

Image Based Search Engine with Deep Learning

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Abstract: The objective of this paper is to present a brief overview of existing Image Based Search Engine (IBSE) technique. The IBSE method is used to retrieve relevant images from the database based on the query image submitted by the user. The retrieval of images from a database relies purely on the image features such as color, shape and object identification using texture(s) in the query image. The CBIR area is more diverse as it is used in different domains like medical image diagnosis, classification and face recognition etc. The objective of this paper is to analyzing and discussing the latest developments in this field. Comparison contains the methodological analysis along with the prospective advantages and disadvantages. The results discussion of the previous methodologies has been analyzed also. It provides the gap identifications and future challenges which can be redirected in the near future. This discussion is based on the retrieval techniques which used the color, texture, shape and dominant color in the image retrieval.

Keywords: IBSE, Feature Extraction, Feature Dimension, Dimensionality Reduction, Relevance Feedback, Similarity Measures.

I. INTRODUCTION

The aim of this project is to examine the current state of Image-Based Search Engines (IBSE), which allow users to find images based on visual content rather than text-based queries. In today's digital age, the ability to search for images efficiently is becoming increasingly important. Traditional text-based search engines are not always effective when it comes to finding visual content. As a result, there's a growing demand for image-based search engines that can understand and retrieve images based on their visual content rather than relying solely on textual descriptions.

Image-Based search engines that quantify the contents of an image are called Content-Based Image Retrieval (CBIR) systems. The term CBIR is commonly used in the academic literature, but in reality, it's simply a fancier way of saying "Image-Based Search Engine", with the added poignancy that the search engine is relying strictly on the contents of the image and not any textual annotations associated with the image.

Image based search engines cater to various professional groups, including designers, architects, and visual artists, who often need to locate specific images quickly and efficiently. These engines utilize advanced computer vision techniques to extract features such as colour, texture, and shape from images, enabling users to search for visually similar content.

When a user submits an image query, the query image undergoes similar preprocessing and feature extraction steps as the indexed images, followed by a comparison with the indexed features using various similarity metrics such as Euclidean distance, cosine similarity, or learned distance metrics from siamese or triplet networks. The retrieved images are then ranked based on their similarity to the query image, with the most relevant images presented to the user. In response to the increasing demand for efficient visual content retrieval, our project focuses on developing an image-based search engine capable of accurately retrieving images based on user provided queries.

The project involves several key components, including image preprocessing to extract relevant features, feature extraction to represent images in a high-dimensional feature space, indexing to organize the feature representations for fast retrieval, query processing to match user queries with indexed images, and ranking algorithms to present the most relevant images to the user. Challenges such as selecting discriminative features, handling large datasets efficiently, and bridging the semantic gap between low-level features and high-level semantics are addressed throughout the development process.

A user-friendly interface is also implemented to facilitate interaction with the search engine, allowing users to upload images, view search results, and refine their queries. The project aims to provide a powerful tool for image retrieval, with future enhancements focusing on incorporating multimodal features, improving the user interface, and exploring novel deep learning architectures to further enhance retrieval accuracy.

II. REVIEW OF LITERATURE

A. **Radha Rani, Tarun Kumar GMT College Haryana – 2016** : This paper presents a modified approach for Content-Based Image Retrieval (CBIR) systems, aiming to improve the accuracy and efficiency of image retrieval processes. The authors highlight the limitations of traditional text-based image retrieval methods and introduce CBIR as a more effective alternative, where images are indexed and retrieved based on their visual content, such as colour, texture, and shape. The proposed approach utilizes the K Nearest Neighbor (KNN) classifier along with the Jaccard coefficient to enhance the relevance of retrieved images. By employing the Jaccard coefficient, the authors claim to achieve better results compared to previous methods.

