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Design and Implementation of a Content Based Image Retrieval System

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Dedication

I write this dedication with tears, in which i thank everyone who stood with me and supported me in my academic journey. I dedicate this fruit of my effort to the dearest and dearest person in my life, who illuminated my path with her advice and was a clear sea flowing with a flood of love, to the person who adorned my life with the light of the full moon and candles of joy to the one who gave me strength and determination to continue on my path and was the reason for continuing my studies for the one who taught me patience and diligence on the heart My dear mother. And to the RIHANI family and BELLIL family, my brothers, sisters, friends, and colleagues, and to my soul, my father, and I (Khaled) won't forget my teacher RHMANI Chikh
and i (Youcef) to my father BELLIL MOHAMED and my uncle KADI MEDJDOUB who were keen on my success more than myself

Abstract

The primary objective of this thesis is to examine the primary methods used in the field of content-based image retrieval (CBIR) and to develop an application that utilizes this knowledge. Our particular interest lies in color and texture features. To create the application, we chose color histograms for color features and co-occurrene matrix for texture features. Here, features are extracted from specific QI(Query Image). Accordingly, an innovative similarity evaluation with a metaheuristic algorithm has been attained between the QI features and those belonging to the database images. For an image entered as QI from a database, the distance metrics are used to search the related images ,The proposed CBIR techniques are described and constructed based on RGB space and histogram for color features , and gray-level co-occurrence matrix to extract texture features. Furthermore, the results' precision–recall value is calculated to evaluate the system's efficiency.

Abbreviation List

CMY (cyan-magenta-yellow)
HSL hue, saturation, and lightness
CIE Commission Internationale de l'Elcairage
LAB 'L'is the lightness, whereas'A'(green/magenta) and 'B'(blue/yellow)
DWT Discrete Wavelet Transform
LBP Local Binary Pattern
LBPV LBP variance
LIOP Local Intensity Order Pattern
CNN convolutional neural network

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GENERAL INTRODUCTION

General Introduction :

The field of image search has evolved over time according to the needs of the user and advance technologies have greatly influenced this development. Pictures are everywhere. Around us, on television, in the press, on the Internet, This world of images, which we all live in every day, has its own codes and references, and image processing is at the intersection of many scientific and technical fields. Extract information that is ubiquitous today, but must be systematically processed to overcome poor acquisition conditions, in order to isolate and analyze the relevant elements. Pictures can convey a huge amount of information that can be difficult to put into words. By searching for images based on their content, users can discover similar or visually related images that they might not have come across otherwise.

Traditional text-based search engines may struggle to index and retrieve visual content effectively. By using image search by content, users can find specific images or objects within images, even if they lack proper metadata or text descriptions.

Search by content is a powerful tool that allows users to find and discover visual information based on the content and context of the image rather than relying on text queries. This process, called Content-Based Image Retrieval, (CBIR) involves using computer vision algorithms and techniques to analyze visual attributes and patterns like color,texture,shape... etc to index and represent them in a form of numerical vectors using tools such as histogram,co-occurrence matrix ,gabor filters...etc and then match them within an image With a database of indexed images. most of the times it uses similarity metrics and distances such as Manhattan Distance, Euclidean ,cosine...etc

Overall, image search by content expands the possibilities of visual exploration, information retrieval, Its importance lies in its ability to bridge the gap between the visual and textual worlds, opening up new avenues for discovery and interaction with visual content

The main objective of this memory is to study the principle of image retrieval by the content and is to use the knowledge drawn from this study and build a prototype of a content-based image search system In our case, we are interested in color and texture attributes . They are considered among the most used low-level attributes for image retrieval in image databases and they have been used in several content search systems. The second objective is to add a web interface to this system using flask framework

Thesis Organization

We have organized this memory as follows: After this introduction This thesis is structured in five chapters. The first chapter deals with a generality of image processing. This chapter describes the definition of an image, their characteristics, the principle of the image processing system, filtering, segmentation and some concrete operations in image processing.

The second chapter concerns the definition of the domain, it is about the search for images by the contents. This chapter explains how search systems work. of images by content,their components, and metrics to evaluate a system of image search by content.

The third chapter describes image descriptors such as than color, texture and shape, this chapter also represents an overview of the similarity measures between the images of the database.

The fourth chapter presents the different stages of our work.

The fifth chapter shows what we've reached in our study and the different experiments that we did in order to obtain a good accuracy

In conclusion, we present the important points of this work and some perspectives that derive from this study.

Chapter 1

General Information on Image Processing

1.1 Introduction

Image processing is a multidisciplinary field that involves the manipulation and analysis of digital images using computer algorithms. It is a branch of computer vision and has applications in various domains such as medicine, robotics, entertainment, and surveillance. Image processing techniques enable us to enhance, interpret, and extract meaningful information from digital images.

In this chapter we present some basic notions of the field of digital image processing such as: image definition, image types, image formats, image characteristics, image processing system, analysis elementary, filtering, segmentation and finally some concrete examples of image processing.

1.2 Image Definition

An image is a visual representation or depiction of something, typically captured or created using various mediums such as photography, painting, or digital graphics. It is a two-dimensional representation of objects, people, scenes, or concepts, formed by capturing or generating visual information.

It can be described as a continuous analog function I(x, y), defined in a bounded domain, such that x and y are the spatial coordinates of a point in the image and I is a function of light and color intensity. Under this aspect, the image is unusable by the machine, which requires its digitization

1.3 Numeric Image (Digital)

A numeric image, also known as a digital image, is a representation of visual data in a discrete numerical form. It is composed of a grid of pixels, where each pixel corresponds to a specific location in the image and stores a numerical value that represents the color or intensity at that location according to the level we choose either grayscale or RGB .

1.4 Image Types:

Digital images can be classified according to two criteria :

1.4.1 Bitmap Images

Bitmap images, also known as raster images, are a type of digital image that is composed of a grid of individual pixels. Each pixel in a bitmap image contains information about its color or grayscale value. Bitmap images are commonly used to represent photographs, complex graphics, and detailed illustrations.

1.4.2 Vector Images

Vector pictures, also known as vector graphics, are digital images that are created using mathematical equations instead of pixels. They are composed of lines, curves, and shapes defined by mathematical formulas, allowing them to be resized and scaled without losing quality or becoming pixelated.

1.4.3 Difference Between Them

Unlike raster images, which are made up of a grid of pixels, vector images are resolution-independent. This means that no matter how much you zoom in or out, the lines and shapes in a vector image remain smooth and sharp. This scalability makes vector graphics ideal for logos, icons, illustrations, and any design that needs to be resized frequently.

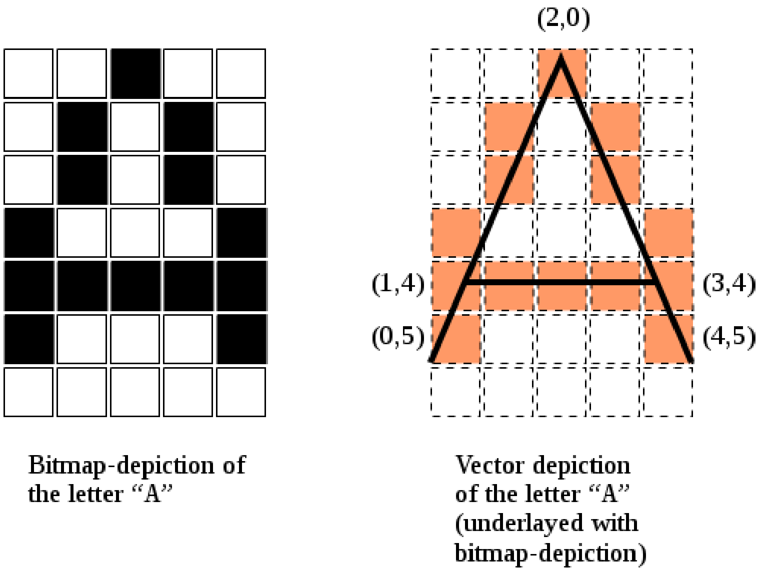

Figure 1.1: difference between
[6]

1.5 Image Formats

An image format is a computer representation of the image, together with information about how the image is encoded and possibly providing hints on how to decode and manipulate it.
Most formats consist of a header containing attributes (image dimensions, encoding type, LUT, etc.), followed by data (the image itself).

The structuring of attributes and data differs for each image format. In the Table we present the most known and most used image formats

	Type (matriciel/ vectoriel)	Compression des données	Nombre de couleurs supportées	Affichage progressif	Animation	Transparence
JPEG	matriciel	Oui, réglable (avec perte)	16 millions	Oui	Non	Non
JPEG2000	matriciel	Oui, avec ou sans perte	32 millions	Oui	Oui	Oui
GIF	matriciel	Oui, Sans perte	256 maxi (palette)	Oui	Oui	Oui
PNG	matriciel	Oui, sans perte	Palettisé (256 couleurs ou moins) ou 16 millions	Oui	Non	Oui (couche Alpha)
TIFF	matriciel	Compression ou pas avec ou sans pertes	de monochrome à 16 millions	Non	Non	Oui (couche Alpha)
SVG	vectoriel	compression possible	16 millions	ne s'applique pas	Oui	Oui (par nature)

Figure 1.2: Different image formats.
[1]

1.6 Main Characteristics of a Digital Image:

There are several characteristics that describe the content of an image, among these characteristics we find:

1.6.1 The Pixel

The pixel, being the tiniest unit of an image, possesses a measurable form and magnitude. While the bit serves as the smallest unit of computable information, the pixel assumes the role of the most minute component within display or printing technology, both in terms of hardware and software capabilities. [10]

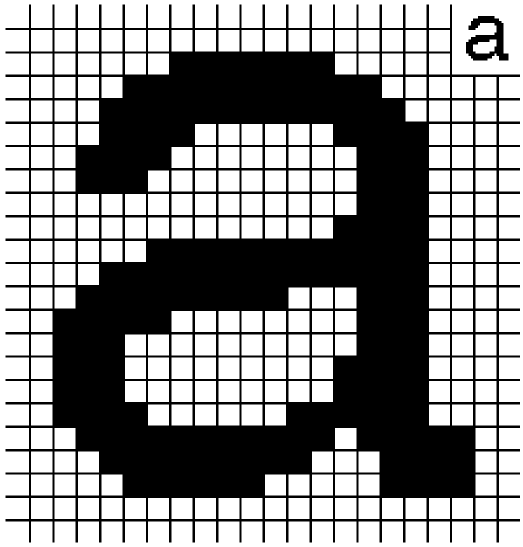

Figure 1.3: representation of "A" by a group of pixels

1.6.2 The Dimension

The dimension of an image corresponds to the matrix structure, with each element in the matrix denoting a numerical value representing the light intensity of a pixel. The total number of pixels in an image is obtained by multiplying the number of rows by the number of columns in this matrix.

1.6.3 The Resolution

Resolution refers to the level of clarity or level of fine detail that a monitor or printer can achieve when rendering images. For computer monitors, resolution is typically measured in terms of the number of pixels per unit of measurement, such as inches or centimeters. Additionally, we use the term resolution to describe the total number of pixels that can be displayed horizontally or vertically on a monitor. A higher number indicates a better resolution

1.6.4 The Noise

Noise in an image refers to unwanted random variations or disturbances that affect the quality and clarity of the visual information. It appears as random pixels or patterns that deviate from the intended image content. It can manifest as graininess, speckles, or pixelation, and can degrade the overall sharpness and detail of an image. Image denoising techniques are commonly employed to reduce or eliminate unwanted noise and enhance the visual quality of the image.

1.6.5 Contours and Textures

Contours are visual representations of the borders between objects in an image or between pixels with noticeable variations in grayscale. Textures, on the other hand, depict the arrangement and pattern of these objects. The process of contour extraction involves identifying specific points within the image that act as dividers between distinct textures.

1.6.6 Histogram

An image histogram is a graphical representation of the distribution of pixel intensities in an image. It provides a visual summary of the tonal range and helps to understand the contrast, brightness, and overall distribution of pixel values in an image.

The horizontal axis of the histogram represents the range of pixel intensity values, usually from 0 to 255 in an 8-bit grayscale image or in each color channel of a color image. The vertical axis represents the frequency or the number of pixels that have a particular intensity value within that range.

1.6.7 Luminance

Luminance refers to the brightness level of the points within an image. It can be understood as the ratio between the luminous intensity of a surface and its apparent area as perceived by a distant observer. In this context, luminance is used interchangeably with the term brilliance, which relates to the brightness of an object. Desirable luminance is characterized by the following factors:

- Bright and vivid images.
- Optimal contrast, avoiding extremes of pure white or black, as they can cause loss of detail in dark or bright areas.
- Absence of unwanted artifacts or disturbances.

