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OPTIMIZING CONTENT BASED IMAGE RETRIEVAL SEARCH USING DEEP BELIEF NETWORK TECHNIQUE

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Abstract

Using image content features, content-based image retrieval (CBIR) searches and retrieves digital images from a sizable database. To accomplish the searching goal, a variety of visual feature extraction techniques have been used.There are several good algorithms that are not used because of the computation time requirement. A content-based image retrieval system's retrieval effectiveness heavily depends on the feature representation and similarity measurements. The final goal of the suggested approach is to offer an effective algorithm to address the problem specification described above. Due to the development of a significant amount of data, the deep belief network (DBN) approach of deep learning is utilised here to extract the features and classify the data. The proposed method is tested through simulation in comparison and the results show a huge positive deviation towards its performance.

Keywords - Image Extraction, Deep belief networks, CBIR, Neural Networks

1. INTRODUCTION

With the aid of creativity and invention, technology is evolving to its fullest in the modern day. With such concepts in the field of ANN, the basic module is stated to be image processing stream, allowing the majority of systems to map inputs to outputs with a variety of uncertainty logic.The image will be destroyed to its matching bits and treated as a digital structure.The classification of images or videos in the current systems is challenging because their methodology focuses on file name searches rather than the content of the files themselves.The ANN should categorise the information using a variety of attributes in accordance with the user's query. In their suggested approach, each and every data point is constrained, and the contents are learned by isolating their features to the deep bottom. The database itself maintains a distinct, independent data centre with a limited number of the most important characteristics. Deep learning approach plays a clever extraction of the content from the data, which is currently in process, and displays its maximum performance to its extent. Deep learning is one of the subcategories of the soft computing phenomenon, and it may be used to extract data from millions of separated images. Although many techniques have been proposed, it remains one of the most difficult problems in current content-based image retrieval systems. The retrieval performance of a content-based image retrieval system critically depends on the feature representation and similarity measurement, which have been extensively studied by multimedia researchers for decades research on content-based image retrieval (CBIR), which is mostly as a result of the well-known "semantic gap" problem between machine-captured low-resolution image pixels and high-level semantic idea that people can perceive. From a high level, such an issue can be anchored in the primary difficulty with artificial intelligence (AI), how to create and programme machines with human-like intelligence undertake practical challenges. One method that has promise for long-term resolution of this issue is machine learning.Some significant cutting-edge new machine learning approaches have emerged in recent years. Deep learning is a subset of machine learning that consists of a family of machine learning algorithms that use deep architectures made up of numerous non-linear transformations to try and model high-level abstractions in data. Deep learning resembles how the human brain functions, which is organised in a deep architecture and processes information through numerous stages of transformation and representation, in contrast to typical machine learning techniques that frequently use "shallow" architectures. Deep learning techniques enable a system to learn complex functions that directly map raw sensory input data to the output, without relying on human-crafted features using domain knowledge. This is accomplished by exploring deep architecture features at multiple levels of abstraction from data automatically. Applying deep learning techniques to a range of applications, including speech recognition, object recognition, and natural language processing, among others, has produced positive results in numerous recent research. In this study, they aim to investigate deep learning techniques with application to CBIR challenges, motivated by the achievements of deep learning. Despite considerable academic interest in employing deep learning for image classification and recognition in computer vision, the applications of CBIR are currently receiving relatively little attention. In the suggested approach, they look into deep learning techniques for deriving feature representations from the photos and evaluating how comparable they are to CBIR tasks.

2. ANALYSIS

A deep belief network was trained in large scale for learning effective feature representation of images and framed out for CBIR. Where features of the images were first extracted and on later run those extracted features were used in training the deep belief network.

2.1 DEEP BELIEF NETWORK

A sort of deep learning technique called deep belief networks (DBNs) aims to solve the issues with conventional neural networks. They accomplish this by exploiting the network's layers of stochastic latent variables. These binary latent variables, also known as feature detectors and hidden units, are binary variables and are referred to as stochastic since they have a chance of taking on any value falling within a given range. In DBNs, the top two layers lack direction but have directed links to lower layers in the layers above them. DBNs can be generative and discriminative models, which sets them apart from conventional neural networks. For example, you can only train a conventional neural network to categorise images. DBNs differ from other deep learning techniques like restricted Boltzmann machines (RBMs) or autoencoders since they don't use raw inputs like RBMs do. Instead, they begin with an input layer that has one neuron for every input vector, proceed through numerous layers, and finally arrive at the final layer where outputs are generated using probabilities derived from the activations of the levels before it! In the DBN, there is a hierarchy of layers.The visible units are found in the lowest layer, while the top two levels include the associative memory. Arrows pointing in the direction of the lowest layer closest to the data are used to denote relationships between all lower layers. Directed acyclic connections transform associative memory into quantifiable variables in the lower layers. The lowest layer of visible units receives data input as binary or real data. Similar to RBM, DBN lacks intralayer connections. The hidden units function as features to reflect the correlations in the data. A proportional weights matrix connects two layers (W). Each layer's units will be interconnected with those in the one above them.

