraction from the image database. A feature database is formed by the feature vectors of images in the database. Query images or desired type of images are used to retrieve images from the retrieval system.

This research proposes an Interlinked Feature Query-based Image Retrieval Model for accurate image extraction from the image database. A feature database is formed by the feature vectors of photos in the database. Query images or drawn figures are used to retrieve images from the retrieval system. The remaining sections of the paper are as follows, and section 2 discusses the literature survey of existing models. Section 3 discusses the feature extraction, selection and feature linking model for an accurate query-based image retrieval model, section 4 discusses the proposed model's results, and section 5 concludes the research.

2. Literature Review

According to Cao et al. [Cao et al. (2020)], obtaining photos using their labels and annotations is impossible. A new way of obtaining images was developed, relying on the image's content. Two stages of clustering are utilized to build a short picture descriptor that can be altered. According to Wang et al. [Wang et al. (2020)], a technique for retrieving photos based on their content is developed by merging the colour and texture properties of the photographs. This approach allows for a precise and adaptable assessment of how early people saw visual content. A rich feature set that considers colour and texture has been developed to help retrieve colour images.

In comparison to previous systems, this one retrieve photos with more precision. This method requires less processing time than other methods, but the feature dimensions are more diminutive. A similarity measure of both low-level characteristics is needed to compute the similarity metric, which may become a bottleneck.

Numerous studies have been conducted on the completeness of invariant descriptors.A picture can be represented using orthogonal basis moment functions, Zernike and pseudo-Zernike polynomials, and other mutually independent descriptors. In terms of visual noise resistance, PZMs exceeded Zernike moments. Dai et al. [Dai et al. (2018)] have developed new pseudo-Zernike moment invariants. The initial step in the procedure is to establish a connection between the pseudo-Zernike moments in the original image and images with the same form but different orientations and scales. A list of all potential scale and rotational invariants can be derived from this relationship. In terms of pattern recognition, this innovative technique exceeded the competition of feature extraction.

Tekeste et al. [Tekeste et al. (2018)] suggested a novel method based on error diffusion for indexing images. Two colour quantizers and a bitmap image with vector quantization are used in the proposed model to construct the image feature descriptor (VQ). As a result of these two new capabilities, users can now assess whether or not an image in the query matches in the database with more accuracy. Using a VQ-indexed colour quantizer, CHF and BHF are calculated. To determine how comparable the two photographs are, one might compare their distances from CHF and BHF. Experiments have shown that the proposed method outperforms current methods for retrieving images. The capacity of the proposed model for CBIR image compression and indexing is exceptional. An algorithm known as SIFT, which can withstand scaling and rotation, is used in image categorization and retrieval systems. Discrimination capabilities have led to various SIFT variants being created by researchers. Boualleg et al. [Boualleg, et al. (2018)] explained how to combine SIFT and PCA to minimize the number of dimensions in the SIFT-generated feature vector. In contrast to the SIFT, the SURF is illumination-invariant, faster, and more resistant to transformations than the latter. The Hessian blob detector is used for key-point detection. SURF and SIFT were then combined by Xiao et al. [Xiao et al. (2020)] to boost retrieval rates even further. LBP describes the area surrounding SIFT key points, blended using a rotation-invariant local binary pattern (LBP).

R. S. Shankar et al. [Shankar et al. (2022)] developed models to detect objects to enhance the performance using the YOLO algorithm, and image denoising was implemented using SGO and APSO [Gupta et al. (2021)]. Image Colorization [Murthy et al. (2020)], sharpening blur images [Mahesh et al. (2020)] and recognition of flower species [Shivashankar et al.(2021)] were implemented by using Deep Learning models. Facial expressions were identified by using Bezier curves [Babu et al. (2017)], and the noise was removed on PGM images by using a Fuzzy filter [Shivashankar et al. (2012)] and query processing for determining the sequences in Video [Krishna et al. (2021)]. By using a genetic algorithm, they retrieved an image [Sravani et al. (2017)], and a mechanism was implemented to retrieve information by using XML [Rajanikanth et al. (2016)] and captured images using Stroke width properties [Srinivas et al. (2021)]. Li et al. [Li et al. (2018)] have recently combined SIFT and center-symmetric LBP, using only the intensity of centre-symmetric pixels. To characterize the structural construction of local level structure by embracing all four directions for the centre pixel, CS-LTP and LTP have been developed. A binary wavelet pattern is employed for indexing and retrieval of biological images. According to Qin et al. [Qin et al. (2014)], good feature representations and similarity measurements are critical to the retrieval performance of a CBIR framework. Despite the years of work in this area, it is still a significant obstacle to developing real-world CBIR frameworks. It is necessary to bridge the gap between low-level image pixels obtained by computers and higher-level semantic conceptions observed by people.