1.6.8 The contrast

Image contrast refers to the difference in brightness and color between different parts of an image. It determines the visual distinction between the light and dark areas in a picture, influencing its overall clarity and visibility. A high-contrast image has distinct, well-defined edges and a broad range of tonal values, while a low-contrast image appears more washed out or flat.
if L1 and L2 are the degrees of brightness respectively of two neighboring areas B1 and B2 of an image, the contrast C

$$C = \frac{L_2 - L_1}{L_1 + L_2} \tag{1.1}$$

1.6.9 Grayscale

In a grayscale numeric image, each pixel value represents the brightness or intensity of that particular location. The pixel values range from 0 (black) to 255 (white), with the values in between representing different shades of gray

Figure 1.4: The different levels of gray

1.6.10 Colour

Even if it is sometimes useful to be able to represent images in black and white, multimedia applications most often use color images. there are several computer color coding modes CMY, HSL, CIE, LAB, but the most used for handling images is the Red, Green, Blue (RGB or RGB - Red green Blue) colorimetric space. [15]
In a color numeric image, each pixel is represented by multiple values, typically three, to represent the red, green, and blue (RGB) color channels. The values for each channel range from 0 to 255, and by combining different intensities of these channels, a wide range of colors can be achieved.this table [3] shows some examples of colors represented in the RGB model

1.6.11 Texture

Image texture refers to the visual and tactile qualities of the surface of an object or scene depicted in an image. It represents the patterns, details, and variations in the texture of different elements within an image. Texture can range from smooth and uniform surfaces to rough and highly detailed ones, and it plays a crucial role in the perception

	Red	Green	Blue
	0	0	0
	255	255	255
	255	0	0
	0	255	0
	0	0	255
	255	128	0
	255	255	0
	128	128	128

Figure 1.5: some examples of colors represented in

and interpretation of visual information.

In digital images, texture is captured through variations in pixel values, colors, and patterns It can be influenced by factors such as the materials, lighting conditions, and the imaging technique used to capture the image. Understanding and analyzing texture in images is important in various fields, including computer vision, image processing, and computer graphics.

1.7 Image Processing

Image processing systems refer to the technologies and techniques used to manipulate, analyze, and enhance digital images and extract information . These systems can be found in various applications :

- Entertainment
- Photography

- Medical imaging
- Surveillance.
- Handwriting recognition.
- Image search by content .
- Checking the ripening level of fruits on a packaging line.

1.7.1 The Different Possible Transformations

We can distinguish four (04) types or modes of transformations, which can be performed from or to a digital image: [2]

1. Image processing image $\rightarrow$ image ("image processing").
2. Image Analysis: image $\rightarrow$ measurements ("image analysis") semantic analysis
3. High-level image description: images $\rightarrow$ Object classes ("image understanding or recognition").
4. Image Reconstruction: Information Set Operators $\rightarrow$ image

1.7.2 Key components and concepts

1. image Acquisition : The process of capturing images using cameras, scanners, or other devices. This step converts the physical image into a digital format; The representation obtained cannot be perfect because of the noise introduced into the image during its acquisition.
2. Feature Extraction : The process of identifying and extracting specific visual features from an image. These features can include edges, corners, textures, shapes, and colors. Feature extraction is a fundamental step in many computer vision and pattern recognition tasks.

3. Morphological Operations : Mathematical operations applied to binary or grayscale images to manipulate their shape and structure. These operations include erosion, dilation, opening, and closing, and are used for tasks like noise reduction, edge detection, and shape analysis.

1.8 Filter

A filter is a mathematical transformation (called convolution product) allowing, for each pixel of the zone to which it applies, to modify its value according to the values of the neighboring pixels, affected by coefficients. A distinction is generally made between the following types of filters :

1. low-pass filters: consisting of attenuating the components of the image having a high frequency (dark pixels). This type of filtering is generally used to attenuate the noise of the image, this is the reason why we usually speak of smoothing. Averaging filters are a type of low-pass filter whose principle is to average the values of neighboring pixels. The result of this filter is a blurry image.

2. High-pass filters: unlike low-pass filters, attenuate the components of low frequency of the image and allow in particular to accentuate the details and the contrast, which is why the term "sharpening filter" is sometimes used. ‘

3. Band-pass filters: allowing to obtain the difference between the original image and that obtained by applying a low-pass filter.

4. Directional filters: applying a transformation along a given direction. We call adaptive filtering the filtering operations having a prior step of pixel selection.

‘

1.9 Segmentation

Image segmentation is an image processing operation that aims to group pixels together according to predefined criteria. The pixels are thus grouped into regions, which constitute a tiling or a partition of the image. Segmentation is an essential step in image processing. To date, there are many segmentation methods, which can be grouped into four main classes :

- Segmentation based on regions There are eg: region growth, decomposition/merge
- Edge-based segmentation
- Segmentation based on classification or thresholding of pixels according to their intensity
- Segmentation based on cooperation between the first three segmentations

1.10 Conclusion

In this chapter, we have presented the basic concepts of digital images and some methods relating to the manipulation of these images (their analysis and processing). because In a CBIR it is better to do a preprocessing before moving on to the indexing of the images base and then the image search by content to eliminate the noise present in these pictures. In the next chapter we present the basics of search systems. by content (CBIR).

Chapter 2

Content-Based Image Retrieval Systems

2.1 Introduction

The term "content-based image retrieval" seems to have originated in 1992 when it was used by Japanese Electrotechnical Laboratory engineer Toshikazu Kato to describe experiments into automatic retrieval of images from a database, based on the colors and shapes present. Since then, the term has been used to describe the process of retrieving desired images from a large collection on the basis of syntactical image features. The techniques, tools, and algorithms that are used originate from fields such as statistics, pattern recognition, signal processing, and computer vision[14]

The interest in CBIR has grown because of the limitations inherent in metadata-based systems, as well as the large range of possible uses for efficient image retrieval. Textual information about images can be easily searched using existing technology, but this requires humans to manually describe each image in the database. This can be impractical for very large databases or for images that are generated automatically, e.g. those from surveillance cameras. It is also possible to miss images that use different synonyms in their descriptions. Systems based on categorizing images in semantic classes like "cat" as a subclass of "animal" can avoid the miscategorization problem, but will require more effort by a user to find images that might be "cats", but are only classified as an "animal". Many standards have been developed to categorize images, but all still face scaling and miscategorization issues [7]

2.2 CBIR Applicatons

- Architectural and engineering design
- Art collections
- Crime prevention
- Geographical information and remote sensing
- systems
- Intellectual property
- Medical diagnosis
- Military
- Photograph archives

2.3 CBIR Query Types

are described in the below figure

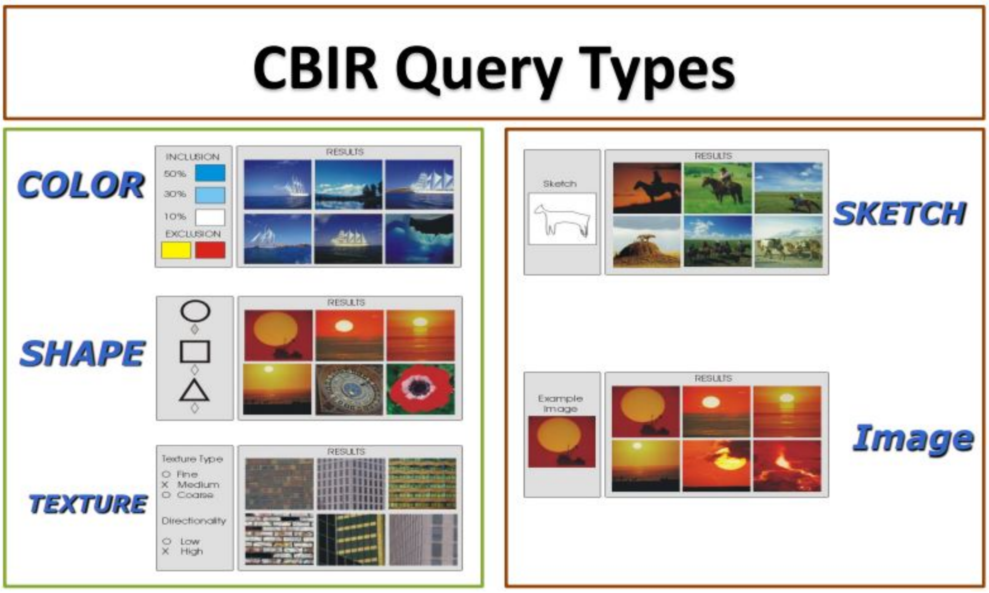

Figure 2.1: CBIR Query Types

2.4 CBIR Structure

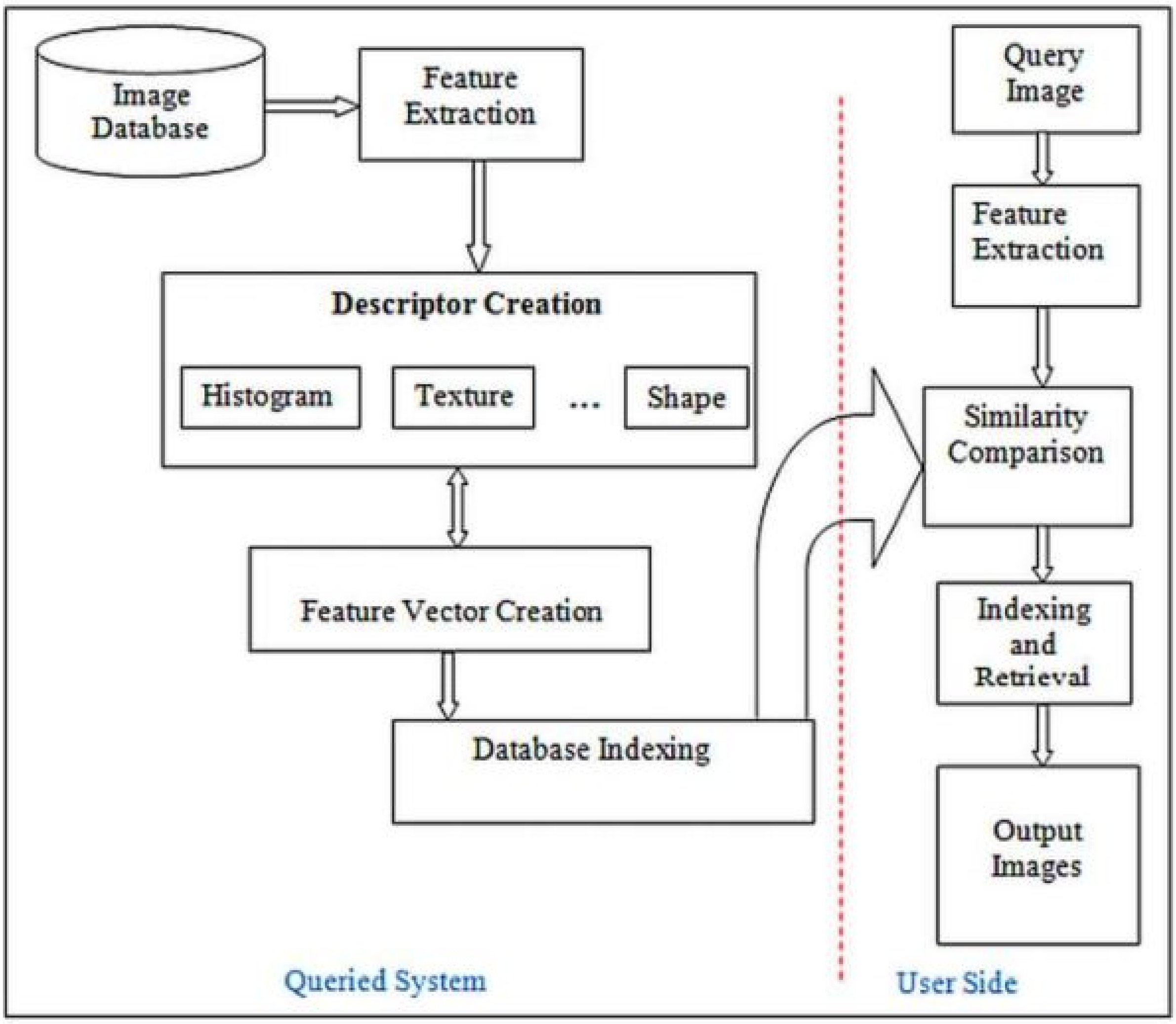

Figure 2.2: CBIRS from the functional point of view of the user and the queried system [11]

Firstly, we create a descriptor to our images .The extracted data (now representative of the image content of the point view of the system) constitute the index base. The requests of the user are then transformed in order to be comparable with the index base ; a matching between the transformed query and the index base using a similarity metric then makes it possible to produce the result of the request . The system may also have an optional preprocessing stage which could include resizing, segmentation, de-noising, and rescaling, etc. This optional stage is followed by the feature extraction stage

2.5 A Description of Each Component

2.5.1 Image Database

The collection (or base) of images is the main data of the system.In CBIR domain, a wide range of databases vary in the number of images they may contain, the type of images, and the way they are collected.and so choosing the dataset requires careful attention.some widely used image datasets: corel, holiday, and brodatz

Figure 2.3: Samples from corel, holiday, and brodatz image datasets
[12]

2.5.2 Feature Extraction

Feature extraction can be done by text-based features and/or visual features. In the first case, keywords and annotations are used to build to portray and to index images. As for the second,it include a low-level features such as color,texture,shape and high-level features like Object Recognition , Face Expressions.

