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Near Duplicate Image Detection Using Image Net Model

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Abstract: The rapid development in the technology of Internet and the increase in the usage of mobile devices, it is very easy for users to capture, communicate and share the images through the networks. The spectacular achievement of convolution neural networks in the area of computer vision, will help us to match the features that are very similar between the images for detecting the duplicate version of the image. In this project we use Image Net model that mainly provide a large database that contains many images of different categories. Flask framework is used in this project, which includes many libraries, modules that helps the web developer to write web application. In this project the user is allowed to upload the image, then the image features will be extracted and fed to the CNN model. The CNN model will calculate the similarity distance between the images that is already present in the database and detect the top four images that are duplicate version of the uploaded image.
Keywords: CNN features; near-duplicate image detection; max- pooling

I. INTRODUCTION

The rapid development in the technology of Internet and the increase in the usage of mobile devices, it is very easy for users to capture, communicate and share the images through the networks. In this photo detail, duplicate images play a large part. The task of getting a close-up photo is to quickly and successfully get back the duplicate version of a given input image from a large image database. The near image detection has been successfully used in many applications, such as legal right protection, hide anonymous information shared by private photos and in elimination of redundancy.

Currently, deep learning strategies such as convolutional neural networks (CNNs) has received a lot of attention in the field of computer vision. Due to this fact, some researchers tend to use CNN features instead of manually manipulated objects to perform tasks such as locating an image or retrieving an image. It has been proven that the traditional handmade features achieve less performance than the features that are designed for CNN.

During this work, we encountered an issue pertaining to object recognition, which is the process of finding and identifying objects in the real world from images or videos. As a topic of

computer vision research, it is still a hot topic because it poses many challenges. So here we are proposing tensor-flow, which is CNN based similarity finding by using cosine similarity algorithm to recognise nearby images based on the features selected. This project will detect the top four images that are the duplicate versions of the input image.

II. RELATED WORKS

With the increasing popularity of CNNs, the recent near-duplicate image detection methods tend to use the features extracted from pre-trained CNN models instead of the traditional hand-crafted features. The existing models for detecting the duplicate images from the large images are surveyed in this section.

In paper [1], due to the lack of good distance metrics that include large divisions within the collection of duplicate images and remove false alarms, identifying duplicate images, or acquiring duplicate photo collections, is a challenging task with billions of Internet images. In this paper, we investigated existing local and global image features widely used in image retrieval and indexing, and presented a two-step process for combining local and global image features. In this paper, hashing techniques are used in both aspects and the MapReduce framework, and it can retrieve 553.8 million duplicate images in the primary 2,000 collection, in 13 hours, from two billion Internet images.

In Paper [2], we analyze our project based on graph-based methods that identify duplicates of two-dimensional and three-dimensional objects in still images. The method that is used in this paper can be used to find the same objects regardless of where or from what angle the images are taken. RANSAC is used as an iterative approach to estimate mathematical models from data containing outliers. The RANSAC algorithm identifies outliers in a dataset, and it uses them to estimate the model from those data sets that doesnot contain them.

The paper [3], involves the design of new solutions and the development of application software for detecting and recognizing objects captured by a camera. Following earlier digital processing of data delivered by the camera, the sensed scene objects are determined and recognized. In this paper, for feature extraction computer vision learning neural-based methods were used. The proposed application software can be used in a wide variety of applications that require an understanding of real-world scenes and object tracking. The global CNN features are usually extracted by feeding the whole region of an image into a pre-trained CNN model and then pooling the outputs of the intermediate layers such as convolutional layers and fully connected layers. In literature, the popular pooling methods include max-pooling [18–28], sum-pooling [29–32], and average-pooling [33]. Generally, the outputs of a convolutional layer are a set of convolutional feature maps (CFMs), and the global CNN features are extracted by implementing a pooling operation on the CFMs. The max-pooling method computes the maximum value of each CFM and concatenates all the maximum values to form the global CNN features, while sum-pooling and average-pooling methods compute the sum and the average value of each CFM, respectively. To improve the performance of the extracted global CNN features on near-duplicate image detection, researchers have proposed some improved versions of these pooling methods to extract the global CNN features. Babenko et al. [29] proposed the SPoC descriptor, which is generated by an improved version of the sum-pooling, i.e., centering prior-based sum-pooling. Zhang et al. [37] learned a general straightforward similarity function from raw image pairs for near-duplicate image detection.