Long-term solutions have grown increasingly popular with machine intelligence. An open question remains regarding closing the semantic gap in CBIR and determining how much better CBIR tasks can be achieved using state-of-the-art deep learning techniques for learning visual features and similarity measures. A framework for deep learning with application to CBIR tasks by exploring the most recent deep learning method CNN for CBIR tasks under various set-chime changes is analysed by Xia et al. [Xia et al. (2017)]. Xia et al. [Xia et al. (2019)] used CBIR to locate similar images to a given query image by comparing the content of the photos. Image content is a mathematical explanation of a digital image's aesthetic features. Most of the time, picture retrieval relies on feature extraction and feature vector similarity comparison. Aside from that, how well the CBIR approach performs is based on how well the image compares with each other. Due to the wide variety of shade, surface, and form variances, using a single distance metric may not work effectively for all the features in an image. Cheng et al. [Cheng et al. (2017)] proposed an image retrieval model based on fused deep convolutional features and low-level characteristics like high semantic features in the standard fight-based retrieval technique. A convolutional neural network, LeNet-5, is first enhanced and then used to build a better network design. Two deep convolutional features are extracted using LeNet-5 and AlexNet and then merged. Finally, a similar image can be generated by comparing the similarity between the image being recovered and the image stored in the database using distance work. According to the results, this method improves the accuracy of retrieval.

Srikrishna et al. [Srikrishna et al. (2022)] exhaustively reviewed recent CBIR developments and image representation developments. Various image retrieval and picture representation models have been studied, beginning with basic feature extraction and progressing to the most cutting-edge semantic deep learning techniques. A complete assessment of major CBIR and image representation concepts is undertaken, with suggestions for further research in the field.

Many research papers have studied image retrieval algorithms, as shown in the following literature section. Since images with identical low-level qualities can differ from the query image in terms of semantic positions as seen by users, this system's fundamental flaw is this. The existing model's image retrieval rate results are unsatisfactory, resulting in inappropriate image sets that reduce the performance levels. The feature dimensions are high, increasing the training time and computational load on the system. However, despite years of effort in this field, computation time remains a crucial barrier to developing real-world CBIR frameworks. It is required to bridge the gap between low-level picture pixels produced by computers and higher-level semantic concepts perceived by humans.

3. Methodology

The fields of database administration and computer vision have been actively researching image retrieval since the 1970s. There are two main areas of study: text-predicated and visual-predicated [Cheng et al. (2016)]. As text-predicated database management systems (DBMS) have been more widespread since the 1970s, retrieving images annotated with keywords has become more common. Semantic keywords are attached to images in a text-predicated image retrieval system [Zhang et al. (2016)]. They can be manually entered or extracted from the image captions. With only a few hundred keywords to describe the entire database, it is ideal for small and straightforward picture databases [Ferreira et al. (2019)].