Wide-ranging features from the query and other images stored in the database are extracted, based on their pixel characteristics, so that the CBIRS stores image information in compact form into a separate database known as feature database, which is also known as image signature (Dhobale et al., 2011; Wong, 2002).

2.5.3 Image Descriptors

Descriptors are the first step to finding out the connection between the pixels contained in a digital image and what humans call to mind after having observed an image or a group of images after some minutes.Visual descriptors are divided into two main groups:

a) General information descriptors contain low-level descriptors that represent color, shape, regions, textures, motion, etc.

b) Specific domain information descriptors provide information about objects and events in the scene.
Next,several types of descriptors are discussed in terms of locality so we have global and local descriptors

2.5.4 Similarity Comparison

The similarity measurement determines which images are considered most relevant to the query image and should be returned from the dataset. Therefore, the similarity measure determines the accuracy of the CBIR indirectly and has an effect on the computational complexity of the system. The selection of the similarity measure is affected by the structure of the constructed feature vector (type and dimensionality of input data). This selection is a major challenging task in the literature, the similarity measure can be divided into distance measure and similarity metric (Sergyan, Citation2008).

2.6 CBIR and Machine Learning

Recently, CBIR systems have been shifted toward using machine learning algorithms to obtain a model that can deal with new input data and give correct prediction, which will improve the image search. The most common machine learning algorithms used in the CBIR domain are illustrated in Figure 2.4

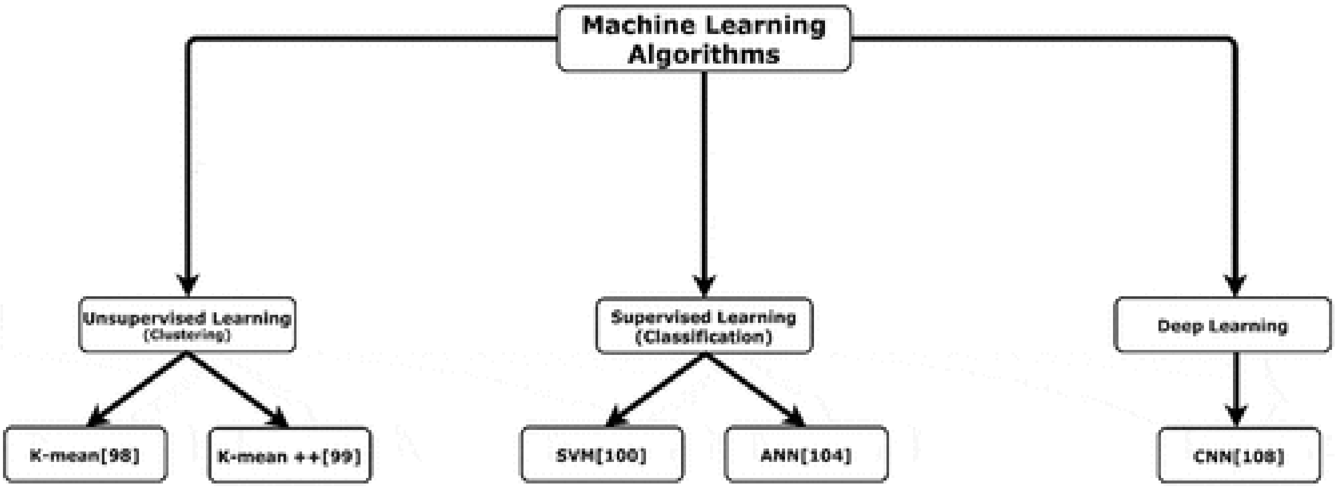

Figure 2.4: CBIR and Machine Learning
[12]

2.7 State-of The art Approaches

In this section,we mention the studies that achieved the highest accuracy in global feature extraction in each feature category.all the investigated studies in this section utilize COREL dataset except studies from machines learning approach which utilizes Paris6k and ALOI. [12]

1. In the global feature approach, Srivastava and Khare (Srivastava Khare, Citation2017) achieved the highest accuracy (0.9995) by extracting texture and shape features.DWT was used followed by the use of LBP.

2. In the local feature extraction approach, Sarwar et al. (Sarwar et al., Citation2019) achieved the highest accuracy. The proposed method was based on LBPV and LIOP.[12]

3. In the machine learning approach, CNN is efficient at feature representation. The method proposed by Tzelepi et al. (Tzelepi Tefas, Citation2018) has the highest accuracy. The strength of their method is the use of CNN for feature representation by using maximum pooling after convolutional layers rather than using fully connected layers because fully connected layers discard the spatial information due to the connection of the entire input neurons. [12]

2.8 Performance Evaluation

To test the effectiveness of a CBIRS,some evaluation metrics are used, below are the most widely used metrics :

1. Precision (P) is the number of the relevant retrieved images to the total number of the retrieved images

$$P = \frac{No.ofrelevantimages}{No.ofretrievedimages} \tag{2.1}$$

2. Recall (R) is the number of the relevant retrieved images to the total number of relevant images in the dataset

$$R = \frac{No.ofrelevantimages}{No.ofallrelevantimagesindataset} \tag{2.2}$$

3. F1-score (F-measure) is a combination of precision and recall in a single measure, which is the harmonic mean that is defined as

$$F = \frac{2 * R * P}{P + R} \tag{2.3}$$

2.9 Steps to Develop a Good CBIR System (CBIRS)

1. Identify requisites and requirements of the needed CBIR system architecture.

2. . Study the existing images retrieval methods and their efficacy

3. Maintain a database of real-world medical cases and pictures collected from various sources and classifying them based upon the information provided by them.
4. Identify prospective visual features to mine and choose a similarity metric.
5. Web deployable structure to make it available to potential users via the Interne
6. Limit access via authorization practices, with anonymity and security of patient data.
7. Efficient web-based GUIs, which allow the user to apply permissions, provide visual queries, investigate retrieved results, and so forth.

2.10 Conclusion

In this chapter, we have tried to describe the basic concepts for building a content-based image search system. We first discussed the different components of a CBIR . Thereafter we spoke about Representation of the images in a CBIR and the different levels of features and we also spoke about the studies that achieved the highest accuracy in extracting those features and we finished by stating some measures to evaluate a CBIR

In the next chapter, we will go through the different descriptors extracted from of an image with details (colors, texture and shape) and the measures of similarity between these descriptors.

Chapter 3

Image Descriptors and Similarity Measures

3.1 Introduction

previously we approached all the necessary notions and concepts, which make it possible to define and understand the operation of a "CBIR" system, as well as the diagram general of the latter ,and names of some accurate CBIR systems outthere In this chapter we will dive deep and we'll present some points in details

3.2 Image Descriptors

like we said in the previous chapter,image descriptors are organized in term of locality so we have global descriptors (i.e., color, texture, shape, and spatial information), which describe the entire image, and local descriptors, which are usually acquired through dividing the image into segments or through the calculation of some key points, such as corners, blobs and edges.

3.2.1 Global Features

Color, texture, shape, and spatial information are the widely used features in image retrieval tasks.the figure below illustrates the classification of global features along with some feature extraction methods.

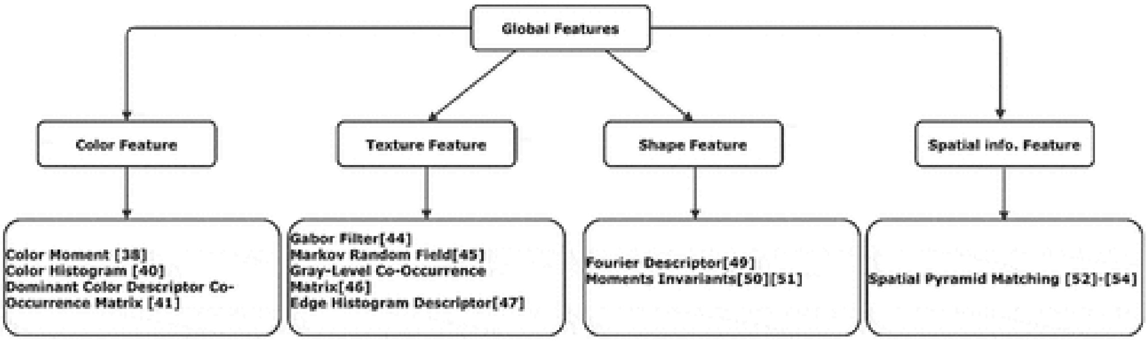

Figure 3.1: Global Features
[12]

3.2.2 Color

since the human eye can distinguish visuals based on their colors, the color feature is considered one of the most significant features that are commonly used by researchers. Color features are calculated according to color spaces. The mostly used color spaces in the CBIR domain are HSV (LSV), YCbCr, RGB, and LAB. These color spaces are characterized using color moments (Duanmu, 2010), color correlogram (Huang et al., 1997), color histogram (Flickner et al., 1995).

Color features are considered a robust feature because they are invariant against translation, rotation, and scale change. However, they have a spatial information constraints, necessitating the use of other descriptors cope with this drawback

3.2.3 Color Spaces

Color spaces are mathematical models that represent colors in a structured and systematic way. They define the range of colors that can be displayed or represented,we mention the most used: RGB (Red, Green, Blue): RGB is an additive color model widely used in digital imaging and displays. It represents colors by specifying the intensity levels of red, green, and blue components
HSV (Hue, Saturation, Value): HSV is a cylindrical color model that represents colors based on their hue, saturation, and value. Hue refers

to the dominant wavelength of the color, saturation represents the intensity or purity of the color, and value corresponds to the brightness or lightness of the color.

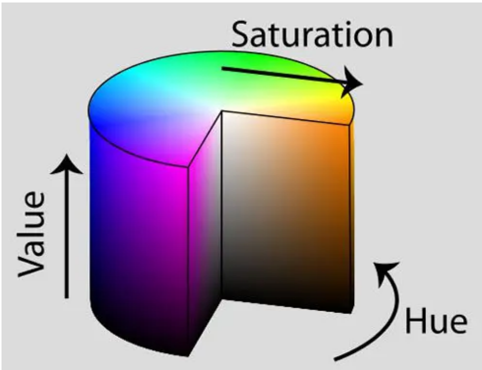

Figure 3.2: HSV example

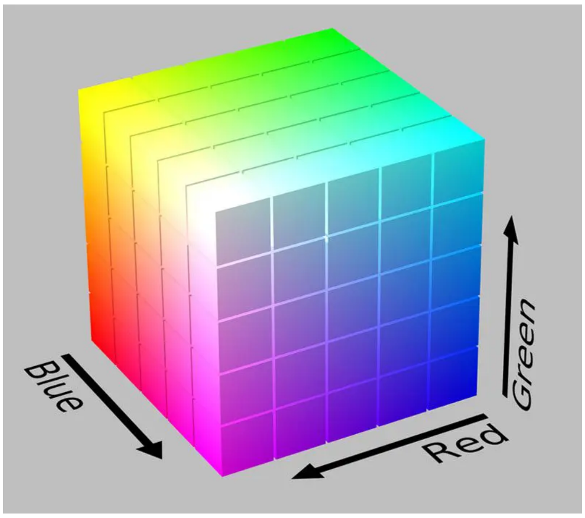

Figure 3.3: RGB example

3.2.4 Histogram

We can define the histogram of an image as a 2D bar plot. it represents the distribution of colors in an image. It quantizes the color space into a set of bins and counts the number of pixels that fall into each bin. The histogram provides a statistical representation of the color content in an image, capturing the overall color composition and distribution.a color histogram is typically computed by converting the color space of the image to a different one , which is then devided into a specific number of bins,the image pixels will align to there corresponding bin ,histograme normalization is optional the figure below shows the histogram of the previous image :

3.2.5 Color Moments

Color moments are measures that can be used differentiate images based on their features of color. Once calculated, these moments provide a measurement for color similarity between images. These values of similarity can then be compared to the values of images indexed in a database for tasks like image retrieval.