B. **D Vetrithangam , Dr N Uma Maheswari, Dr R Venkatesh R.V.S. College of Engineering-2017**: Provides Content Based Image Retrieval Based On Low Level Features Using Genetic Algorithm with K-MEANS Clustering Advanced Content-Based Image Retrieval (CBIR) system designed to enhance the accuracy and efficiency of image retrieval based on content descriptors. The system employs a combination of colour, texture, and shape features to describe image content comprehensively. Colour features are extracted using an Improved Colour Coherence Vector method, while shape features utilize the Fast Fourier descriptor method, and texture features are extracted through the multi-resolution Gabor filter. These distinct descriptors are fused to form a unified feature vector, facilitating a more thorough representation of image content.

C. **Abhra Chaudhuri University of Exeter, UK- 2022**: Presents Cross-Modal Fusion Distillation for Fine-Grained Sketch-Based Image Retrieval. The paper introduces a novel approach to fine-grained sketch-based image retrieval (FG-SBIR) by proposing a cross-modal fusion framework for Vision Transformers (XModalViT). Traditionally, FG-SBIR systems discard modality-specific information, missing out on potentially valuable complementary details. Instead, the authors advocate for a method that preserves and integrates such information from both photo and sketch modalities. Representation learning for sketch-based image retrieval has mostly been tackled by learning embeddings that discard modality-specific information. Our framework first maps paired data points from the individual photo and sketch modalities to fused representations that unify information from both modalities. We then decouple the input space of the aforementioned modality fusion network into independent encoders of the individual modalities via contrastive and relational cross-modal knowledge distillation. Such encoders can then be applied to downstream tasks like cross-modal retrieval.

D. **Umer Ali Khan, Ali Javed, Rehan Ashraf – 2021**: The paper introduces an effective hybrid framework for content-based image retrieval (CBIR) to address the challenges posed by the increasing volume of images on the internet. Traditional CBIR systems rely on textual annotations, but the proposed framework aims to reduce this dependency by analyzing image content directly. In the proposed work, first three-color moments mean, standard deviation and skewness are used to extract color features of the RGB image. Scale invariant and rotation invariant are important properties of color moment methodology. In the proposed work, we used the first three lower-order color moments because maximum information about the color distribution exists in the lower-order color moments. The usage of lower-order color moments also provides an added advantage of processing only the portion of the entire color distribution that helps to reduce the computational cost of features extraction.

E. **Thomas M Deserno, Sameer Antani, Rodney Long – 2007**: The paper provides a systematic analysis of content-based image retrieval (CBIR) in the medical field, focusing on gaps that hinder its routine use in clinical practice. It introduces a comprehensive framework comprising 13 gaps related to image content, features, system performance, and usability, along with six system characteristics impacting CBIR applicability. By categorizing prominent CBIR approaches, such as cbPACS, medGIFT, and IRMA, the paper demonstrates how the framework can be applied for system comparison and future research direction. Content-based image retrieval (CBIR) is a promising technology to enrich the core functionality of picture archiving and communication systems (PACS). CBIR has a potentially strong impact in diagnostics, research, and education.

F. **Shriram K V, P L K Priyadarshini, Subashri V – 2012**: The paper presents an analysis and suggestions for improvement in Content-Based Image Retrieval (CBIR) systems. It begins by discussing the limitations of keyword-based image search engines and emphasizes the need for more accurate and efficient retrieval methods. Delves into the intricacies of Content-Based Image Retrieval (CBIR) systems, aiming to improve their efficiency and accuracy. It critiques the reliance on keyword-based image search engines, which often yield irrelevant results due to manual naming constraints. Instead, the authors advocate for a more robust approach based on image content analysis, particularly focusing on color and texture properties.

G. Nitisha Soni, Latika Pinjarkar Shri Shankaracharya Technical Campus Bhilai, India – 2017:

The paper titled "Content Based Image Retrieval (CBIR): Review and Challenges" by Soni and Pinjarkar (2017) provides an overview of CBIR systems and discusses the challenges associated with them. The authors highlight the significance of CBIR in various fields such as medical imaging, remote sensing, and satellite imaging. They emphasize the importance of features like color, texture, and shape in indexing database images and retrieving relevant information. The paper reviews existing research in CBIR, citing examples from recent studies and discussing the techniques and methodologies employed. It presents a comparative analysis of different feature extraction methods, including color moments, color histograms, texture measures like Gabor filters and wavelet transform, and shape descriptors like moment invariants and Fourier transform.