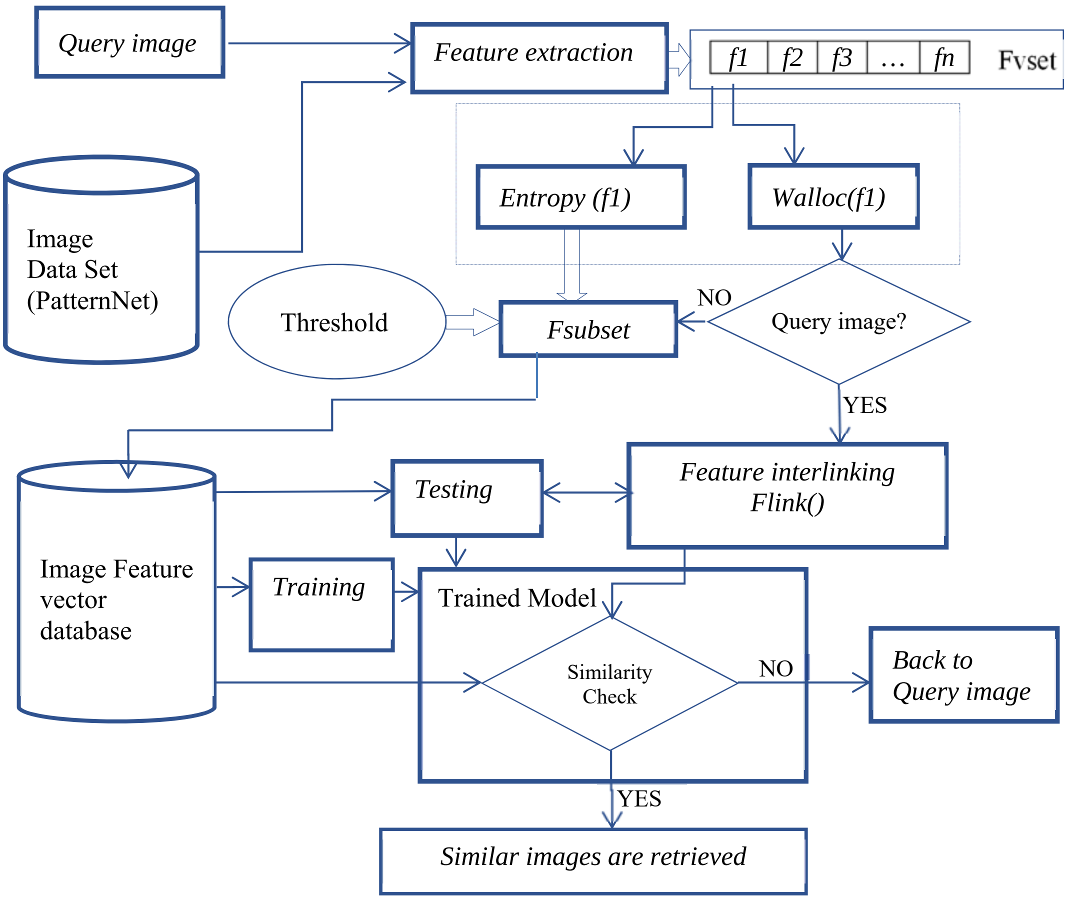

Fig. 2. Proposed Model Framework

Image databases grew considerably in size in the 1990s, with massive advances in processors, memory, and storage. Semantic keywords cannot adequately describe photographs with great content as the image database grows in size and the number of images is added. Additionally, there is a significant increase in the need for workers to annotate photos [Cheng et al. (2017)]. An efficient and effective tool for querying an astronomically extensive database of images is strongly required. Sophisticated digital picture databases are now possible due to recent technological advancements in various sectors. As a result, the importance of a well-structured database and effective data retrieval methods cannot be overstated. Picture retrieval algorithms were created. As a result of the burgeoning field of Information Retrieval in the 1940s, the concept of Image Retrieval emerged [Singh et al. (2013)]. Precise and quick access is becoming increasingly challenging when dealing with massive data. The proposed model working process is shown in Figure 2.

In the proposed research, the images from the image dataset are initially considered, image processing techniques are applied to the idea, and all the features are extracted using an edge clustered segmentation model [Devareddi et al. (2022)]. Weight allocation is done on the highly correlated features. The weighted features train the model to retrieve the images based on a query image. The user considers the query image to extract the relevant images based on the feature similarity. The weight allocation is also done for the query image, and the feature interlinking is performed. The query image and the single image extracted from the database similarity check are portrayed. The image will be stored in the final display set if a similarity is found. The process will be performed by considering the query image features with all the images in the image database and displaying the final relevant images.

A reference picture and a modification text presented as a phrase for the composed query job make up the image query. Users need a way to merge the content from these two separate sources into one cohesive model. All the query text's feature vectors are integrated with the picture feature vectors using the proposed method. To complete a built query image retrieval task, an intuitive understanding of the language and visual content of the image is necessary. These two approaches will be brought together using a cross-modal attention module. The proposed model considers the features extracted from the image after applying segmentation to the images. The weights are allocated to the features for accurate image retrieval. This research proposes an Interlinked Feature Query-based Image Retrieval Model (IFQ-IRM) for proper image extraction from the image database. The process of query-based image retrieval is clearly explained in the algorithm.

