IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

ISO 3297:2007 Certified ⁜ Impact Factor 8.066 ⁜ Peer-reviewed / Refereed journal ⁜ Vol. 10, Issue 5, May 2023

DOI: 10.17148/IARJSET.2023.10529

An Adaptive Approach to Content Based Image Retrieval using Deep Learning

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Abstract: Large picture datasets are now possible thanks to developments in image capturing and data storage. In this case, it's essential to create the right information systems to manage these collections effectively. The method in question is known as a content-based picture retrieval system. In essence, these systems attempt to find images that match a user-defined standard or pattern (for example, a form drawing or a mage example). Their objective is to facilitate picture retrieval based on feature vectors that are often stored with content qualities (such as form, colour, and texture). The ability to perform automatic retrieval instead of the extra keyword-based technique, which typically necessitates very hard and time-consuming earlier annotation of database photos, is one of the main benefits of the Content Based Image Retrieval (CBIR) approach. Applications of the CBIR technology include fingerprint identification, biodiversity information systems, digital libraries, crime prevention, medical, and historical research. This project intends to highlight the state of the art of the current research in this field, define the problems and challenges related to the response of CBIR systems, and describe the existing solutions and applications.

Keywords: Deep Learning, Content Based Image Retrieval, Keras, TensorFlow.

I. INTRODUCTION

The overview of this project is to review the current state of the art in content-based image retrieval (CBIR), a technique for retrieving images on the basis of automatically-derived features such as color, texture and shape. Our findings are based both on a review of the relevant literature and on discussions with researchers in the field. The need to find a desired image from a collection is shared by many professional groups, including journalists, design engineers and art historians. While the requirements of image users can vary considerably, it can be useful to characterize image queries into three levels of abstraction: primitive features such as color or shape, logical features such as the identity of objects shown and abstract attributes such as the significance of the scenes depicted. While CBIR systems currently operate effectively only at the lowest of these levels, most users demand higher levels of retrieval.

The key distinction between content-based and text-based retrieval systems is that the latter system absolutely requires human engagement. Humans typically utilise high-level features (concepts), such as text descriptors and keywords, to analyse photos and determine how similar they are. While the low-level features (colour, texture, shape, spatial arrangement, etc.) automatically extracted using computer vision techniques. Generally speaking, there is no symbiotic relationship between high-level concepts and low-level aspects.

Though numerous complex algorithms have been developed to characterise colour, shape, and texture attributes, these methods fall short when it comes to modelling image semantics and have numerous restrictions when working with image databases containing a wide range of information. Numerous CBIR system experiments demonstrate that low-level contents frequently fall short of describing the high-level semantic notions.

Since the past ten years, research has been ongoing in the field of content-based image retrieval (CBIR). Numerous applications, including security, medical imaging, and audio and video recovery, still require a lot of work. The primary focus of this essay is on the significant contributions made by different researchers to the field of CBIR approaches. After that, it talks about various gaps in the literature that were discovered when existing image retrieval algorithms were modified to create viable systems. Three features, namely colour, form, and texture, are combined to successfully execute the CBIR system in this case. The primary goal of the effort is to develop an analysis that can more efficiently gather the most comparable photos from a large number of databases.

The rest of this paper is organized as follows. The next section composes a review of similar researches that have been implemented and tested for CBIR. In Section III, the proposed algorithm is described. The stages of the CBIR algorithm. In Section IV, experimental results are reported. Finally, some conclusions are given and future work is proposed.

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II. REVIEW OF OTHER METHODS

Literature Survey is most important step in the software development process. Before developing the tool, it is necessary to determine the time factor, economy and company strength. Once these things are satisfied, the next step is to determine which operating system and language can be used in developing the tool.