3. WORKING

The digital image can be handled using either the spatial domain or the frequency domain, depending on which type of transformation is needed. With some systems, image segmentation may be used to aid in content extraction. While the frequency domain characteristics will provide information relating to the frequency, etc, The spatial domain extraction will provide data on visual aspects such as colour, radiance, brightness, structures, etc. Due to the vast amount of data, the deep learning technique will have these two features, which are in fact tough. Significant features will be extracted from this vast amount of data, improving processing (as it avoids time-intensive processing to the maximum). To improve categorization and computer vision calculation, this data will be carefully computed. One of the key processes in creating a trustworthy and effective picture retrieval resource is the extraction of visual properties including colour, texture, shape, spatial relationship, etc. Each datum will be generated with a suitable content-based text by taking into account the above sequence of data or picture extraction phenomena. Every data structure that contains an image will have its neural networking structure used to analyse it. Deep learning will be heavily utilised at the advanced degree of such data extraction generation. In every single content-based text structure, every single character will be identified. Only with the aid of such a feature extraction phenomena will the output be able to process and a significant percentage of critical faults be eliminated. Every piece of information is used in every segmentation module to compare the internal representation of the relevant data. The deep learning phenomena can be used not only for feature processing, but also through this process for property-based extraction. The feature representation and similarity measurements, which have been thoroughly investigated by multimedia researchers for decades, are key components that determine how well a content-based image retrieval system performs in retrieving images. Due to the well-known "semantic gap" problem, which exists between the high-level semantic notions that humans are able to understand and the low-level picture pixels that machines collect, several different techniques have been proposed. From a broad perspective, this problem can be closely related to the central problem of artificial intelligence (AI), which is how to create and train intelligent machines that can do activities that are relevant to everyday life. The long-term solution to this enormous problem is machine learning. There have been some significant developments in new machine learning approaches recently. One significant method is "deep learning," which refers to a family of machine learning algorithms that make use of deep architectures made up of numerous non-linear transformations in an effort to model high-level abstractions in data. The "shallow" structures used by traditional machine learning techniques contrast with the "deep" architectures used by deep learning, which analyses data through a number of steps of transformation and representation. Deep learning is organised similarly to the way the human brain works. Deep learning approaches enable a system to learn complicated functions that directly transfer raw sensory input data to the output, without relying on human-crafted features utilising domain knowledge, by exploring deep architectures to learn features at several levels of data abstraction. Deep learning techniques have shown promising results in a number of recent investigations, including speech recognition, object recognition, natural language processing, and others. In this study, we aim to explore deep learning approaches with application to CBIR challenges in light of deep learning's track record of success.

Deep learning techniques for image classification and recognition are receiving a lot of academic attention in computer vision, while CBIR applications are still receiving very little attention.

3.1 DEEP BELIEF NEURAL NETWORK

Many academics have created an advanced artificial neural network called deep learning to push the boundaries of machine learning. This deep learning technique' primary function is to extract information using a high level abstraction
Methodology.

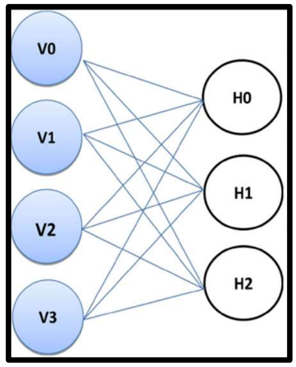

Fig 1.1 RBM structure

Typically, this technique is composed of multistage nonlinear transformers, which are similar to cascading numerous neural networks. With distributed representation, high level data abstractions are carried out, meaning that data will be studied using several dimensions and parameters. Each abstraction is carried out via a hierarchy of explanatory factors, in which a single prior level of generated information is used to generate a number of sublevels of information (Fig 1.1)[25].