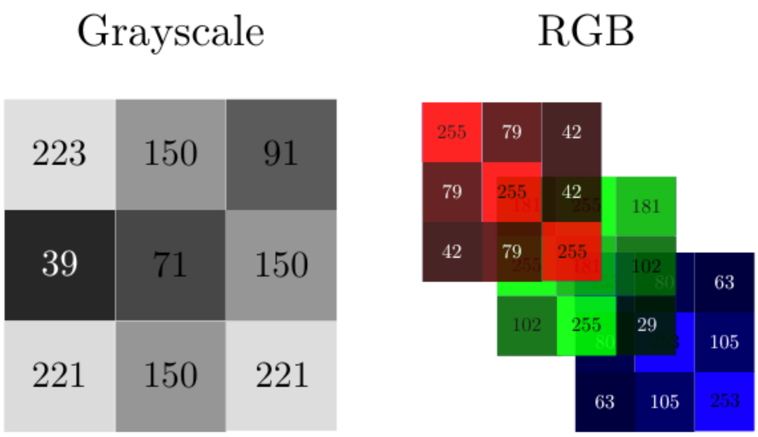

Figure 3.4: 3x3 pixel image in grayscale and in RGB
[8]

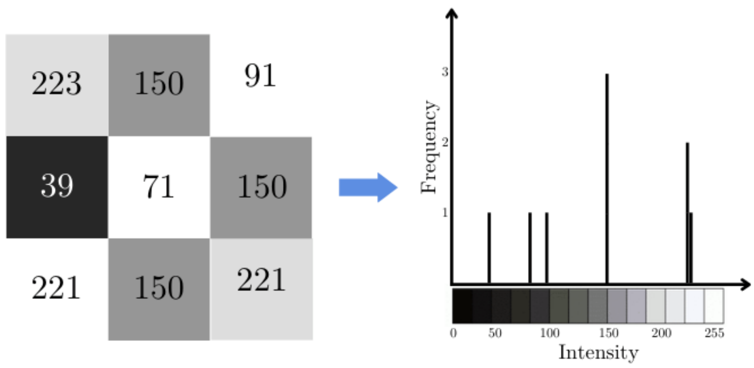

Figure 3.5: Histogram
[8]

Stricker and Orengo [1] use three central moments of a image's color distribution. They are Mean, Standard deviation and Skewness.The three color moments can then be defined as:

Mean : Mean can be understood as the average color value in the image

$$E_i = \sum_N^{j=1} \frac{1}{N} p_{ij}$$

Standard Deviation : The standard deviation is the square root of the variance of the distribution.

$$\sigma_i = \sqrt{\left(\frac{1}{N} \sum_N^{j=1} \left(p_{ij} - E_i \right)^2 \right)}$$

Skewness : Skewness can be understood as a measure of the degree of asymmetry in the distribution.

$$s_i = \sqrt[3]{\left(\frac{1}{N}\sum_{N}^{j=1}\left(p_{ij} - E_i\right)^3\right)}$$

3.2.6 Texture

Image texture refers to the characterization of the surface of a given object or phenomenon present in the image. Texture occurs in many different types of images such as natural and remote sensing and medical images. Image texture has been an active area of research in pattern recognition and image analysis. Although a formal definition of image texture is not available in the literature,Various authors have proposed different definitions for texture but we present the definition proposed by the author Hung Song and Lan [5]
image texture is a natural characteristic in many images that we perceive in our environment. In general, a texture can be informally defined as a set of texture elements (called texels) which occurs in some regular or repeated pattern such as the image.unlike colour, texture cannot exist on a point, but needs an area large enough for the variation to be perceived figure (3.6) shows 2 examples of image textures:

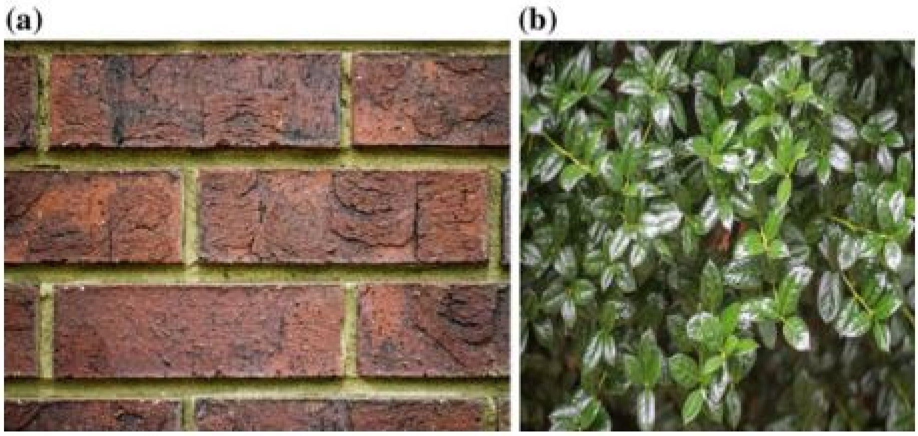

Figure 3.6: a brick arranged in regular pattern and b tree leaves grew in random pattern [5]

Some of the popular operators specifically defined for extracting these textural properties(texture features) are the GLCM and LBP algorithm

3.2.7 Gray-Level Co-Occurrence Matrix (GLCM)

The gray-level co-occurrence matrix (GLCM) is one of the earliest methods using spatial relationships for describing image texture features to be exact it was first introduced by Haralick in 1973 [9]. The GLCM is a statistical method which calculates properties of the spatial relationships among pixels. The spatial relationships between a pair of two pixels in a neighborhood are recorded in the co-occurrence matrices which are then used to calculate textural features The spatial relationships are measured using distances and angles between two pixels in a textured region. This relationship is the joint probability density of two pixels for the transition (or relation) of gray levels in both locations.
The GLCM is a two-dimensional matrix in which each element p_{i_j} represents the frequency of occurrences of a pair of pixels (where i and j are the gray levels) in a spatial relation separated by distance d and angle a. Let G be an image texture with the size of M x N. An element p_{i_j} can be calculated by counting the number of relationships with the following equation[5]:

$$p_{i_j} = G(m,n) = i, G(m+d, n+d) = j \text{for each a}$$

where m = 0; 1; ...; M 1, n = 0; 1; ...; N 1, and a = 0°; ...; 360°

below is an example of GLCMs with angles at 0°, 45°, 90°, and 135° and the distance is one unit

$$\begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 2 & 2 & 1 & 1 \\ 2 & 2 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 4 & 4 & 1 \\ 4 & 4 & 1 \\ 1 & 1 & 4 \end{bmatrix} \text{ a=0°}$$
$$\begin{bmatrix} 2 & 2 & 2 \\ 2 & 4 & 1 \\ 2 & 1 & 2 \end{bmatrix} \text{ a=45°}$$
$$\begin{bmatrix} 0 & 7 & 1 \\ 7 & 2 & 1 \\ 1 & 1 & 4 \end{bmatrix} \text{ a=90°}$$
$$\begin{bmatrix} 1 & 4 & 1 \\ 4 & 2 & 1 \\ 1 & 1 & 2 \end{bmatrix} \text{ a=135°}$$

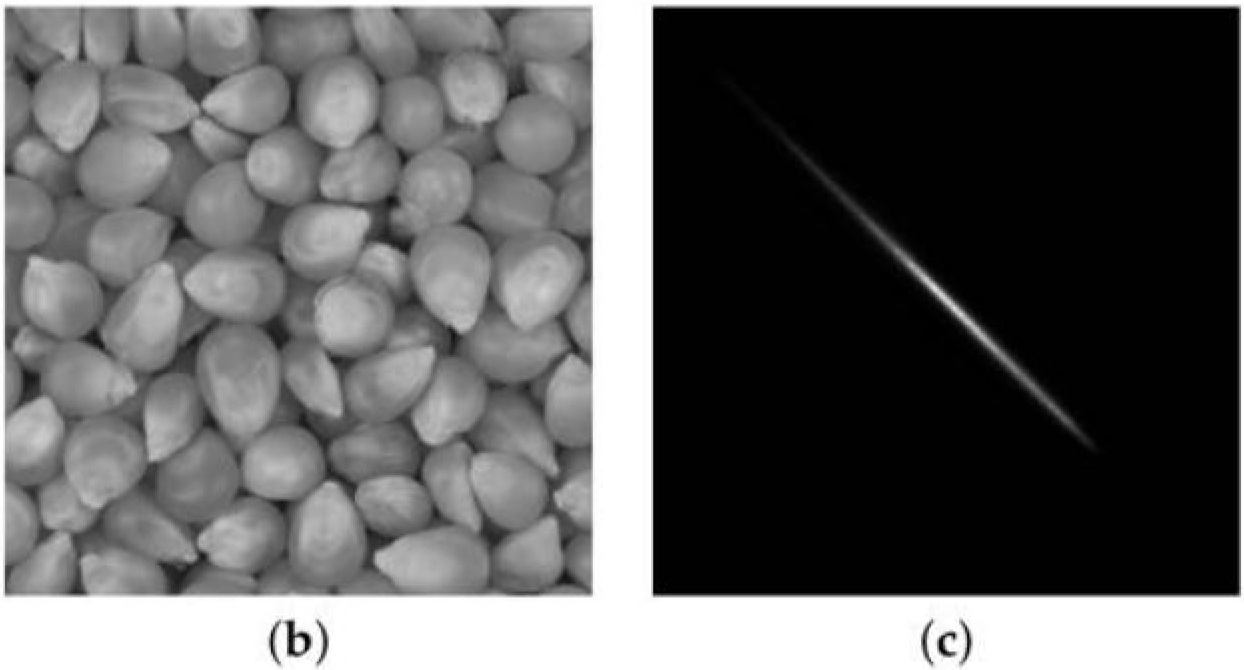

Figure 3.7: b sample image and c corresponding GLCM [9]

Haralick et al. proposed several textural features(properties) to be extracted from the GLCM method :

$$
\begin{aligned}
\text{Con} &= \text{Contrast} = \sum_{i,j} |i-j|^2 p_{ij} \\
\text{Cor} &= \text{Correlation} = \frac{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} ijp_{ij} - \mu_1\mu_2}{\sigma_1^2\sigma_2^2} \text{ where} \\
\mu_1 &= \sum_{i=0}^{M-1} i \sum_{j=0}^{N-1} p_{ij} \\
\mu_2 &= \sum_{i=0}^{M-1} j \sum_{j=0}^{N-1} p_{ij} \\
\sigma_1^2 &= \sum_{i=0}^{M-1} (i-\mu_1)^2 \sum_{j=0}^{N-1} p_{ij} \\
\sigma_2^2 &= \sum_{i=0}^{M-1} (j-\mu_2)^2 \sum_{j=0}^{N-1} p_{ij} \\
D &= \text{Dissimilarity} = \sum_{i,j} \frac{p_{ij}}{1+|i-j|} \\
E &= \text{Entropy} = -\sum_{i,j} p_{ij} \log p_{ij} \\
H &= \text{Homogeneity} = \sum_{i,j} \frac{p_{ij}}{1+|i-j|}
\end{aligned}
\tag{3.1}
$$

3.2.8 Shape

Shape is a very important descriptor in image indexing. Shape refers to the general appearance of an object, its outline. A shape descriptor is a mathematical representation or set of features that captures the essential characteristics of a geometric shape. It serves as a quantitative measure or description of the shape's properties, allowing for comparisons and analysis. We present in the following the different methods used to recognize a shape given in an image.

3.2.9 Shape Features

Shape features are quantitative measurements or characteristics and they are grouped into two classes: boundary features and region features.They are extracted from geometric shapes : The perimeter ,Rectangularity, Compactness

3.2.10 Geometric Moments

Geometric moments [SHB99] make it possible to describe a shape using properties statistics. They are simple to handle but their calculation time is very long.