A. Color retrieval

Several methods for retrieving images on the basis of color similarity have been described in the literature, but most are variations on the same basic idea. Each image added to the collection is analyzed to compute a color histogram which shows the proportion of pixels of each color within the image. The color histogram for each image is then stored in the database. At search time, the user can either specify the desired proportion of each color (75% olive green and 25% red, for example), or submit an example image from which a color histogram is calculated. Either way, the matching process then retrieves those images whose color histograms match those of the query most closely. The matching technique most commonly used, histogram intersection, was first developed by Swain and Ballard [1991]. Variants of this technique are now used in a high proportion of current CBIR systems. Methods of improving on Swain and Ballard's original technique include the use of cumulative color histograms, combining histogram intersection with some element of spatial matching, and the use of region-based color querying.The results from some of these systems can look quite impressive.

B. Texture retrieval

The ability to retrieve images on the basis of texture similarity may not seem very useful. But the ability to match on texture similarity can often be useful in distinguishing between areas of images with similar color (such as sky and sea, or leaves and grass). A variety of techniques has been used for measuring texture similarity; the best-established rely on comparing values of what are known as second-order statistics calculated from query and stored images. Essentially, these calculate the relative brightness of selected pairs of pixels from each image.

From these it is possible to calculate measures of image texture such as the degree of contrast, coarseness, directionality and regularity, or periodicity, directionality and randomness. Alternative methods of texture analysis for retrieval include the use of Gabor filters and fractals. Texture queries can be formulated in a similar manner to color queries, by selecting examples of desired textures from a palette, or by supplying an example query image. The system then retrieves images with texture measures most similar in value to the query. A recent extension of the technique is the texture thesaurus, which retrieves textured regions in images on the basis of similarity to automatically-derived code words representing important classes of texture within the collection.

C. Shape retrieval

The ability to retrieve by shape is perhaps the most obvious requirement at the primitive level. Unlike texture, shape is a fairly well-defined concept – and there is considerable evidence that natural objects are primarily recognized by their shape. A number of features characteristic of object shape (but independent of size or orientation) are computed for every object identified within each stored image. Queries are then answered by computing the same set of features for the query image, and retrieving those stored images whose features most closely match those of the query. Two main types of shape feature are commonly used – global features such as aspect ratio, circularity and moment invariants and local features such as sets of consecutive boundary segments.

Alternative methods proposed for shape matching have included elastic deformation of templates, comparison of directional histograms of edges extracted from the image, and shocks, skeletal representations of object shape that can be compared using graph matching techniques. Queries to shape retrieval systems are formulated either by identifying an example image to act as the query, or as a user-drawn sketch. Shape matching of three-dimensional objects is a more challenging task – particularly where only a single 2-D view of the object in question is available. While no general solution to this problem is possible, some useful inroads have been made into the problem of identifying at least some instances of a given object from different viewpoints. One approach has been to build up a set of plausible 3-D models from the available 2-D image, and match them with other models in the database. Another is to generate a series of alternative 2-D views of each database object, each of which is matched with the query image. Related research issues in this area include defining 3-D shape similarity measures, and providing a means for users to formulate 3-D shape queries.

D. Retrieval by other types of primitive feature

One of the oldest-established means of accessing pictorial data is retrieval by its position within an image. Accessing data by spatial location is an essential aspect of geographical information systems, and efficient methods to achieve this have been around for many years. Similar techniques have been applied to image collections, allowing users to search for images containing objects in defined spatial relationships with each other. Improved algorithms for spatial retrieval

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are still being proposed. Spatial indexing is seldom useful on its own, though it has proved effective in combination with other cues such as color and shape.

III. METHODOLOGY

Software called Anaconda was used to create our project. A desktop GUI called Anaconda Navigator is included with Anaconda Individual Edition. Without utilising command-line commands, it makes it simple to run apps and manage packages and environments. With over 25 million users globally, Anaconda Individual Edition is the most widely used Python distribution platform. We can rely on our ongoing dedication to assisting the Anaconda open-source ecosystem, which serves as the preferred computing environment for Python data science. You can start using thousands of free Conda, R, Python, and other open-source packages by running the conda-install command. Individual Edition is an open source, adaptable system that offers the tools to cross-platformly create, distribute, install, update, and manage software. Conda makes managing various data environments simple.