III.PROPOSED METHODOLOGY

The architecture of the proposed system is given in the Figure 1. The following are the steps that are undertaken during the implementation of the proposed system:

1) *Feature Extraction:* To identify what category an image belongs to, the classification model is used. Our next step is to extract features from the last fully-connected layer of our classification model.
2) *Input of the Model:* Feature vector of the target image extracted in the previous step.
3) *Similarity Calculation:* The similarity between image pairs is calculated by calculating similarity scores between the feature vector of the target image and the feature vectors of all images in the target category. For computing similarity scores, we took L2 distance, cosine distance, and neural network models into account.
   - L2 Distance: L2 distance between two images i and j is defined as
     sL2 = ||vi – vj||2
     where vi, vj belongs to R *l* are the two corresponding feature vectors,
     l= 4096 is the length of feature vectors.
     The smaller the score *sL*2 is, the more similar the two images are.
   - The cosine distance score is defined as

$$s_{cosine} = \frac{v_i^\top v_j}{\|v_i\|\|v_j\|}$$

     The larger the score scosine is, the more similar the two images are.
4) *Output:* Top k images that are the duplicate version of the target image. In this project we chosen the k value as 4.

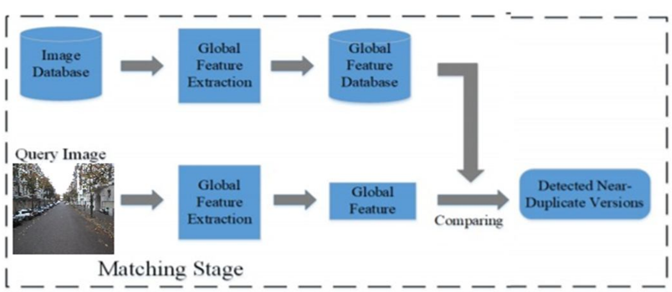

Figure 1: System Architecture

The above Figure 1 represents System Architecture of Near Duplicate Image Detection. The System Architecture includes image database which contains huge amount of images and global feature database which contains the global features that are extracted from the images. When the query image is given as an input to the CNN model, the global feature of that image will be extracted and compared with the global features of the images that are present in the global feature database. If the features matches with the query image features, then the top four duplicate versions of the query image will be detected.

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IV. RESULT INTERPRETATION

Here are the results, or outputs, after each module of the system has been executed step-by-step.

A. Snapshot of Uploading the Image

The below Figure 2 shows the snapshot of image upload where the user will upload the image for duplicate detection. This includes the choose file button for choosing the image and detect duplicate button to detect the top four images that are the duplicate version of the uploaded image.

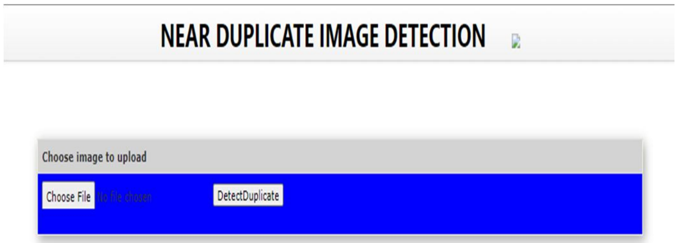

Figure 2: Snapshot of uploading the image

B. Snapshot of Input Image

Figure 2: Uploaded input image

The above Figure 2 represents the input image which is choosen for duplicate detection

C. Snapshot Of Top Four Duplicate Versions Of Input Image

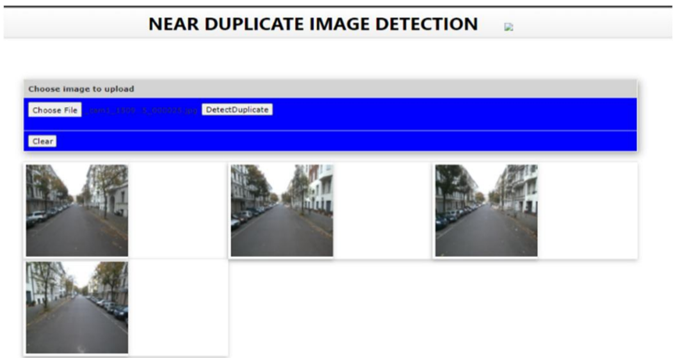

Figure 2: Top four duplicate versions of input image

The Figure 3 represents the top four duplicate versions of input image. The above figure is clearly detecting the building and vehicles which are the similar features present in the input image

V. CONCLUSION

In our work we have build the near duplicate image detection model which will detect the duplicate version of the image that is uploaded by the user by calculating the similarity distance with the images that are already present in the image database. The model at the end will detect the top four images that are duplicate version of the image that is uploaded by the user.

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