3.1. *PROPOSED ALGORITHM*

Algorithm 1: IFQ-IRM

Input: Feature Vector Set (Dataset) and Query Image.

Output: Obtain the Corresponding images.

Step 1: Collect Feature Vector set data [Zhou et al. (2018)].

Step 2: Extract the feature set data from Step 1.

Step 3: Allocate Weights for Each Feature in the Vector.

Step 4:
A. Remove irrelevant Features from Feature Vector using an Entropy-based Mechanism.
B. Generate Feature Subset by using entropy.
C. Allocate Weights for the Step 4 B.

Step 5:
A. Now, Feature Interlink is performed on the feature in the subset.
B. In Step 5 A, dlink Value is Calculated as an intermediate link.
C. Flink is used to reduce the time by providing a sequence of feature vectors.
D. Compute Flink for each Segment.

Step 6: Perform Similarity check for feature subsets.
Query image and images in the database

Step 7: Calculate the Error Rate.

Step 8: Finally, images are retrieved concerning Query Image.

3.2. *ALGORITHM EXPLANATION*

From Step1 Perform Feature Extraction from the query image to extract the relevant features [Zhou et al. (2018)] and these features are used for checking the similarity levels and retrieve images. The feature extraction of query image is performed as Eq. (1).

$$pset[N(i)] = \frac{\sum_{i=1}^{N} \max(Pixelrange(i,i+1)+\lambda+\max(Img\_Filter(i,i+1))}{sizeof(img)} \quad (1)$$

$$\text{Fvset}(i\ ,j,I) = pset[i]^{\delta}(i\ ,j) + \sum_{i=1}^{N} \sum_{j=1}^{i} min\ (Img\_Filter(i,j)) + \frac{Th}{sizeof(img)} + \sum_{i=1}^{M} minrange(seg\big(Img(i,i+1)\big)_N) \quad (2)$$

Here λ is the maximum intensity of a feature, *i* is the index value in the feature vector, N is the feature vector length, *Th* is the threshold value considered as 190 and the image size is calculated using the sizeof() function, max() function considers the maximum pixel range from positions I and i+1, Img_Filter model is applied on the neighboring pixels for noise removal. Here feature vector is calculated as shown above Eq. (2).

In Step 2, Load an image from the image dataset and then extract the features using step-1 and then the weights are allocated for each feature in the query image. The weight allocation is performed as Eq. (3).

$$Walloc\big(Fvset(i)\big) = \sqrt{\frac{\sum_{i=1}^{M} \max(Fvset(i,i+1)}{2}} + \sum_{u=0}^{M-1} \lambda(Fvset(i))) - pset(i) + cos\left(\lambda \frac{Th(2Fvset(i+1))}{sizeof(img)}\right) \quad (3)$$

Here Fvset considers a feature *i* and next feature *i+1* and cos function is applied on the image for extracting pixels in a specific range. Cosine value is calculated by considering the cos() that is used for weight allocation. *M* is the total pixel length in this segment and *u* is the feature location.

By the Step 3, The feature subset is generated based on the allocated weights in which most relevant features are considered in the process of image retrieval. In step 4 A, the feature subset is generated based on entropy-based feature vector as Eq. (4).

$$Entropy\big(Fvset(i)\big) = \sum_{i=1}^{M} max(Fvset(i,i+1))/log_2 min(Fvset(i,i+1)) \quad (4)$$

Here, Walloc is the set of weights considered and max weight feature is considered first for training the model. Entropy () model calculates the range of entropy on the associated pixels.

