Near Duplicate Image Search

Abstract:

Due to the great success of convolutional neural networks (CNNs) in the area of computer vision, the existing methods tend to match the global or local CNN features between images for near-duplicate image detection. However, global CNN features are not robust enough to combat background clutter and partial occlusion, while local CNN features lead to high computational complexity in the step of feature matching. To achieve high efficiency while maintaining good accuracy, we propose a coarse-to-fine feature matching scheme using both global and local CNN features for real-time near-duplicate image detection.

In the coarse matching stage, we implement the sum-pooling operation on convolutional feature maps (CFMs) to generate the global CNN features, and match these global CNN features between a given query image and database images to efficiently filter most of irrelevant images of the query. In the fine matching stage, the local CNN features are extracted by using maximum values of the CFMs and the saliency map generated by the graph-based visual saliency detection (GBVS) algorithm. These local CNN features are then matched between images to detect the near-duplicate versions of the query

Existing System:

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 CNN-based features can be roughly categorized into global CNN features and local CNN features. 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, sum-pooling, and average-pooling. 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 and they were not implemented.

Proposed System:

In this section, we introduce the proposed near-duplicate image detection approach in detail. The proposed approach consists of two main components, which are the coarse matching stage and the fine matching stage, respectively. We first generate convolutional feature maps (CFMs) by feeding images into a pre-trained CNN model and then we extract global features from each image using sum-pooling operation and then match these features between images to obtain the candidate images of a given query from an image database and then matched to further detect the near-duplicate versions of the query.

Software Tools:

1. TensorFlow
2. Keras
3. Anaconda
4. Jupyter Notebook
5. VS Code
6. Colab

Hardware Tools:

1. Laptop
2. Operating System: Windows 11
3. RAM: 16GB
4. GPU
5. ROM: 4GB
6. Fast Internet Connectivity