H. Hui Hui Wang, Dzulkifli Mohamad, N.A. Ismail – 2010: This paper provides an extensive examination of the evolution, challenges, and future trajectories of image retrieval methodologies. It delves into the historical progression, tracing the shift from early keyword-based systems to the advent of content-based approaches in the 1980s, and finally to the current emphasis on semantic-based retrieval. Throughout this evolution, the primary motivation has been the exponential growth of digital image data and the increasing need for effective retrieval mechanisms.

I. Afshan Latif, Aqsa Rasheed, Umer Sajid, Jameel Ahmed, Nouman Ali – 2019: The review on Content-Based Image Retrieval (CBIR) and feature extraction techniques provides a comprehensive analysis of the challenges and advancements in the field. With the proliferation of digital cameras, smartphones, and the internet, the need for efficient image retrieval systems has become increasingly pronounced. Traditional text-based approaches often yield unsatisfactory results due to discrepancies between human visual perception and manual labeling. To address this, researchers have developed automatic image annotation systems that analyze image content based on features such as color, texture, shape, and spatial layout, thereby improving the relevance of retrieved images. CBIR relies heavily on low-level visual features like color histograms, texture descriptors, and shape representations for matching query images with those in the archive.

III. IMPLEMENTATION

The goal of the implementation phase is to translate the system design into code into a programming language which can be executed by computer and that performs the computation specified by the design. The criteria for a good program include reliability, size of the program, execution time and the required memory. The entire project is developed using Python using Anaconda Navigator IDE with NumPy, Keras, TensorFlow, PIL.

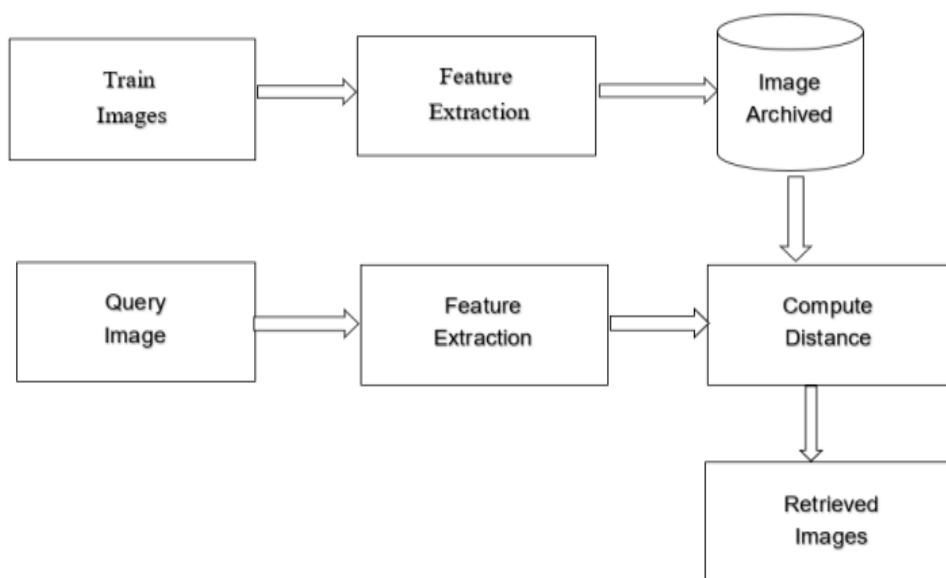
Propose System:

Figure 1: Architecture of Proposed System

The earliest use of the term content-based image retrieval in the literature seems to have been by, to describe his experiments into automatic retrieval of images from a database by color and shape feature. The term has since been widely used to describe the process of retrieving desired images from a large collection on the basis of features (such as colour, texture and shape) that can be automatically extracted from the images themselves.