The system architecture of content based image retrieval is shown below.

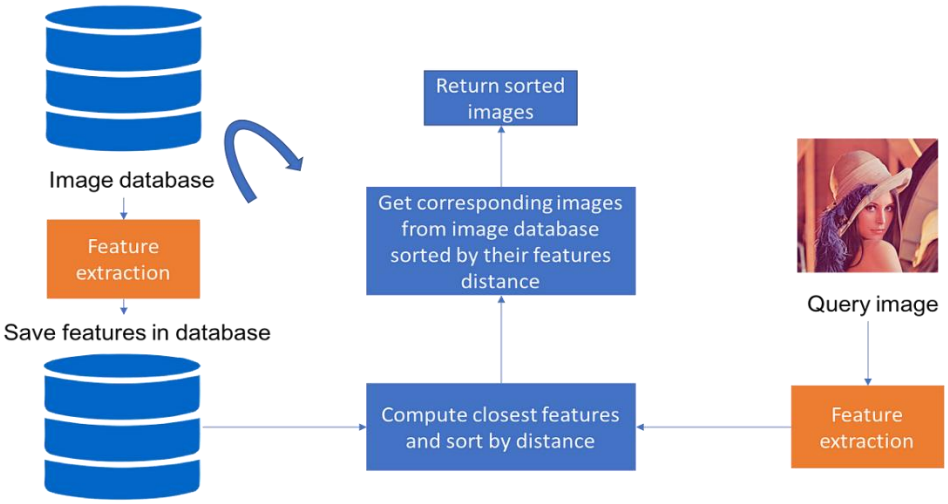

Figure 1: System Architecture

Proposed System

1. CBIR is the application of computer vision to the image retrieval problem, that is, the problem of searching for digital images in large databases.
2. Images have rich content.
3. This content can be extracted as various content features like color, pixel based.
4. Take the responsibility of forming the query away from the user.
5. Each image will now be described by its own features.

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.

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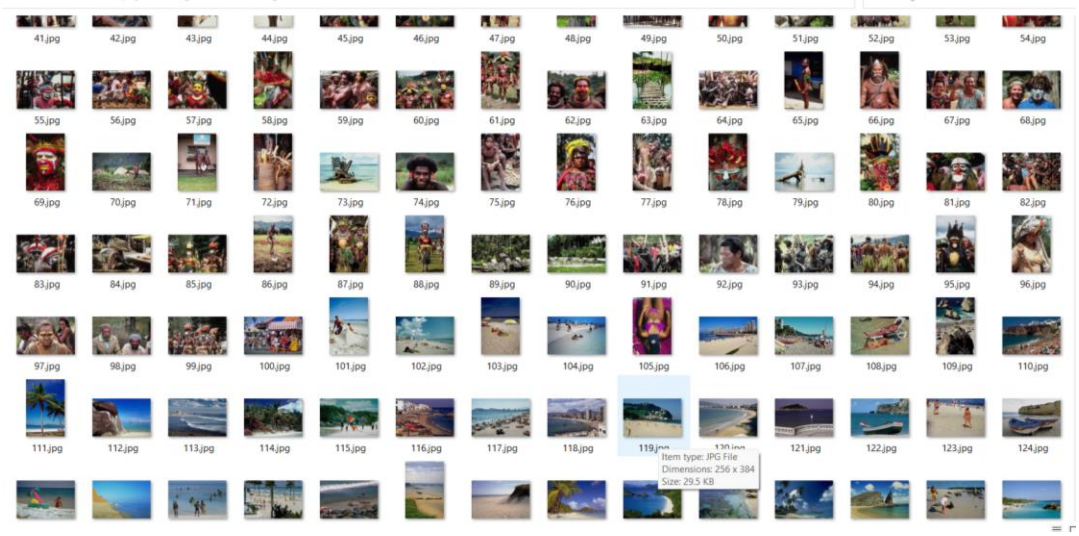