In step 4 B and C are used to generate feature subset along with allocated weights. Feature subset is calculated as Eq. (5).

$$Fsubset(Fvset(i)) = \sum_{i=1}^{M} \sum_{j=1}^{i} Walloc\big(\max(Fvset(i,j)\big) + Entropy(i,j) - \min\big(Fvset(i,j)\big) - (\sum_{i=1}^{M} Min\ Range(\ img(i,j)) - Th) \quad (5)$$

In Step 5 A, The feature interlinking is performed on the features in the subset. The feature interlinking helps in accurate detection of object recognition in images for relevant image retrieval. From Step 5 B, dlink is performed as Eq. (6).

$$dlink(Fsubset(i))_M = \left[\frac{Th+\lambda}{M\times N} \sum_{i=1}^{M} \sum_{j=1}^{N} Fsubset(i,j)^2 - min(\ Entropy(Fvset(i)), Entropy(Fvset(i+1)))\right]^{\frac{\lambda}{2}} \quad (6)$$

In Step 5 C and Step 5 D, Flink is calculated for each segment as Eq. (7).

$$Flink(Fsubset(i)) = dlink(i) + \bigcup_{i=1}^{M} \bigcup_{j=1}^{N} \quad max(\ Fsubset(i,i+1)) + max(\ Fsubset(j,j+1)) \quad (7)$$

In Step 6, The extracted features from the query image and the extracted features from the image database will undergo similarity check. Based on the similarity difference, the relevant images which similarity is same is retrieved as a set. The similarity check is performed as Eq. (10). Similarity value for database image is computed as Eq. (8) and for query image as Eq. (9).

$$isim(Fsubset(i), Fsubset(i+1)) = \sqrt{min(\,Flink(i,i+1) + \frac{\lambda}{2}} \tag{8}$$

$$qsim(Fsubset(i) = \sqrt{\sum_{i=1}^{min\{M,N\}} \lambda_i^2 (max(\,Flink(i.i+1)) \in isim(Fsubset(i))} \tag{9}$$

For each i in range(Fsubset(N))
do
    If(isim(Fsubset(i)!=qsim(Fsubset(i))
    Continue
Else
    Img[i]=img(Fvset(i)
Done (10)

From Step 7, The error rate of the proposed model is calculated to identify whether any irrelevant images are extracted. The error rate is calculated as Eq. (11).

$$Errorrate = \frac{1}{sizeof(qsim)} \sum_{i=1}^{M} \big(Walloc(pset(Im\,g\,(i))_{i,j} + min(\,Fvset(i))^2 - min(\,Fsubset(i,i+1))\big) - Th \tag{11}$$

Finally in Step 8, the respective images are displayed according to the Query images.

This proposed algorithm would be used to retrieve the accurate images within less time with the help of interlinking the features of query image with the data base images with weight mechanism.

4. Results

The main goal of the proposed system is to generate an accurate result with little processing time. The proposed model is developed in Python and runs on Google Colab. The image PatternNet dataset [Zhou et al. (2018)] was used for this model run. In the context of content-based image search, it is equivalent to comparing image candidates to a given query. Image similarity measures have two essential aspects: picture characteristics and metrics.

Images include information that can be retrieved using image characteristics. There are many features, such as the quantized components of the discrete cosine transform. Images can be recognized with the use of these attributes. Image recognition may be used to identify a specific characteristic in an application. Features can be used in various ways to represent images, depending on the context in which they are used. Like most vision-related tasks, deep learning models have taken over CBIR in the previous decade. Many studies aimed at optimizing neural networks for CBIR train and test their models on specific datasets. For now, a general-purpose image feature extractor can't be made from such networks.

Using a query image, users can identify other photos that are similar in a vast database. This is a crucial challenge in computer vision. The techniques used to measure the similarity between an image query and picture candidates are known as similarity metrics. The proposed Interlinked Feature Query-based Image Retrieval Model (IFQ-IRM) is compared with the traditional Fast Local Spatial Verification for Feature-Agnostic Large-Scale Image Retrieval (FLSV-FALS-IR) Model [Brogan et al. (2021)].

Extraction of features is a phase in the process of dimensional reduction, which splits and lowers a huge set of raw data into smaller groups. Consequently, processing will be simplified. The features from the input image are extracted, and the extraction accuracy levels are represented as graph in Figure 3 and Table 1.