3.2.11 Spatial Information

Spatial feature is basically related to the objects' location in a two-dimensional image. For instance, two different regions with two different spatial contents in the same image may have an equal histogram. Spatial information usually suffers from computational complexity. Spatial pyramid matching is one of the best methods that capture the spatial attributes of images it divides the image in several regions (in the spatial pyramid way) and use a BoW(Bag of words) on every region

3.2.12 Local Features

local image features are gaining popularity because they are superior to global features in terms of being invariant to scale and rotation, and they provide reliable matching in a range of conditions (Low, Citation2004). The most common local detectors and descriptors that are widely used in the CBIR domain are listed, as shown in figure 3.8

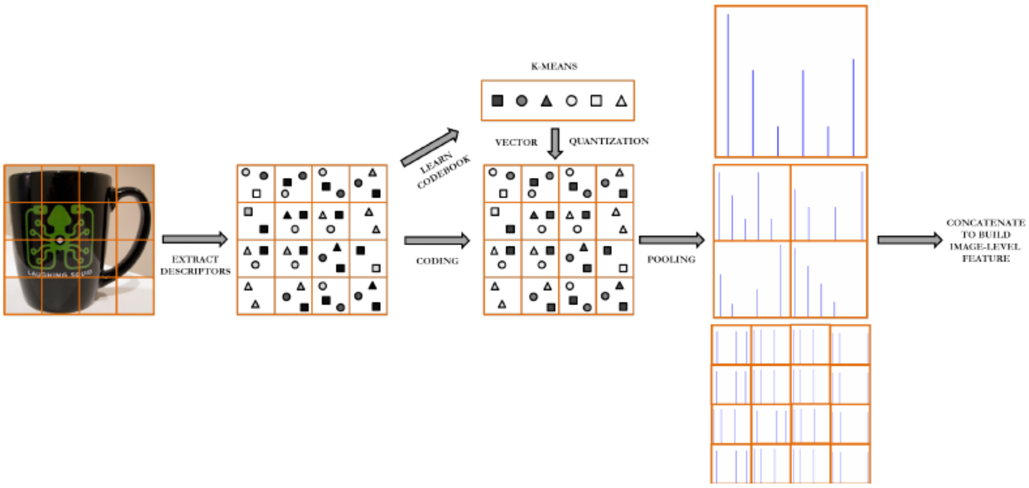

Figure 3.8: Illustration-of-the-spatial-pyramid-matching-algorithm [13]

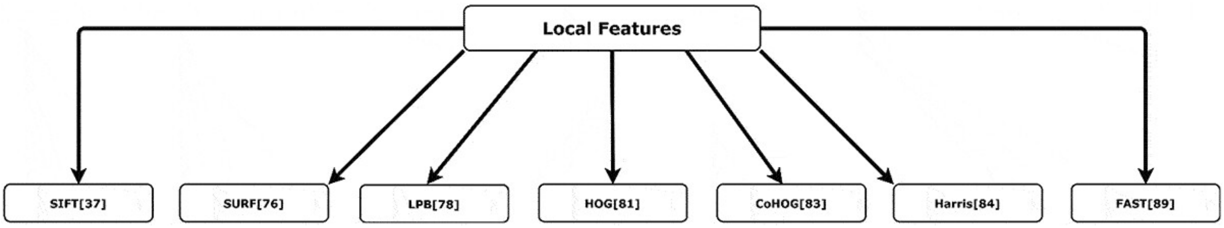

Figure 3.9: Local Features

3.3 Similarity Measures

after choosing the image descriptors and after extracting the features, we can calculate the similarity value between the base images and our query image. Instead of an exact match, image search by the content calculates visual similarities between a query image and the images of theimage database.Therefore, the result of a search is not a single image but a list of images ordered according to their degree of similarity with the requested image. There's Several similarity measures that have been proposed in the literature and most of them are based on the distance between two points (Minkowski family) .

But as we said in chapter 2 The selection of the similarity measure is affected by the structure of the constructed feature vector its type and the dimensionality of input data and the level of abstraction of the image representation whether its pixels or visual attributes Also the similarity measure determines the accuracy of the CBIR indirectly and has an effect on the computational complexity of the system therefor

the expert should choose wisely
we cite below some similarity metrics and some similarity distances

3.3.1 Histogram Comparison Metrics

1. histogram intersection:
   The histogram intersection algorithm was proposed by Swain and Ballard in their article “Color Indexing”.it measures whats common between two given histograms.Given the histogram I of the input image (camera frame) and the histogram M of the model (object frame), each one containing n bins, the intersection is defined as:

$$\sum_{i=1}^{N} \mathrm{min}(I_j, M_j) \tag{3.2}$$

   after normaliwation:

$$\sum_{i=1}^{N} min(I_j, M_j)_{\overline{\sum_{i=1}^{N} M_j}} \tag{3.3}$$

2. La distance de Bhattacharya: exploite la séparabilité entre deux distributions gaussiennes représentées par leur covariance

$$D_B = \frac{1}{8}\left(\mu_1 - \mu_2\right)^T \Sigma^{-1}\left(\mu_1 - \mu_2\right) + \frac{1}{2}\ln\frac{\det(\Sigma)}{\sqrt{\det\left(\Sigma_1\right)\det\left(\Sigma_2\right)}} \tag{3.4}$$

$$where\Sigma = 0.5 * \left(\Sigma_i + \Sigma_2\right) \tag{3.5}$$

3. Chi-square Statistic: is another distance metric which is widely used for computing the difference between histogram functions it tests the fit between a distribution and observed frequencies.Chi-square takes into account that the difference between large bins is less important than the difference between small bins and that should be reduced

$$\sum_{i=1}^{N}\left(\frac{\left(x_i - y_j\right)^2}{x_i + y_i}\right) \tag{3.6}$$

3.3.2 Similarity Distances

1. The Earth Mover's Distance:The Earth Mover's Distance (EMD) is a method to evaluate dissimilarity between two multi-dimensional distributions in some feature space where a distance measure between single features, which we call the ground distance is given. The EMD "lifts" this distance from individual features to full distributions. Intuitively, given two distributions, one can be seen as a mass of earth properly spread in space, the other as a collection of holes in that same space. Then, the EMD measures the least amount of work needed to fill the holes with earth. Here, a unit of work corresponds to transporting a unit of earth by a unit of ground distance. Computing the EMD is based on a solution to

the well-known transportation problem:

$$\begin{aligned} f_{ij} \geq 0 \quad 1 \leq i \leq m, 1 \leq j \leq n \\ \sum_{j=1}^{n} f_{ij} \leq w_{p_i} \qquad 1 \leq i \leq m \\ \sum_{i=1}^{m} f_{ij} \leq w_{q_j} \quad 1 \leq j \leq n \\ \sum_{i=1}^{m}\sum_{j=1}^{n} f_{ij} = \min\left(\sum_{i=1}^{m} w_{p_i} : \sum_{j=1}^{n} w_{q_j}\right), \end{aligned} \tag{3.7}$$

after normalization by the flow:

$$\frac{\sum_{i=1}^{m}\sum_{j=1}^{n} f_{ij} d_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n} f_{ij}} \tag{3.8}$$

2. Manhattan distance: is a metric in which the distance between two points is calculated as the sum of the absolute differences of their Cartesian coordinates. In a simple way of saying it is the total sum of the difference between the x-coordinates and y-coordinates.

$$Manhattandistance = |x1 – x2| + |y1 – y2| \tag{3.9}$$

3. Distance from Kullback Leibler (KL): The Kullback Leibler divergence expresses the relative entropy of two distributions:

$$D_{KL} = \sum_{i} f_1(i) \log \frac{f_1(i)}{f_2(i)} \tag{3.10}$$

4. Euclidean distance is the most common use of distance measure. In most cases when people say about distance, they will refer to Euclidean distance.

   Euclidean distance is also known as simply distance. When data is dense or continuous, this is the best proximity measure.

   The Euclidean distance between two points is the length of the path connecting them. The Pythagorean theorem gives this distance between two points.

$$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{3.11}$$

5. The cosine similarity metric finds the normalized dot product of the two attributes. By determining the cosine similarity, we would effectively try to find the cosine of the angle between the two objects.Cosine similarity is particularly used in positive space, where the outcome is neatly bounded in [0,1]. One of the reasons for the popularity of cosine similarity is that it is very efficient to evaluate, especially for sparse vectors.

$$cosinesimilarity = \frac{(X.Y)}{|X|.|Y|} \tag{3.12}$$

3.4 Conclusion

In this chapter we describe low-level image descriptors (general features) and some extraction algorithms for these features. We also mentioned some distances and metrics used in retrieving similar images. choosing the similarity metric has been a challenging task for experts because the similarity measure determines the accuracy of the CBIR indirectly,but generally this selection depends on the type and dimensionality of input data.

In the next chapter we'll discuss briefly our project from its structure to its interface

Chapter 4

The Proposed Method :

4.1 Introduction

After having approached all the necessary notions and concepts of a "CBIR" system and its general diagram
we built 2 cbir systems one using the image color as a descripture and the 2nd uses the texture for our color image search engine, we have integrated the RGB space,and color histogram as a descriptor(feature) and GLCM for texture ,most of the CBIR systems are based on the transformation of images into image vector representations and ours is no different .

4.2 Application Architecture

A user will submit a query image to your system (1),the system will extract features from this query image (2) and then apply the similarity function (3) to compare the query features to the features already indexed (4) . From there, the system returns the most relevant results according to your similarity function.(5)

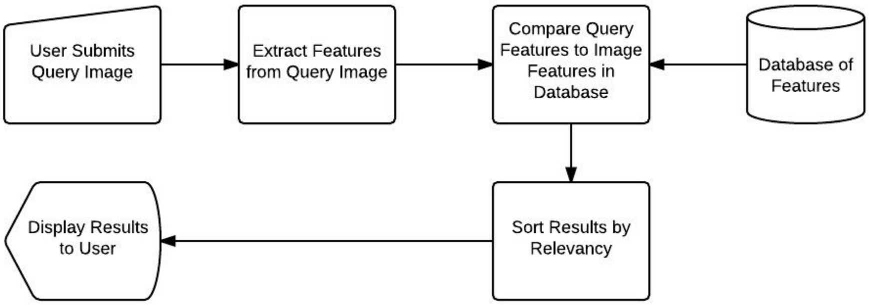

Figure 4.1: Application Architecture

1. indexation : is the phase where we transform the image into a vector representation after extracting the features to abstractly represent and quantify images.

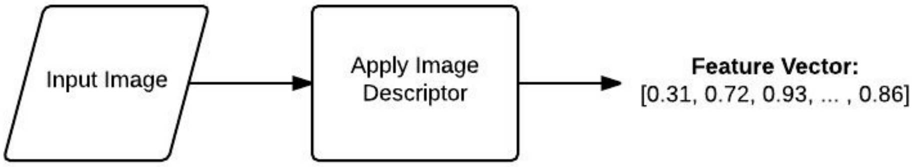

Figure 4.2: apply image descriptor

in our case we used color histogram as a way of indexation exp:

Figure 4.3: Histogram of 9 bins

and its corresponding vector :

[182.868.2424......692.454.1654.1368.472.]

figure (4.4) shows an illustration on how to build a GLCM for a gray scale image while the distance between the pixel pair is 1 and the angle varies

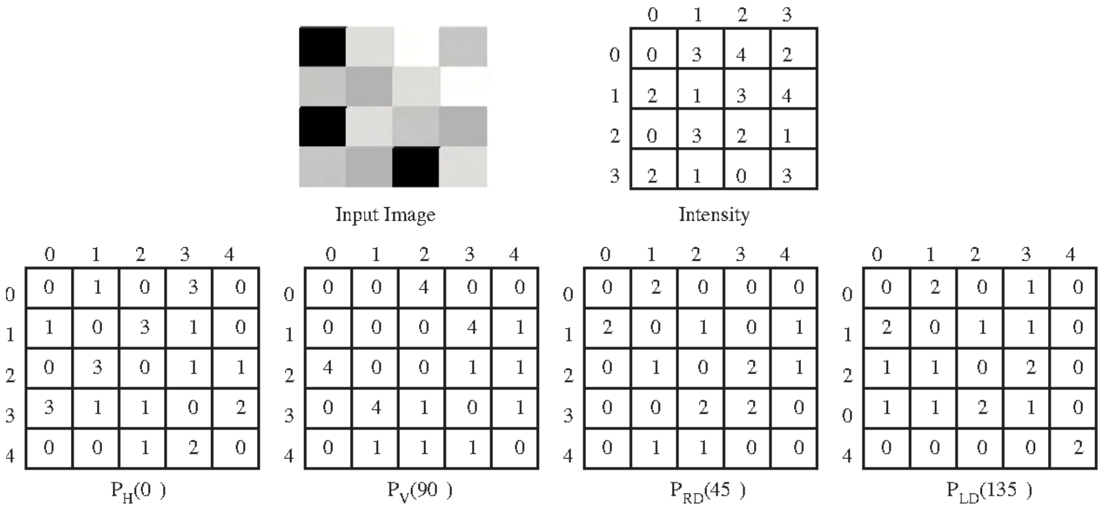

Figure 4.4: GLCM Example

2. Database of Features : is the result of our image dataset indexation and this phase is regarded as the offline treatment in the CBIR systems

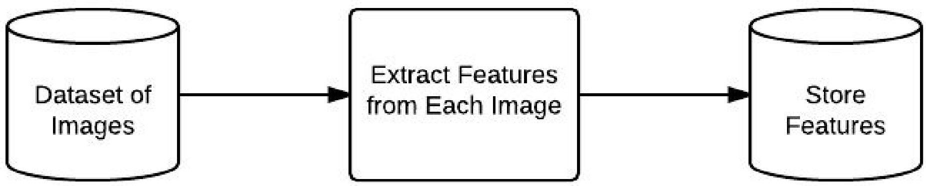

Figure 4.5: Extract features

in our case we stored the database as a csv file containing: image path , image vector