The features used for retrieval can be either primitive or semantic, but the extraction process must be predominantly automatic. Retrieval of images by manually-assigned keywords is definitely not CBIR as the term is generally understood – even if the keywords describe image content. There exists many steps which are involved in CBIR namely, database collection, feature extraction for images, image archive, distance of retrieved images. Each of these steps consists of many methods that contribute to improved results.

Step 1: Database collection – Different databases are available, which are related to CBIR such as Clatech256, Cifar10, RSSCN7, ISIC2018, ISIC2019, AID etc. The general block diagram of image based search engine is represented in the above figure.

Step 2: Feature Extraction for train images – Feature extraction is used to achieve better performance. Significant transformations such as rotation, translation, changes in illuminations does not affect the single or limited number of extracted features. This work is mainly related to the image objects, background and foreground. The reduction of the dimension in an image object is referred to as feature extraction. In this step, mainly feature extraction of train images is made. The extracted features are gathered together and combined within the generated features. After the extraction of the features from the database images, the comparison is made between the relevant images and the input query images.

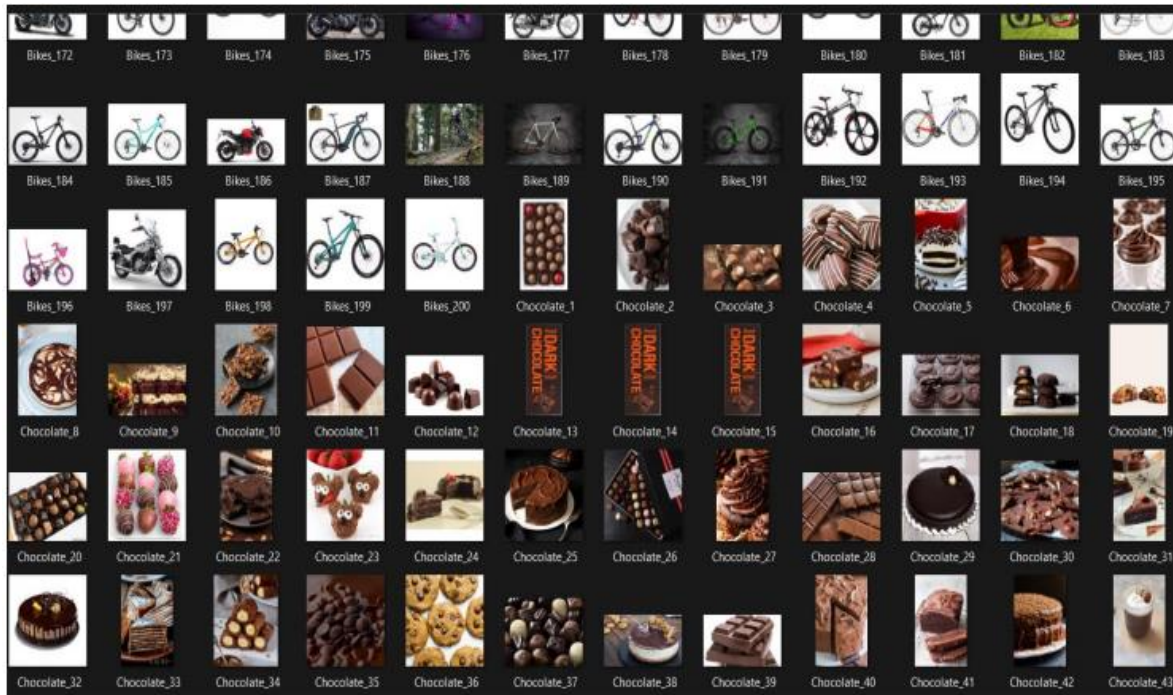
Step 3: Image archive – Feature extraction of the train images is followed by image archive. The collection of images which are created or brought together by an individual or institution. It acquires the images from different sources and assembles them into the collections that can be accessed and qualified further. The image which followed the feature extraction is dumped into the image archive, which is always available for the further extraction process.