Model / No. of images	IFQ-IRM Model	FLSV-FALS-IR Model
100	47	10
200	67	20
300	80	40
400	87	50
500	97	60

Table 1. Image Feature Extraction Accuracy Range

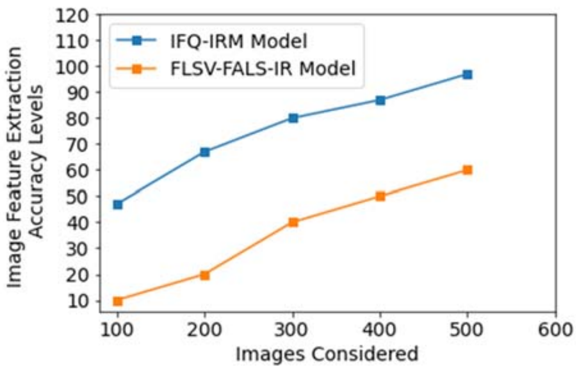

Fig. 3. Image Feature Extraction Accuracy Levels

Feature subsets will be generated from the features extracted from the image. Feature Subset selection assesses the suitability of a group of components. Wrappers, filters, and embedding techniques are the three types of subset selection algorithms. Wrappers explore the range of possible features using a search algorithm and assess each subset by executing a model on it. The feature subset generation time levels of the existing and proposed models are shown as graph in Figure 4, and Table 2.

Model / No.of images	IFQ-IRM Model (Milliseconds)	FLSV- FALS-IR Model (Milliseconds)
100	2	10
200	4	15
300	9	21
400	11	22
500	15	25

Table 2. Feature Subset Generation Time in Milliseconds

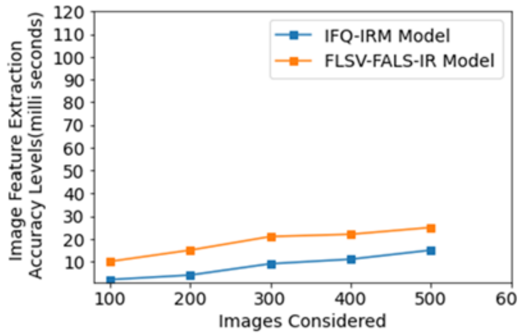

Fig. 4. Feature Subset Generation Time Levels

Feature subset selection is the process of identifying and removing as much redundant and superfluous data as possible. As a result, the dimensionality of the data is reduced, making the work of the classification algorithm easier and faster. Figure 5 and Table 3 represent the feature subset generation accuracy levels of the existing and proposed models.

Model / No.of images	IFQ-IRM Model	FLSV-FALS-IR Model
100	45	10
200	66	25
300	76	22
400	86	35
500	96	42

Table 3: Feature Subset Generation Accuracy Range

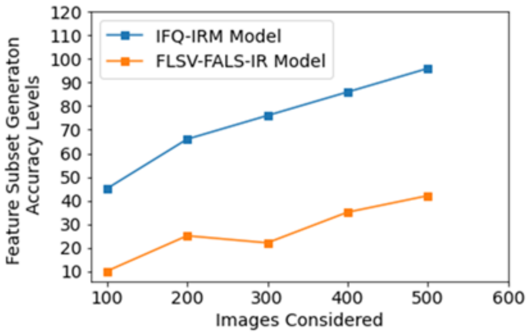

Fig. 5. Feature Subset Generation Accuracy Levels

Content-based image retrieval, also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR), is the application of image processing techniques to the image retrieval issue, the challenge of searching for digital pictures in large databases. The query image is considered, and its features are extracted to find similar images in the image database. The query image feature subset generation accuracy levels are shown as graph in Figure 6 and Table 4.

Model / No.of images	IFQ-IRM Model	FLSV-FALS-IR Model
100	63	22
200	72	32
300	75	42
400	90	52
500	97	67

Table 4. Query Image Feature Subset Generation Accuracy Range

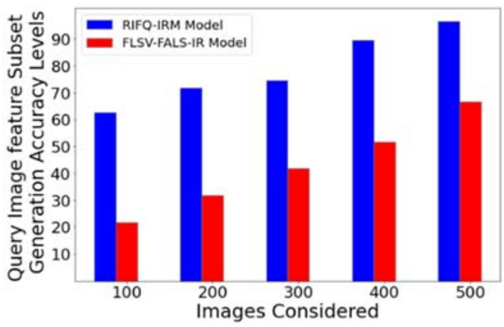

Fig. 6. Query Image Feature Subset Generation Accuracy Levels

The extracted features are interlinked together in the feature subset to identify similar kind of images in the large image databases. The feature interlining accuracy levels of the existing along with the proposed models are represented as graph in Figure 7 and Table 5.