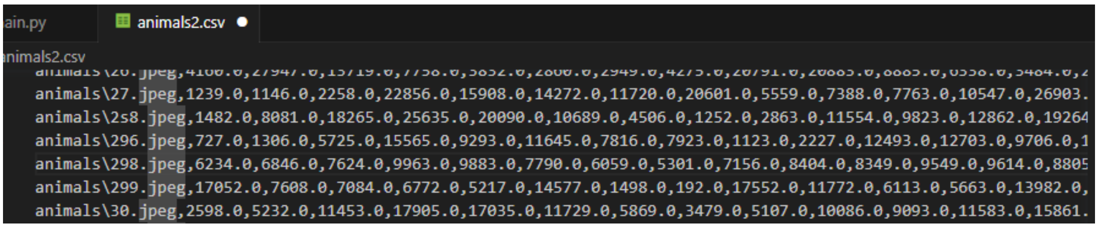

Figure 4.6: image vector

3. Finding Similar Images:
   in this phase we compare our qurey vector to a vector in our dataset,this comparison is done by using a similarity distance from which we mentioned earlier in chapter 3 ,this operation after normalization is going to return a number between [0-1] and this number is what's going to define if the two images of the two vectors are similar or not

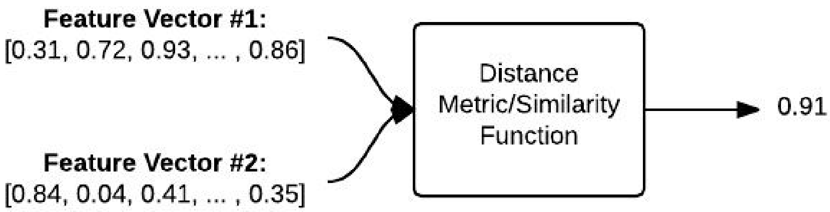

Figure 4.7: Distance metric function

4. Display Results :
   in this phase we display/return the similar images to the user and this can be done in two ways ,we set a threshold in which we seperate the similar images and the non similar ones for example the images with the similarity distance ¡ threshold are similar and vice versa , the 2nd option is to sort the similarity distances according to the nature of the similarity metric

4.3 Conclusion

In this chapter we have detailed the stages of realization of our CBIR system, and the choice of the methods used based on what we've reached in our study ,also describing the general sheme of our CBIR system

Chapter 5

Experimental Study :

5.1 Introduction

This chapter is about the implementation of the "CBIR" system, it concerns in general the development and implementation of the system, i.e. detailing the programming language, the platform or development environment and the different modules that make up the system

5.2 Programming Language

we utilized flask framework for our project which is a popular web framework for Python that allows you to build web applications. It is known for its simplicity and minimalistic design, providing just the essentials for creating web applications without imposing too many constraints
Python is a high-level programming language known for its simplicity and readability. It was created by Guido van Rossum and first released in 1991
HTML (Hypertext Markup Language) is a standard markup language used for creating the structure and content of web pages.

5.3 The Development Environment

VS Code (Visual Studio Code) is a popular source code editor developed by Microsoft. It is lightweight, highly customizable, and supports a wide range of programming languages and frameworks.

5.4 Libraries Used

OpenCV (Open Source Computer Vision) is an open-source library of computer vision and image processing functions. It provides a wide range of tools and algorithms for tasks such as image and video processing, object detection and tracking, feature extraction, and more.
we used open Cv library to calculate our image histograms using the cv2.calcHist() function:
Syntax: cv2.calcHist(images, channels, mask, histSize, ranges[, hist[, accumulate]])
OpenCV provides a builtin function for comparing the histograms as shown below:
cv2.compareHist(H1, H2, method)
in our case the method was "HISTCMPINTERSECT" for our image search engine by texture skimage helped us create the GLCM by providing the function graycomatrix:syntax :graycomatrix(image,distances, angles) distances and angles are the properties that control our GLCM and were discussed back in chapter 3

5.5 The Image Database Used

The image database used contains a total of 350 color images of animals from different categories brought from [4]

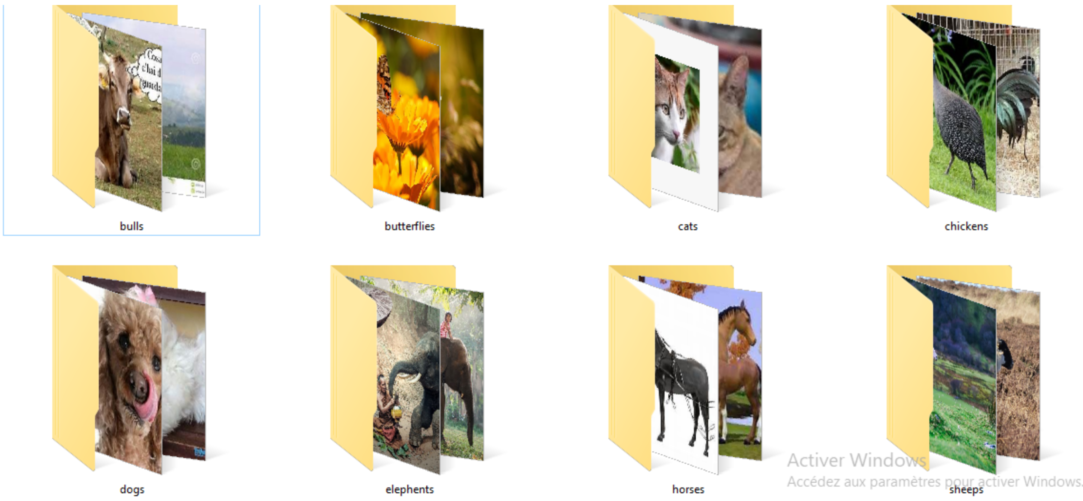

Figure 5.1: Image Database Used

5.6 User Interface

Our web page is very simple it contains 2 image search engines can be seen in the navigation bar and reached by clicking :search 1 is a search engine by color and search 2 is by texture it has a simple input button for the image query and when clicked the image query will be shown along with the similar images from our database
the footer and the text search engine were initially made for our e-commerce

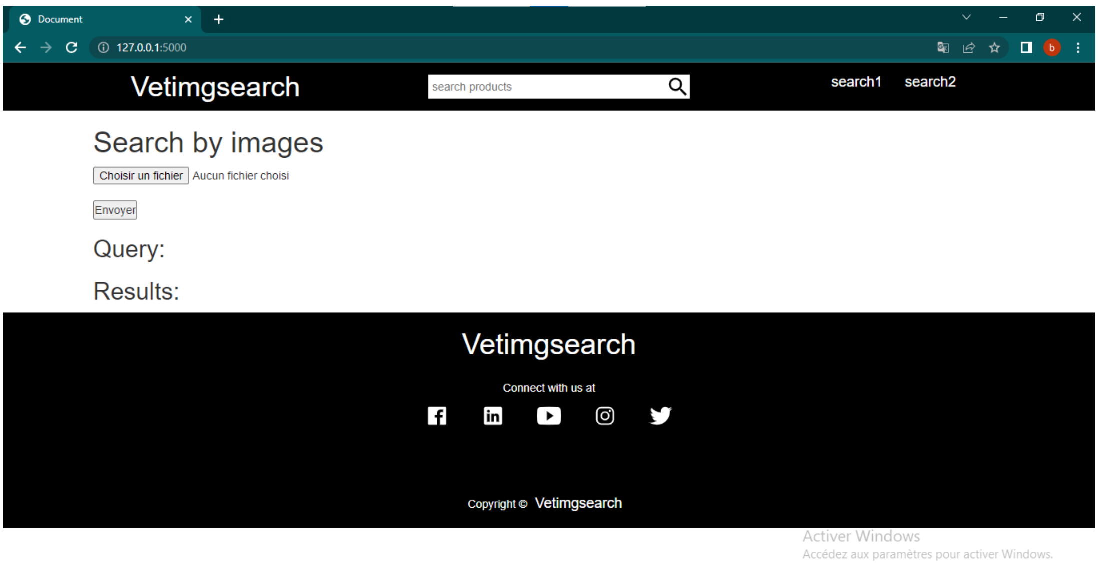

Figure 5.2: home page

Color based search

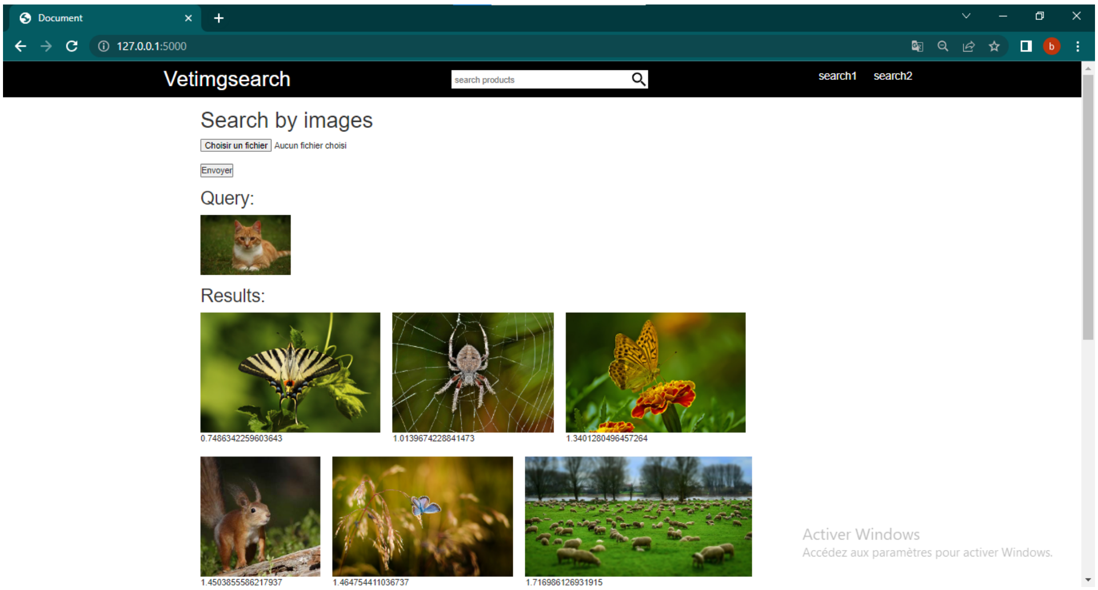

Figure 5.3: search results based on color

Texture based search

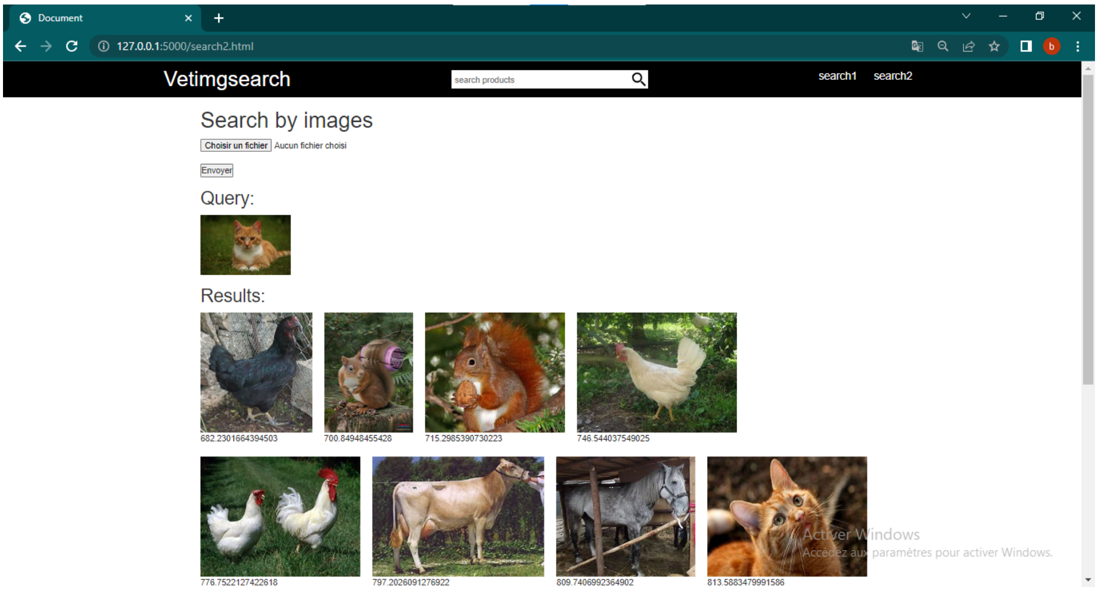

Figure 5.4: search results based on texture

5.7 Performance Evaluation

in this section we study the effect of changing some variables(parameters) on the accuracy of our CBIR by calculating the precision and the recall that we mentioned back in chapter 2 and they are presented in the form of tables.
Our system will return 10 images and we consider the images of the same animal (same class/category) to be the relevant images

5.7.1 Bins Number

the number of bins in our histogram plays a big role in our search accuracy because it can change the results obtained ,throughout the study we found out that the smaller the bin is the better the accuracy and that is because the smaller bins take the smallest details(pixel level) while big bins sums a set of pixels (values) in an interval which leads to image structure loss