Step 4: Feature extraction for Query images – The extracted features are gathered together and combined within the generated features. After the extraction of the features from the database images, the comparison is made between the relevant images and input query images. Due to the development of recent technology, complexity of multimedia is increasing in new research areas. CBIR systems are used in the retrieval of images which are related to the Query Images (QI) from large databases. “Query by example” is the technique used by CBIR algorithm to retrieve the image. The query image extracts the color signature, shape and texture of the image. At last, CBIR performs the similarity measure using the metaheuristic algorithm (MA) in-between the QI features and the database image features. Accordingly, from the image database, most of the images are related to the QI and are retrieved by CBIR.

Step 5: Distance of retrieved images – Retrieved images are the images with the indices, which are denoted with the genes, that the best features are carried out. The CBIR technique system is tested with the use of several query images and similar images that were retrieved from the database images. The measured recall parameter or the recall rate is the true positive rate and is used to evaluate the ability of the CBIR system regarding the number of retrieved relevant images which are compared to all the similar images in the database. The increase in the retrieved images will improve the precision and recall rates. The result will be on the extracted color, shape and texture features which are combined in the overall process of CBIR with respect to its accuracy and efficiency.

Dataset: The dataset we have produced contains thousands of photos, each of which has a resolution of 256x384 pixels. It basically involves uploading an image using a browser, and the deep features, which are done in pure Python, will return images of a similar type.

Similar images will be fetched after the photographs are uploaded for the similarity search in the web interface. The availability of numerous open-source libraries makes it simple to design and deploy an image processing system.

**Figure 2: Dataset**

We use Keras which is the most famous deep learning libraries and flask which is again the most popular web server system and all code approved here. In structure of the directory, we will implement three different python files,.The first one is the feature_extractor.py followed by offline.py and server.py and the includes static, feature, img uploaded and index.html. So, in offline step we take database image as an input then run offline.py so inside this function there is a feature extractor which has keras with VGG16 model by using this we extract deep features.

In online phase, we need the features extracted from the offline.py so this will be server.py, inside server.py there is web server(flask) the user accesses the browser then upload images to this flask and call feature extractor the extract deep features and these deep features are compared with the database feature then the similar one is retired so this is the whole system. First, we need to create a make directory (mkdir) static, feature directory, image directory and uploaded so next we'll put some test images say suppose we select five images in offline.py. Next we implement POST, and we need to return received query image, so when we access this website it is a GET action, inside the index function there is a render template, if we send an image there is a POST action so what happens here, it need to return the revived query image, now we can process query image. So if we select a query image then the similar images will be retrieved in the result.

IV. EXPERIMENTAL RESULTS

```
Anaconda Prompt - python c x + - - - - - x
(base) C:\Users\Intel>
(base) D:\>cd IBSE Project
(base) D:\IBSE Project>python offline.py
2024-04-08 22:11:31.985939: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable 'TF_ENABLE_ONEDNN_OPTS=0'.
2024-04-08 22:11:37.942112: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable 'TF_ENABLE_ONEDNN_OPTS=0'.
2024-04-08 22:12:07.730405: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
static\img\Apple_1.jpg
1/1 ----- 3s 3s/step
static\img\Apple_10.jpg
1/1 ----- 1s 516ms/step
static\img\Apple_100.jpg
1/1 ----- 1s 507ms/step
static\img\Apple_101.jpg
1/1 ----- 1s 705ms/step
static\img\Apple_102.jpg
1/1 ----- 1s 510ms/step
static\img\Apple_103.jpg
1/1 ----- 1s 559ms/step
static\img\Apple_104.jpg
1/1 ----- 1s 532ms/step
static\img\Apple_105.jpg
```

Figure 3: Anaconda Prompt

```
Anaconda Prompt - python s x + v
- □ X

(base) C:\Users\Intel>:

(base) D:\>cd IBSE Project

(base) D:\IBSE Project>python server.py
2024-04-08 22:16:52.545956: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable 'TF_ENABLE_ONEDNN_OPTS=0'.
2024-04-08 22:16:57.909840: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable 'TF_ENABLE_ONEDNN_OPTS=0'.
2024-04-08 22:17:24.052588: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
* Serving Flask app 'server'
* Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
* Running on all addresses (0.0.0.0)
* Running on http://127.0.0.1:5000
* Running on http://192.168.97.58:5000
Press CTRL+C to quit
```