Figure 2: Dataset

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

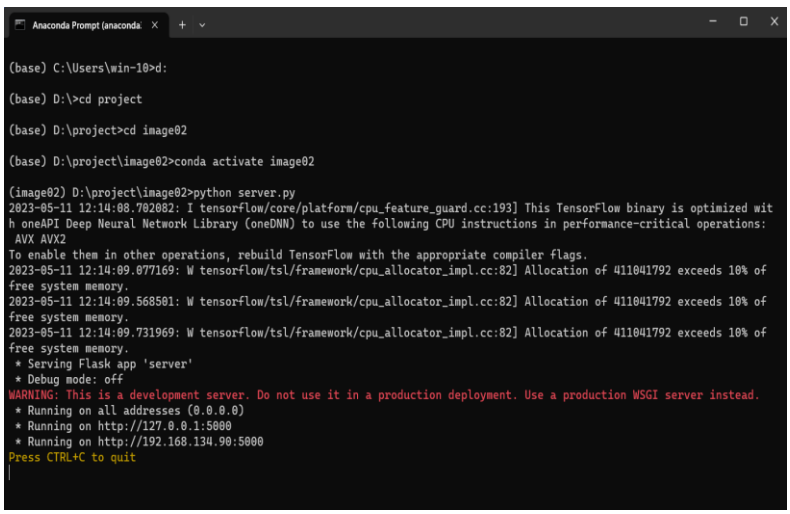

Figure 3: Anaconda Prompt

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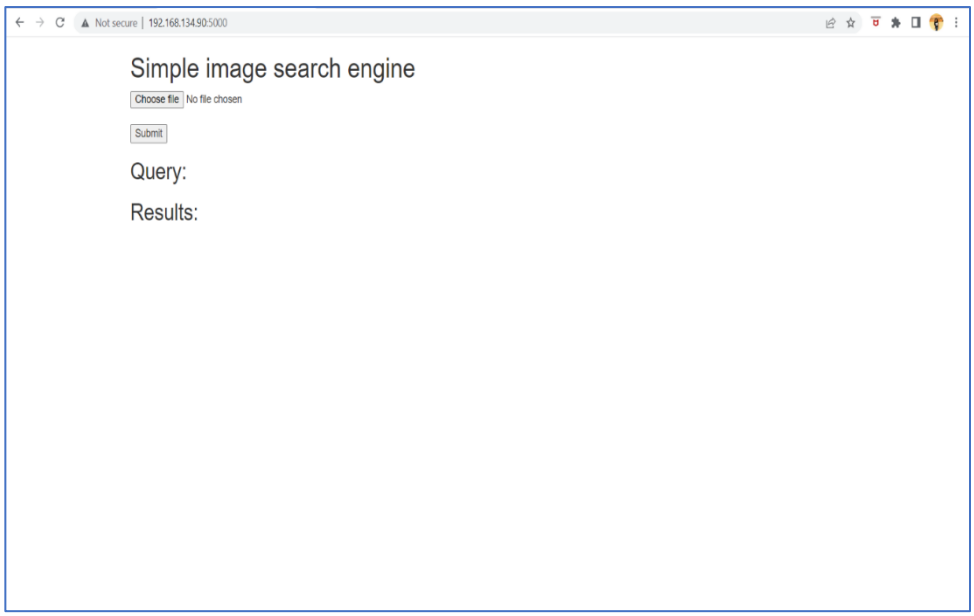