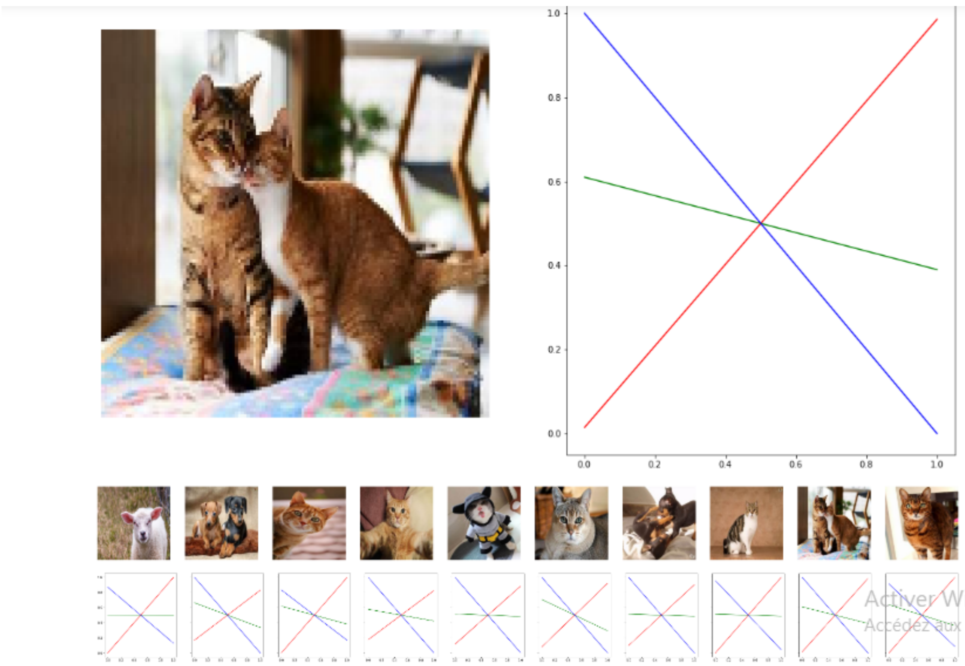

Figure 5.5: results where bins equal 2

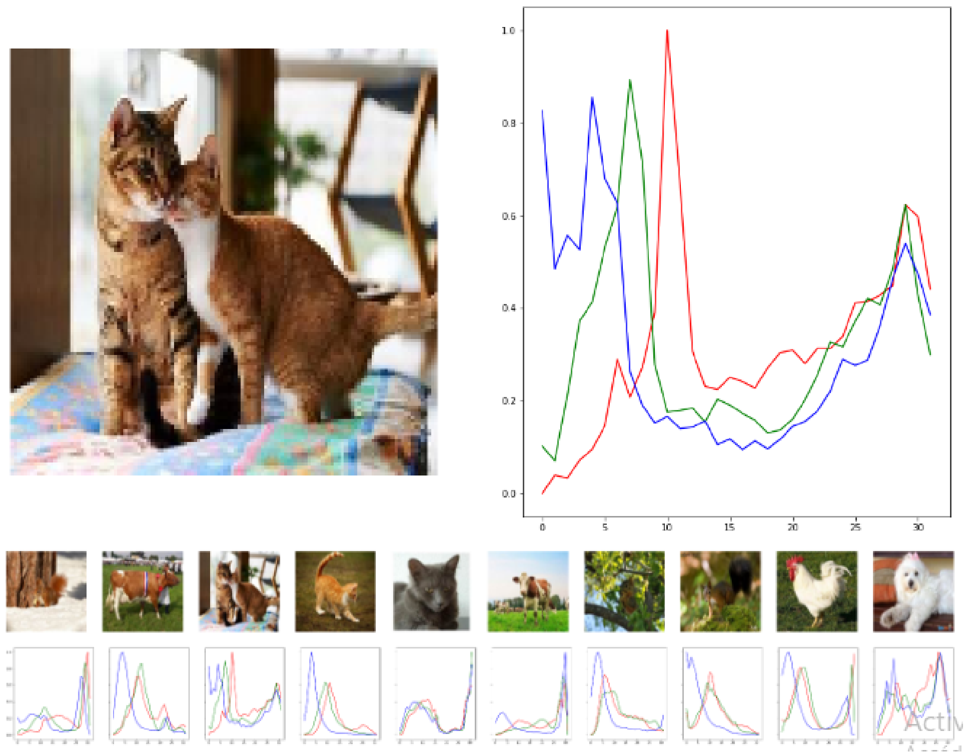

Figure 5.6: results where bins equal 32

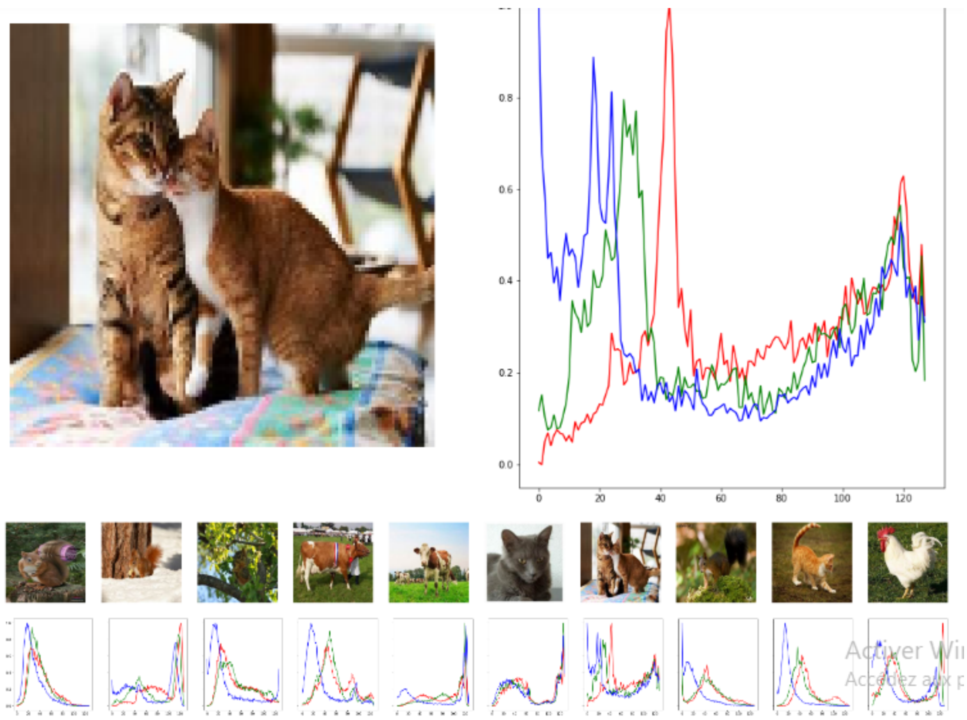

Figure 5.7: results where bins equal 128

bins	precision	recall	f-measure
2	70	13,2	0,39
32	30	5,6	0,16
128	30	5,6	0,16

Table 5.1: the performance metrics for each bin number

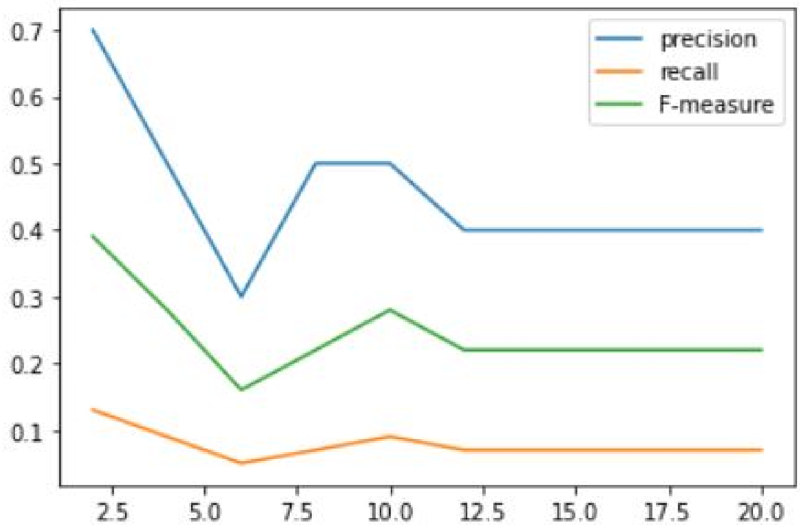

Figure 5.8: a plot showing the changes of the evaluation metrics according to the bins number

5.7.2 Histogram Comparison Metric

after we set our bins number at 2 ,we ran through the different histogram comparison metrics and we found that the chi-square metric returned no relevant images while the correlation and intersection metric each returned 7 relevant images out of 10 i.e accuracy=0.7 thus we can conclude that in our proposed CBIR the correlation metric is better