Figure 4: Fetching IP Address

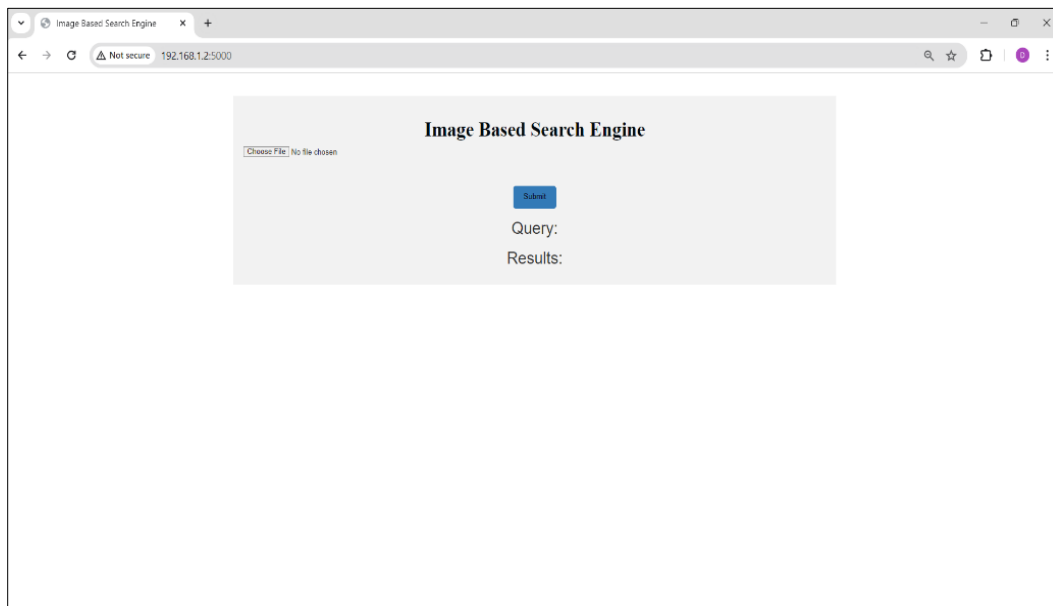


Figure 5: Main Page

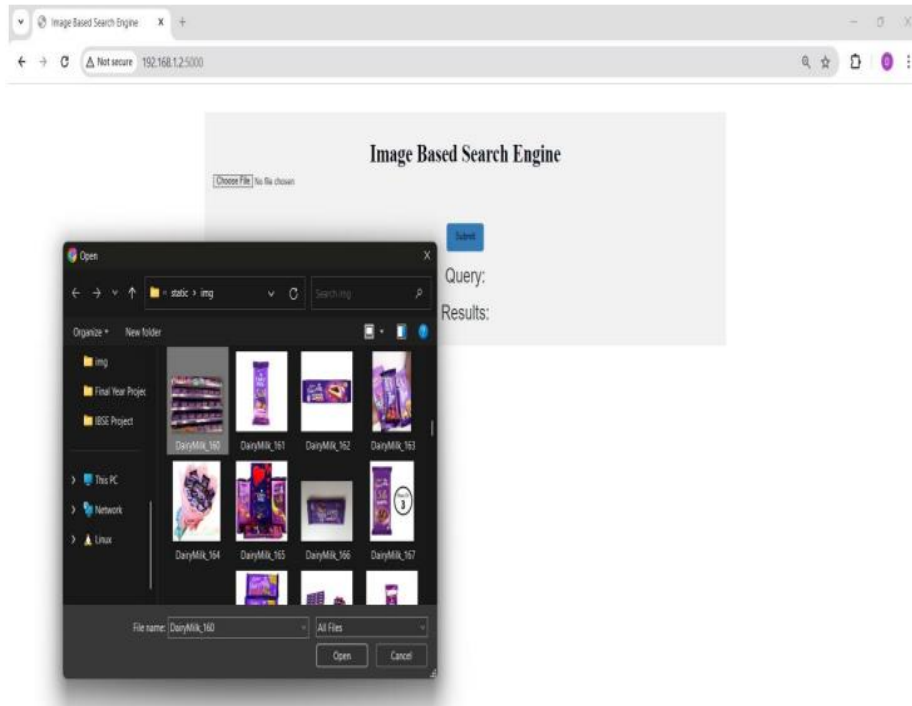


Figure 6: Selecting an Image

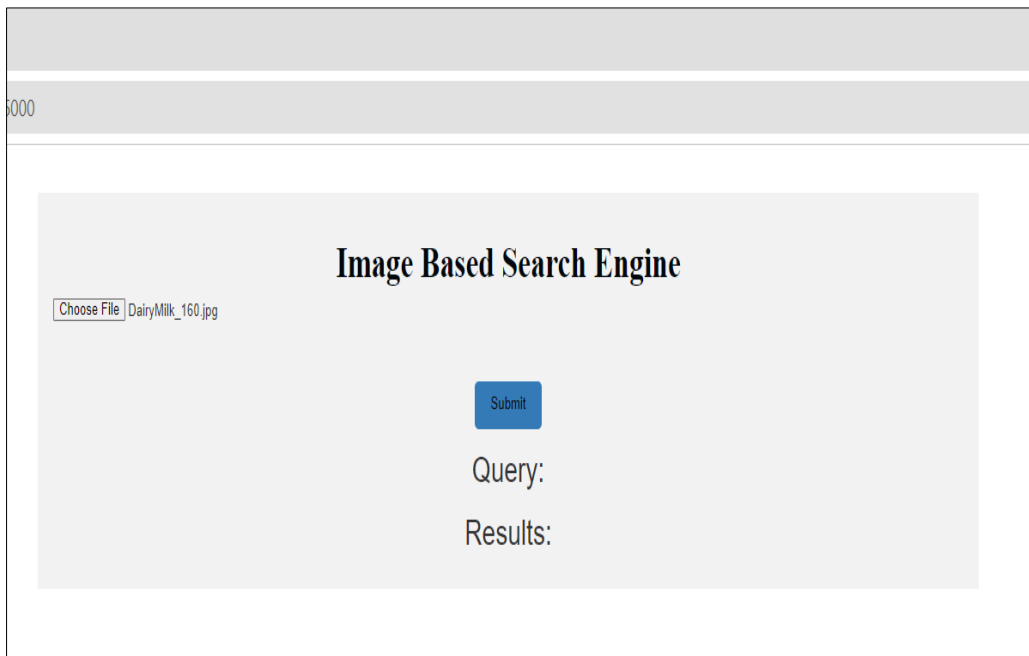


Figure 7: Searching an Image File



Figure 8 : Final Output 1

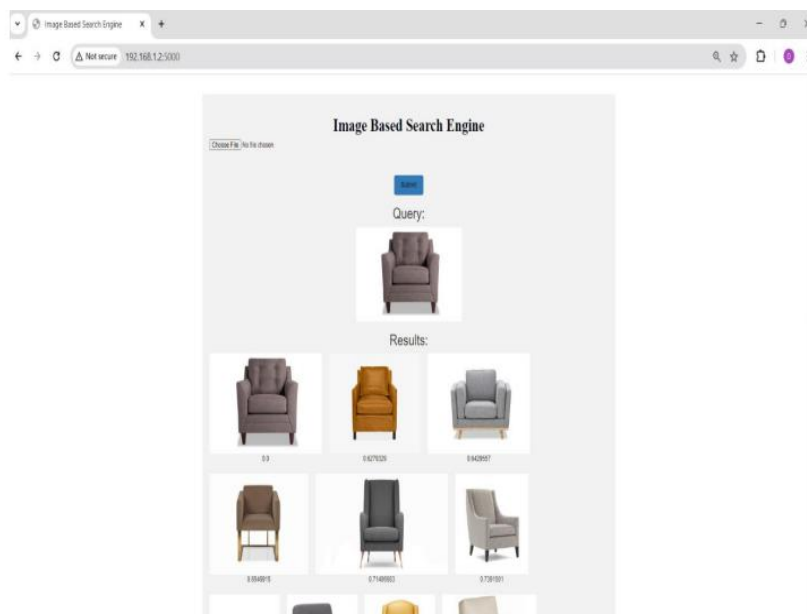


Figure 9 : Final Output 2

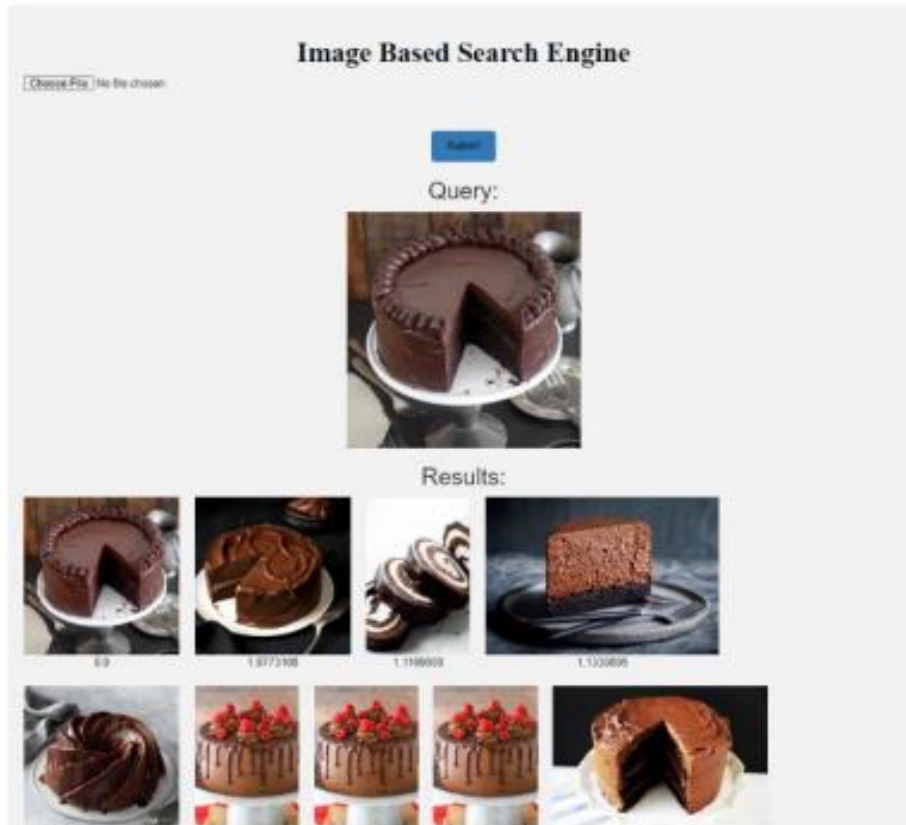


Figure 10 : Final Output 3

V. CONCLUSION

The dramatic rise in the sizes of images databases has stirred the development of effective and efficient retrieval systems. The development of these systems started with retrieving images using textual connotations but later introduced image retrieval based on content. This came to be known as CBIR or Content Based Image Retrieval. Systems using CBIR retrieve images based on visual features such as colour, texture and shape, as opposed to depending on image descriptions or textual indexing.

In this project, we have researched various modes of representing and retrieving the image properties of colour, texture and shape. Due to lack of time, we were only able to fully construct an application that retrieved image matches based on colour and texture only. The application performs a simple colour-based search in an image database for an input query image, using colour histograms. It then compares the colour histograms of different images using the quadratic distance equation.

Further enhancing the search, the application performs a texture-based search in the colour results, using wavelet decomposition and energy level calculation. It then compares the texture features obtained using the Euclidean distance equation.

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