Figure 4: Main Page

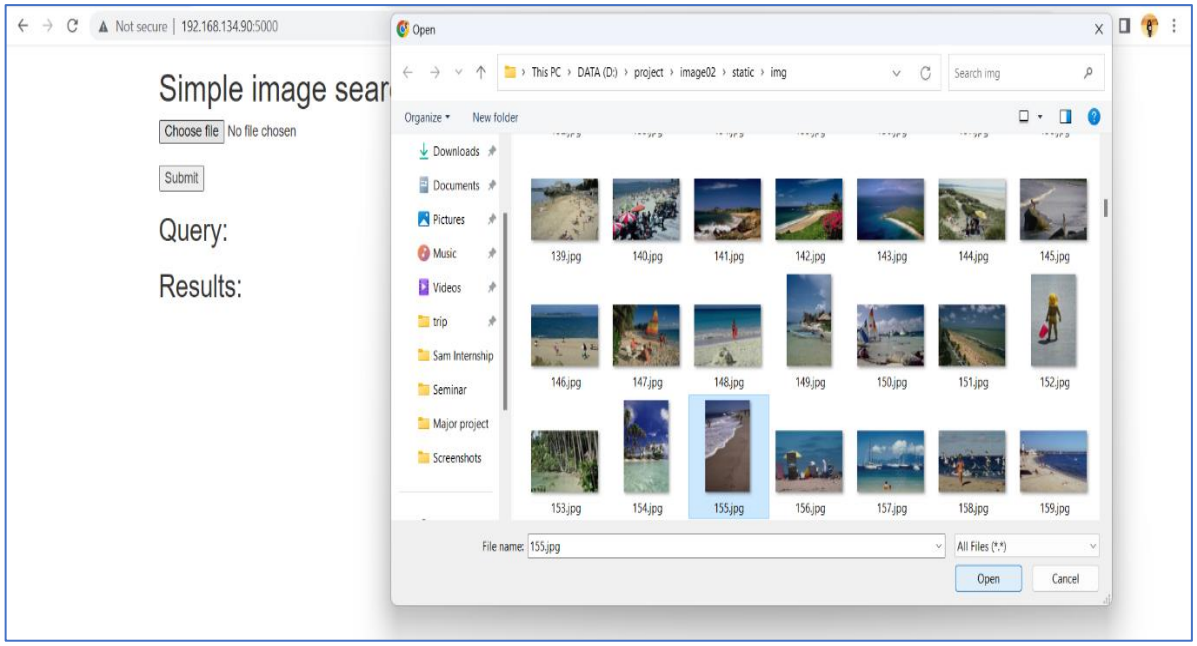

Figure 5: Selecting an image file

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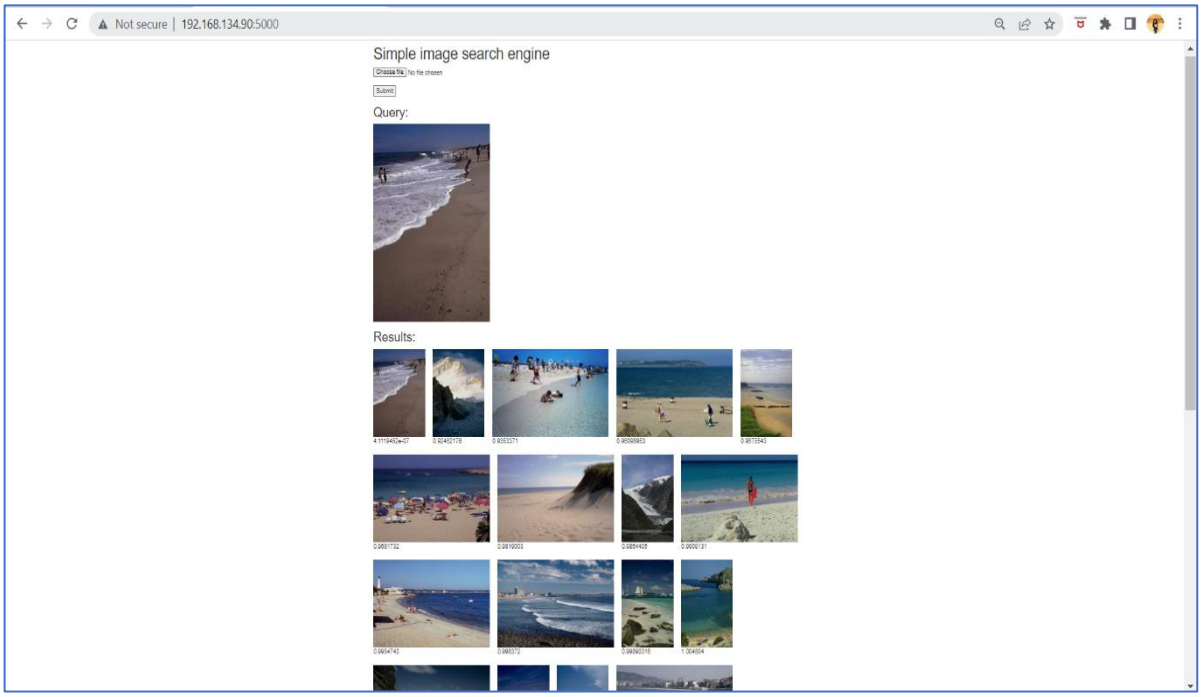