Traditional ANN techniques frequently failed to interpret unlabeled data, however practically all deep learning algorithms are capable of doing so. One deep learning technique that can analyse data in an unsupervised fashion is the deep belief network (DBN).
Additionally, this technique is capable of categorising invariant data with divergent ranges, such as noise, displacement, smoothness, etc. The classic neural networks are ineffective because they require a labelled dataset, make poor parameter choices, and learn slowly. The DBN has the potential to solve these problems. In order to attain the effective local optimal solution. Since all deep learning networks are made up of multistage nonlinear transforms, DBNs have multiple layers, including Restricted Boltzmann machines (RBMs), which are stacked into multistages and each have just one hidden layer to speed up the learning process (Fig. 1.2)[25].

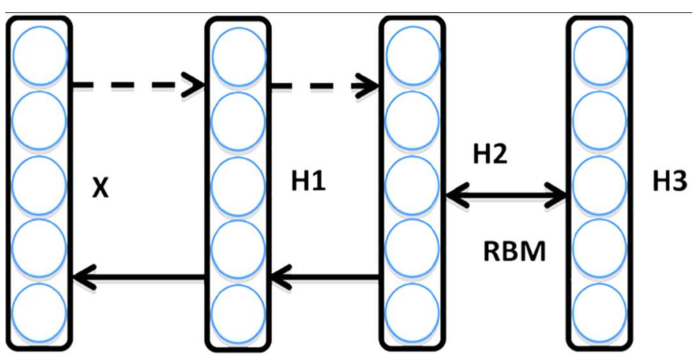

Fig 1.2 Architecture of DBN

The log-linear Markov random field (MRF), in which the energy function is linear in its free parameters, is the foundation upon which the restricted Boltzmann machine is created in order to provide the next RBM with the learning characteristics of the previous RBM.

3.2 FEATURE EXTRACTION PROCESS

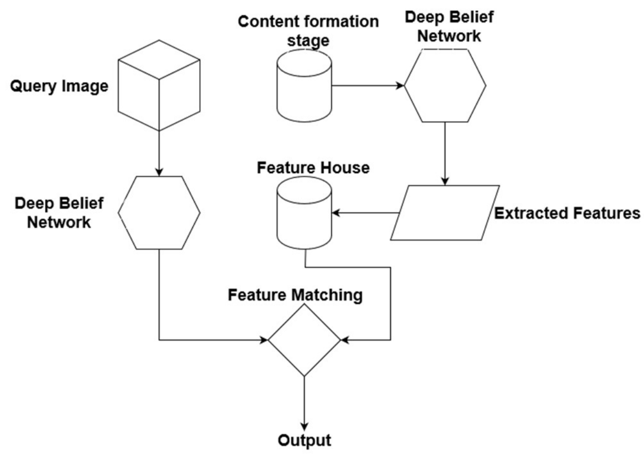

Fig 1.3 CBIR using deep belief network

Image Colour Extraction:
Here the Image Colour extraction is done with the help of Python modules, libraries and functions.
In the below Fig 1.3, assume it as a sample input.

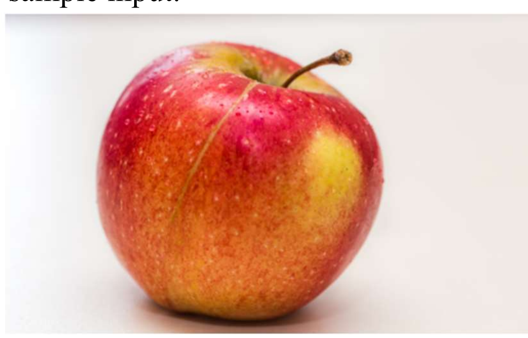

Fig 1.3 Original Image

OpenCv and matplot libraries are used in order to extract a separate colour histogram of the image in (Fig 1.4) and combined colour histogram in (Fig 1.5).