Model / No.of images	IFQ-IRM Model	FLSV-FALS-IR Model
100	62	34
200	71	38
300	78	42
400	89	48
500	96	52

Table 5. Feature Interlinking Accuracy Range

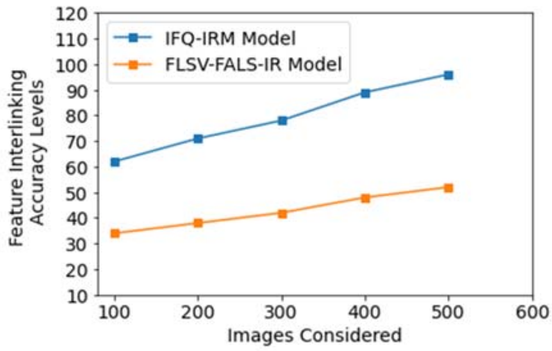

Fig. 7. Feature Interlinking Accuracy Levels (Milliseconds)

The feature weighting technique was utilized in this study to assess the relative importance of each feature and provide it with a correlating weight. A significant trait would be given a higher weight than the less critical or unnecessary features if appropriately weighted. The feature weight allocation accuracy levels of the proposed and existing model's accuracy levels are represented as graph in Figure 8 and Table 6.

Model / No.of images	IFQ-IRM Model	FLSV-FALS-IR Model
100	57	10
200	67	25
300	77	45
400	87	55
500	96	72

Table 6. Feature Weight Allocation Accuracy Range

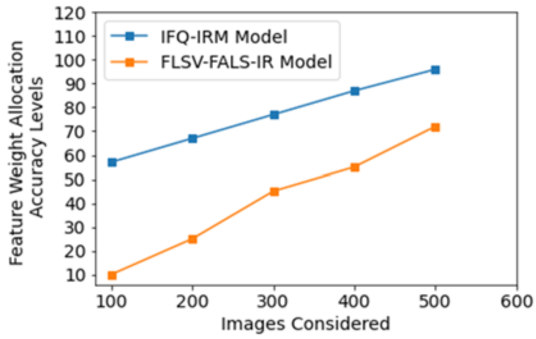

Fig. 8. Feature Weight Allocation Accuracy Levels

An image retrieval system is a computer program that explores, searches, and extracts pictures from a large library of image data. Most traditional and prevalent image retrieval techniques include adding metadata to the images, such as labelling, keywords, titles, or descriptions, so that a search can be conducted over the annotating words. Manual picture annotation is time-consuming, labour-intensive, and costly; numerous studies have been conducted on automated picture annotation.. The image retrieval accuracy levels are shown in Table 7 and as in graph Figure 9.

Model / No.of images	IFQ-IRM Model	FLSV- FALS-IR Model
100	52	5
200	62	12
300	72	22
400	82	35
500	97	50

Table 7. Image Retrieval Accuracy Range

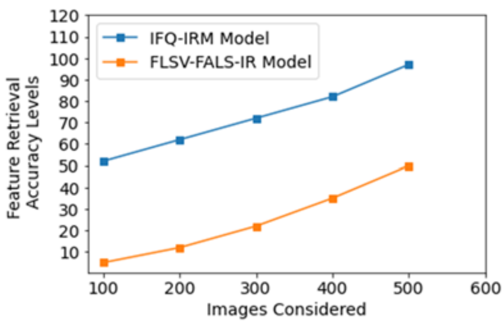

Fig. 9. Image Retrieval Accuracy Levels

5. Conclusion

Despite the development of sophisticated low-level visual descriptors, it is challenging to grasp an image's semantics. It is much more challenging to convey a user's interest in a single image. Query images can help bridge a discrepancy between how a picture is seen and how it is described. Multi-query Image Retrieval systems that combine information from numerous query images must be practical and efficient to increase retrieval performance. This research proposes an Interlinked Feature Query based Image Retrieval Model for accurate image extraction from the image database. Allocation of weights to the most crucial feature entries is performed for accurate retrieval. Weights are calculated by applying an objective function. An image retrieval approach proposed in this research can be used to retrieve images from the datasets. The proposed model has an accuracy of 97.5 percent when it comes to retrieving images based on the query image. The deep feature model and ranking methodology will be improved, and the proposed method will be tested on larger datasets.

Conflicts of Interest

"The Authors have No Conflicts of Interest to Declare"

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