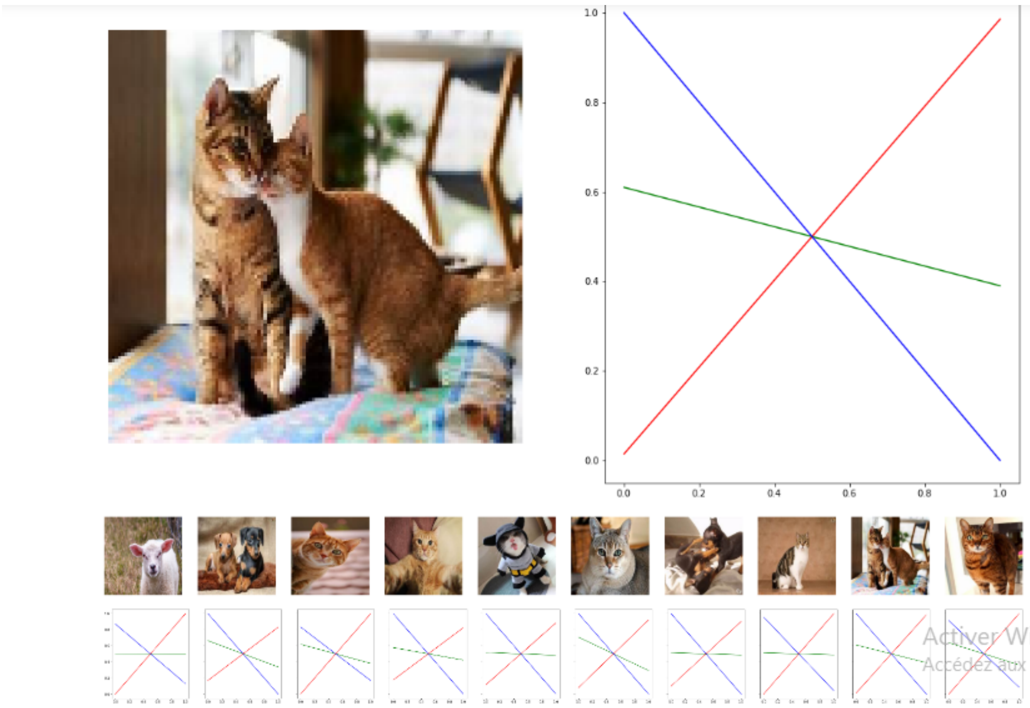

Figure 5.9: Correlation

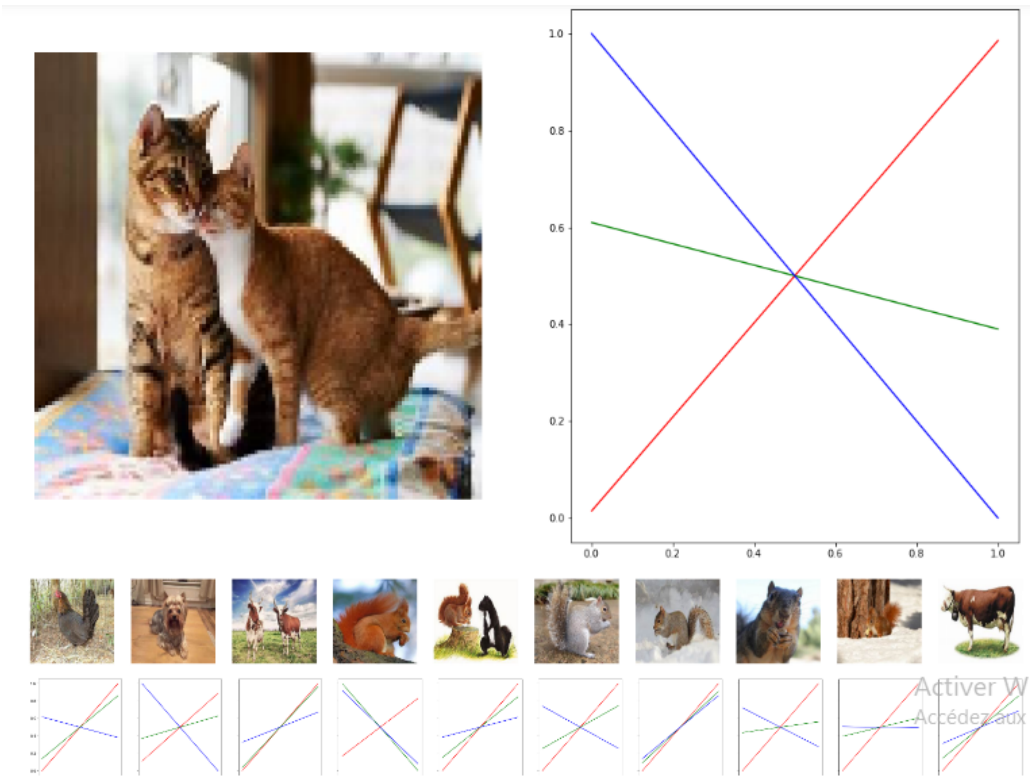

Figure 5.10: Chi-Square

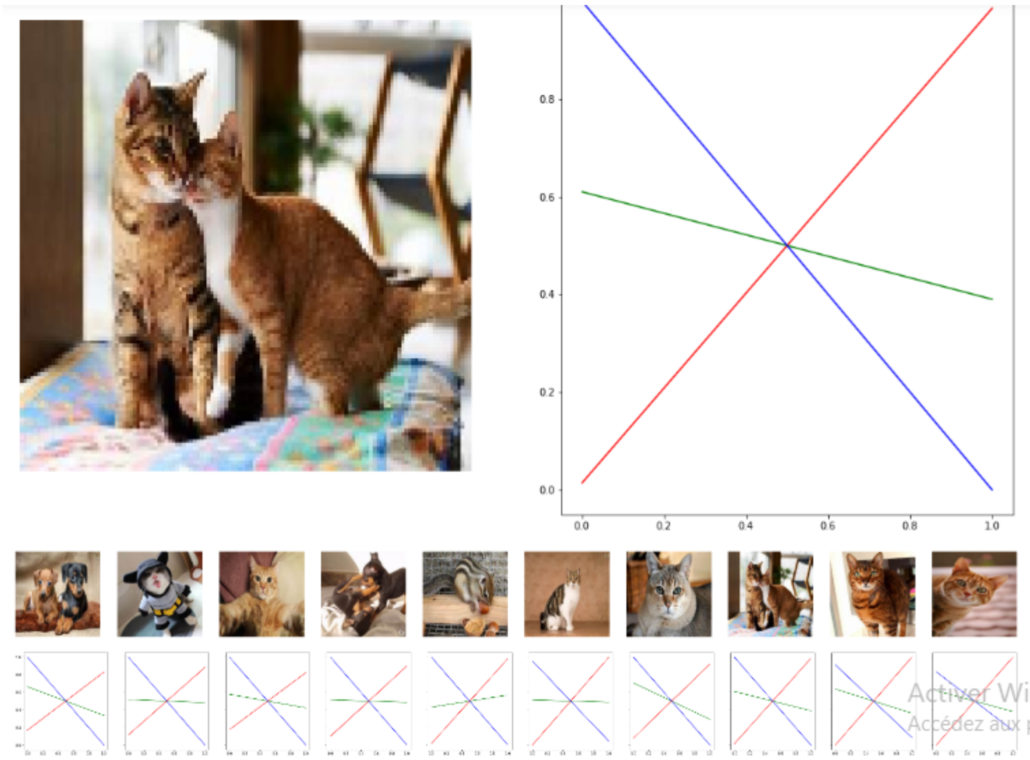

Figure 5.11: intersection

metric	precision	recall	f-measure
chisqr	0	0	0
intersaction	70	13,2	0.39
correlation	70	13,2	0.39

Table 5.2: the performance metrics for each comparison metric

We studied after that the precision of each comparison metric over all the database and the results is shown in the figure below

We found out that the intersection metric has a slightly better precision overall ‘

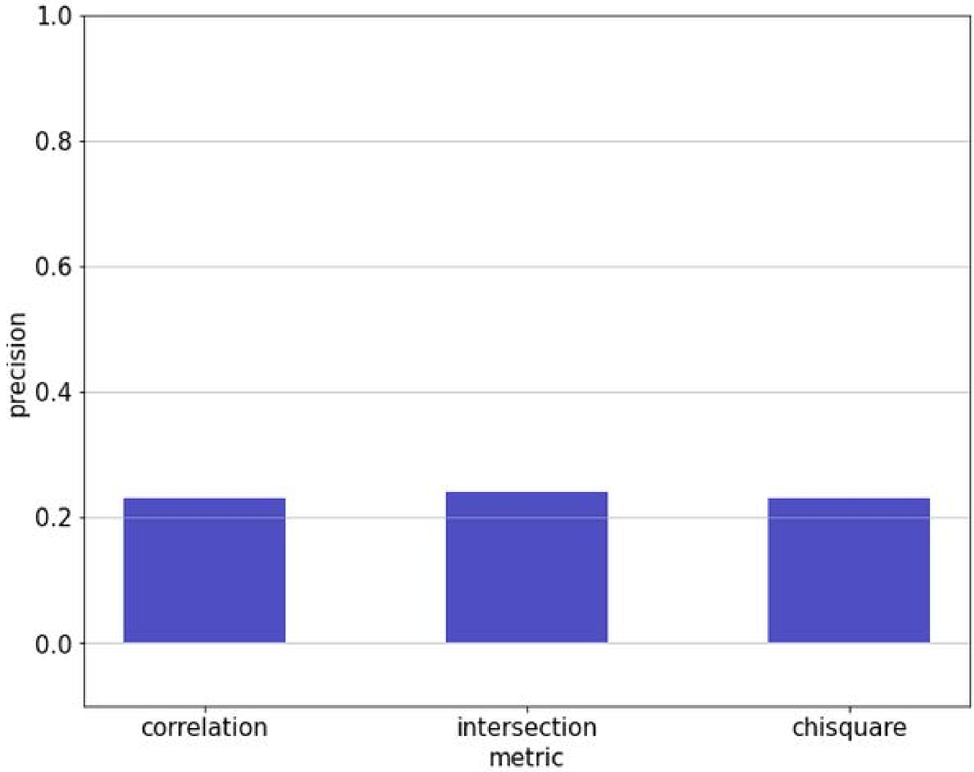

Figure 5.12: mean-precison at each metric

5.7.3 Angle in Co-occurrence Matrix

the angle in the co-occurrence matrix is an important parameter in building it thus if it changes the matrix does as well and that leads to different results(changes in performance).

angle	precision	recall	f-measure
0	20	3,7	6,24
45	40	7,5	12,63
90	50	9,4	15,82
135	30	5,6	9,43

Table 5.3: The performance metrics for each angle

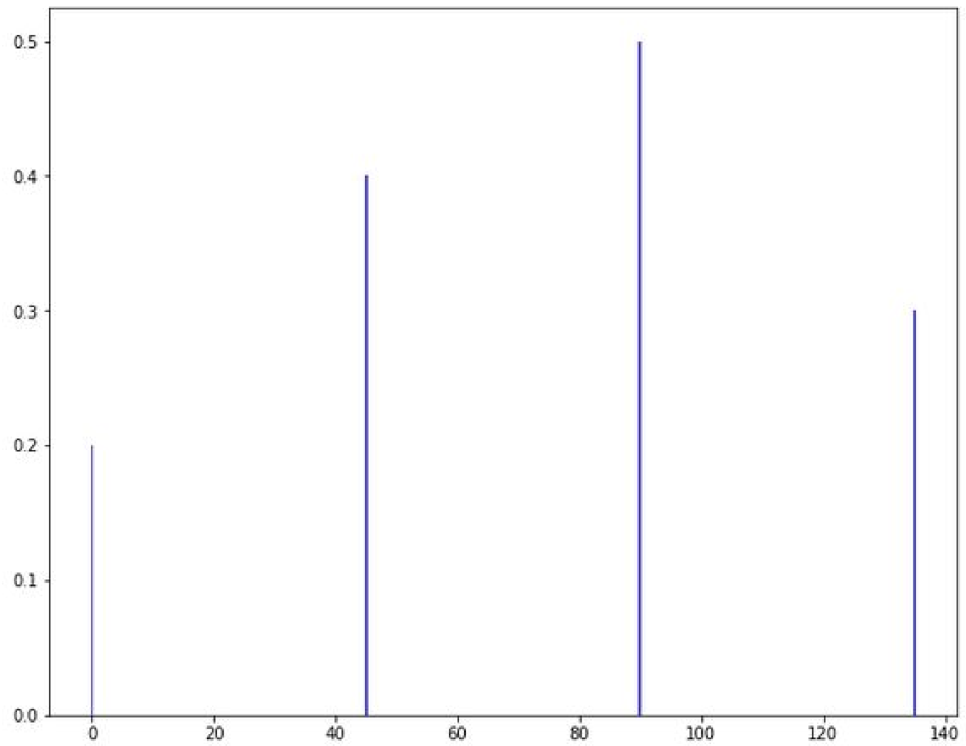

Figure 5.13: CBIR precision at different angles

5.7.4 Similarity Distance

after running the previous experiment we found that the angle 90° is the best in our proposed system so with that in mind we parsed through the different similarity distances in order to find which one is better for our system

distance	precision	recall	f-measure
cosine	50	9,4	15,82
manhattan	0	0	0
euclidean	0	0	0

Table 5.4: the performance metrics of each similarity distance

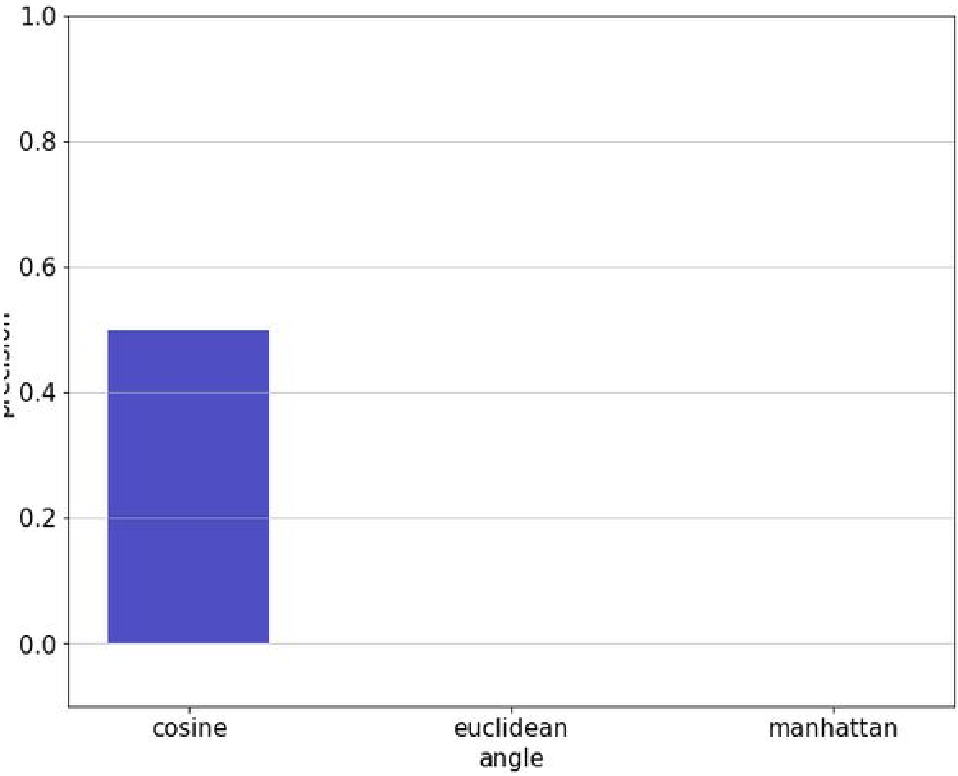

Figure 5.14: precsion at each distance

5.8 Conclusion

in this chapter we presented our work from the database used to the the used programming language and the chosen features and distances for our CBIR system, we also presented a view of our web page , and we showed the ecperiments we did before choosing the similarity distances

After running these tests and experiments we figured that the proposed systems are weak in terms of performance and satisfying user requests, after all these were the first techniques proposed and since then the CBIR domain has had a big evolution and we're seeing deep learning algorithms being performed on it such as cnn and its variant models (vggnet,resnet,densenet.....etc)

GENERAL CONCLUSION

Indexing and searching images based on their content present is complex and unavoidable challenges due to the pervasive role digital images play in our daily lives. This is particularly evident on the Internet. In our study, we focused on two main aspects: content-based image indexing and content-based image search.

Regarding image indexing, we proposed an automated approach to calculate image indexes. Our method involved analyzing color, specifically emphasizing the significance of color histograms and statistical moments.

In terms of image search, we employed a similarity-based research principle, utilizing an example image as a reference.

Throughout our work, we discovered two fundamental and critical points. Firstly, while color is a discriminating characteristic of an image, relying solely on color for content-based image retrieval (CBIR) is insufficient. It is necessary to incorporate additional descriptors such as texture and shape to enhance CBIR performance.

The domain of content-based image search is highly diverse, encompassing a wide range of techniques. There is no strict rule mandating the selection of a particular technique for image extraction based on content.

We sincerely hope that our thesis has successfully accomplished its goal, as it represents more than just a minor contribution within this expansive domain.

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