Code used:

```
blue_color=cv2.calcHist([imageObj],[0], None, [256], [0, 256])

red_color= cv2.calcHist([imageObj], [1], None, [256], [0, 256])

green_color=cv2.calcHist([imageObj],[2],None,[256], [0, 256])
```

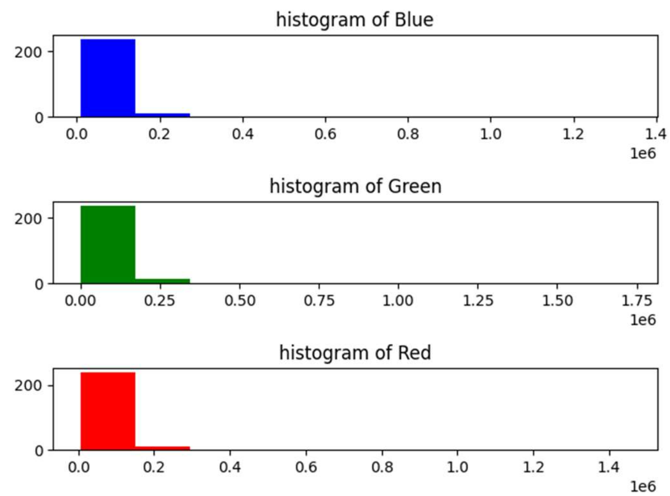

Fig 1.4 Separate Colour Histogram

The output of extracting each colour's histogram separately is shown in the figure above. A colour histogram is a graphic representation of the distribution of colours in an image used in image processing and photography. A digital image's colour histogram displays the percentage of pixels that fall inside each of a preset set of colour ranges that encompass the entire image's colour space. The term "colour histogram" can be created for any sort of colour space, even though it is most usually connected to three-dimensional colour schemes like RGB or HSV. For monochrome photos, the term "intensity histogram" may be used instead.

Code Used:

```
plt.hist(blue_color, color="blue")
plt.hist(green_color, color="green")
plt.hist(red_color, color="red")
```

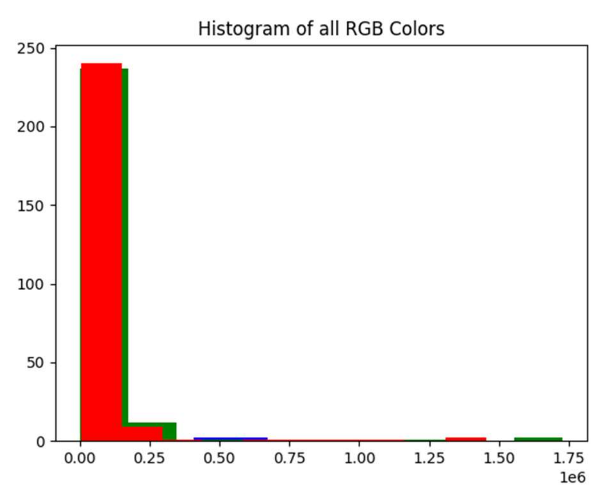

Fig 1.5 Colour histogram of all RGB

Edge detection of Image:

The below figure 1.6 is the extracted edge feature of the input image. It is done with the help of the PIL(Pillow) library which is built on top of the Python Image Library. A number of mathematical techniques are used in edge detection to find curves in digital images where the brightness of the image abruptly changes or, more formally, where there are discontinuities. Step detection, the issue of identifying discontinuities in one-dimensional signals, and change detection, the issue of identifying signal discontinuities across time, are two variations of the same problem.

Code Used:

```
image = image.convert("L")
image = image.filter(ImageFilter.FIND_EDGES)
```

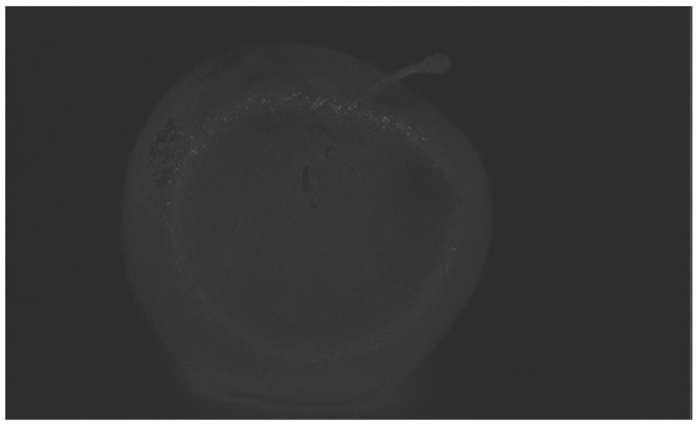

Fig 1.6 Edge detection of the input image

Edge Histogram of Image:

The below figure 1.7 is the edge histogram of the input image which is carried out with the help of opencv and matlpotlib.