Figure 6: Resultant Image 1

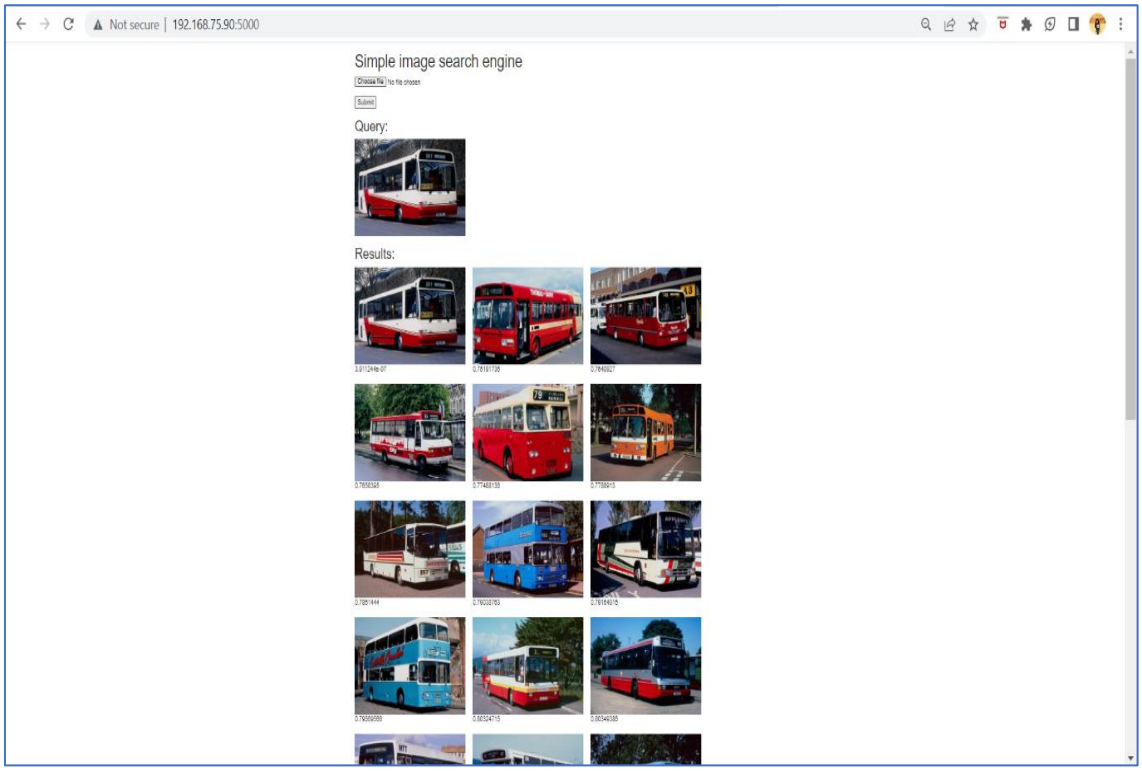

Figure 7: Resultant Image 2

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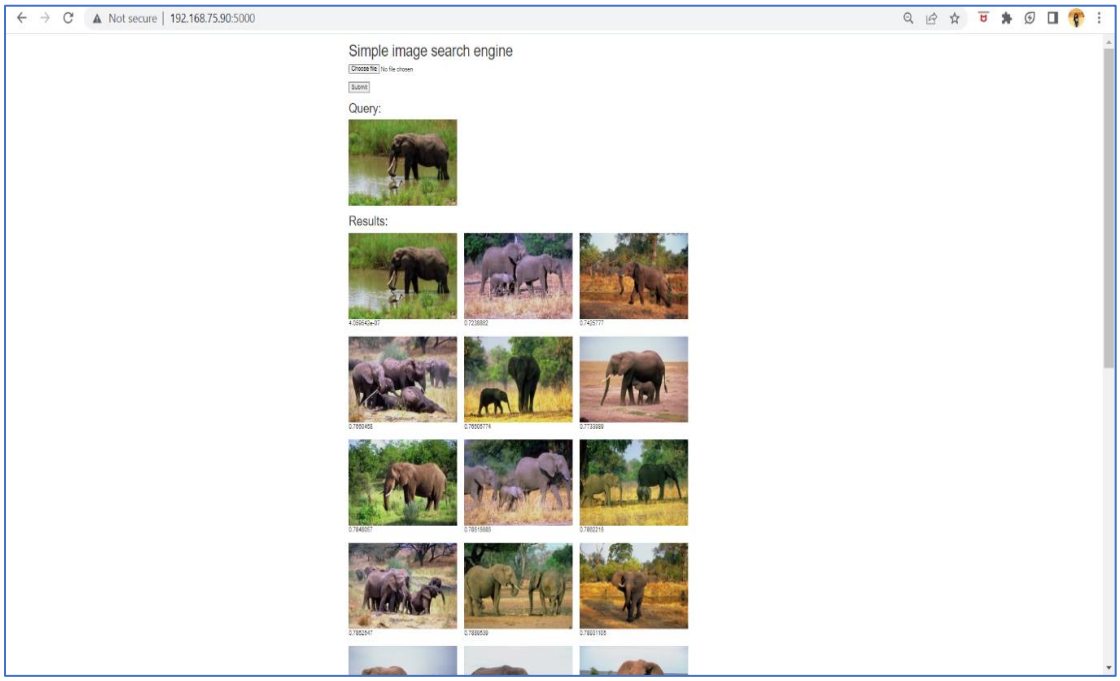

Figure 8: Resultant Image 3

V. CONCLUSION

The development of effective and efficient retrieval methods has been sparked by the sharp increase in the size of image databases. These systems' creation first focused on obtaining images based on textual connotations, but eventually added image retrieval based on content. CBIR, or content-based image retrieval, became the name for this process. Instead than relying on image descriptions or textual indexing, systems implementing CBIR retrieve images based on visual qualities including colour, texture, and shape. In this study, we investigated alternative ways of storing and retrieving the colour, texture, and geometry of an image. We were only able to fully build an application that only obtained image matches based on colour and texture due to time constraints.

The programme uses wavelet decomposition and energy level computation to do a texture-based search in the colour results, further enhancing the search. The texture features that were produced using the Euclidean distance equation are then compared. These texturing results would be improved further by a more thorough stage that utilised a shape-based search. CBIR is still a young scientific field. CBIR keeps the rate of advancement in the research sector steady as techniques for image compression, digital image processing, and image feature extraction advance. Additionally, the growth of greater processing power as well as quicker and less expensive memories has a significant impact on CBIR development. This innovation indicates a wide range of CBIR uses in the future.

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