Code Used:

```
histr = cv2.calcHist([img],[0],None,[256],[0,256])
```

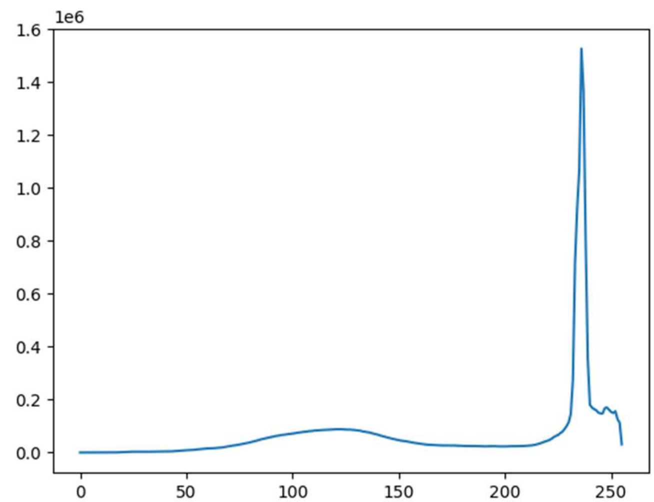

Fig 1.7 Edge Histogram of input image

Haralick Features:
The below figure 1.8 and 1.9 are the haralick features of the input image which is carried with the numpy and mahotas python libraries.

Code Used:

```
img = img[:, :, 0]
gaussian = mahotas.gaussian_filter(img, 15)
gaussian = (gaussian>gaussian.mean())
labelled, n = mahotas.label(gaussian)
h_feature = mahotas.features.haralick(labelled)
```

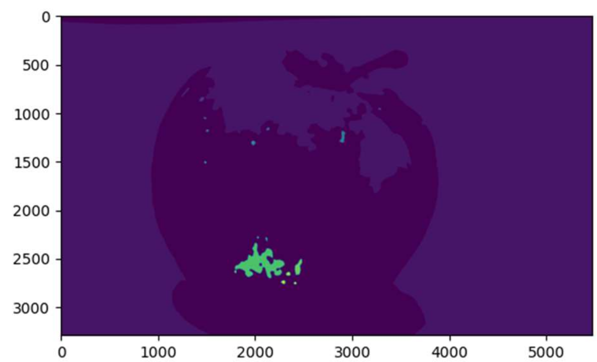

Fig 1.8 Haralick features of input image

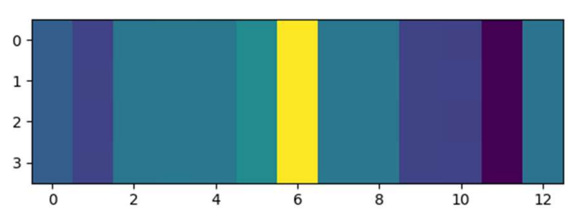

Fig 1.9 Haralick features

The characteristics of the Haralick texture are determined using a Gray Level Co-occurrence Matrix (GLCM), a matrix that counts the co-occurrence of close-by grey levels in the image. The dimension of the square matrix that makes up the GLCM is equal to the number of grey levels N in the region of interest (ROI).

4. CONCLUSION

CBIR, a fast developing technology, offers a wide range of applications in fields like engineering design, criminal justice, history study, and medical. However, the efficiency of current CBIR systems is inherently limited because they only operate at the fundamental feature level. Additionally, the technology is still in its infancy and not widely used. Research therefore examines the different CBIR system techniques. A wide range of CBIR-related papers were examined for the study. According to the study, CBIR can infer three basic properties, including shape, texture, and colour. The study also showed that each of these features can be extracted in a variety of ways. For instance, colour can be extracted from images using the colour histogram, geometric moments, colour space, and colour moments. The study listed the benefits and drawbacks of each of these techniques. For instance, the colour space method is straightforward to use but inaccurate, whereas the colour histogram is speedier and more efficient than other colour extraction techniques. Two images with different colour palettes could, however, be comparable. The research also indicates that the GLCM, Tamura, Fourier transform, Ranklet transform, and discrete wavelets are typical instances of textural extraction approaches. Similar to this, the edge approach, Fourier descriptors, and Zernike method were found to be effective shape extraction techniques. The study also examined approaches for figuring out how closely two database images are related to a search image. The results of the study showed that some examples of similarity metrics used in CBIR are city block distance, sum of absolute difference, and sum of squared differences of absolute values. There hasn't been much progress in CBIR recently despite the numerous methods and tools developed to design and execute searches in large databases based on their visual contents. Future research should therefore concentrate on developing CBIR systems that would overcome the problem of the semantic gap in CBIR.

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