Image Retrieval by Fusion of Features from Pre-trained Deep Convolution Neural Networks

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Abstract - **Image retrieval is a challenging problem in computer vision domain. Traditional content based image retrieval (CBIR) systems were built to retrieve images based on low level content representations like color, texture and shape. These domain specific handcrafted features performed well in various image retrieval applications. The choice of image features greatly affects the performance of such systems. Also, one needs deeper understanding of the domain in order to choose right features for image retrieval application. Recent advances in image retrieval focus on creating features which are domain independent. Machine learning can help to learn important representations from images. Convolution neural networks (CNN) are an important class of machine learning models. CNNs can derive high-level multi-scale features from image data. CNNs with deep layers are widely used in image classification problems. Creating a new effective deep CNN model requires huge training time, computing resources and big datasets. There are many deep CNN models like VGG16, ResNet, Alexnet etc., which are pre-trained on huge datasets and model weights are shared for transferring the learnt knowledge to new domains. Pre-trained CNNs can be applied to image retrieval problem by extracting features from fully connected layers of the model before output layer. In this work, two leading pre-trained CNN models VGG16 and ResNet are used to create a CBIR method. Learnt features from these pre-trained models are used to create a fusion feature and use them for image retrieval. The proposed CBIR framework is applied to image retrieval problem in a different domain, satellite images.**

Keywords – Deep convolution neural networks, Content based image retrieval, Learnt features, VGG16, ResNet

I. INTRODUCTION

The tremendous growth in multimedia and imaging technology has led to creation of vast image databases. Image processing techniques are used to derive suitable knowledge from these image databases to solve various computer vision issues. Image retrieval deals with fetching relevant images from an image collection corresponding to a given query image. Traditional image retrieval applications were built on text description matching. Such system will need all images to be annotated hence a cumbersome system to build where image collections are huge. This led to development of Content based image retrieval (CBIR) technique, where image content representations at lower level are used for computing image similarity. These representations or features can be derived from underlying images and found to perform well in image retrieval. There are various features which are carefully designed based on the target domain. These are called handcrafted features. The prominent handcrafted features used in CBIR are color, texture and shape properties.

Color property of an image is consistent with variation in image scale and alignment. Color histogram portrays the statistical distributions of color property. It quantizes the color space representations for effective color depiction. Global color histogram is a commonly used handcrafted color feature in retrieving color digital images.

Texture property characterizes a recurring pattern of the local variation in image intensity. Gray level co-occurrence matrix (GLCM) method is generally used to statistically measure texture distribution. GLCM quantifies the texture property by assessing the positions of pixels having related gray level values. Statistical representations derived from GLCM help to signify texture more densely. Correlation, Homogeneity, Energy, Dissimilarity and ASM are important GLCM statistical features applied to represent texture property in CBIR.

Shape features help to identify image regions which contain underlying object in an image. Shape features help to identify, index and compare objects in digital images. Hu moments are effective shape features as they are consistent with variation in object scale, translation and rotational changes. Hu moments use the concept of algebra moments invariants and perform better in shape related CBIR applications.

A baseline CBIR framework is created by using above said color, texture and shape features. The results from proposed framework are compared with this baseline framework to gauge the performance improvement.

The performance of CBIR system directly depends on the set of features used for image similarity measurement. Use of improper features will yield inefficient image retrieval results. Domain knowledge also influences the choice of features. In recent times there is a lot of focus to design features which are independent of domain knowledge and which can be learnt automatically from an input image.

Machine learning is a significant branch of artificial intelligence. It is developed on the concept that systems can automatically learn from input data, recognize patterns and take decisions with minimal human interference. Machine learning has been successfully applied in many fields like financial services, healthcare, transportation, oil and gas, and defense etc. Machine learning methods find great use in various real world applications like classification, medical diagnosis, prediction, learning association and regression etc. In image processing domain, machine learning has been explored for tasks like classification, clustering, and object recognition etc.

Development of Convolution neural networks (CNN) has made deep learning more adaptable to image processing domain. Image holds important information in the spatial regional relationship amongst adjoining pixels. CNNs use local receptive fields, shared weights and pooling to process such spatial relationship. CNNs contains multiple layers of neurons which self-augment by acquiring knowledge as they learn. CNNs can progressively convolve an input image with learned filters to construct an order of feature maps. The hierarchical methodology results into highly efficient features which are invariant to translation and distortion. Hence CNNs have found great success in image processing applications like classification, clustering and object recognition.

Constructing a best performing deep CNN method for a new domain application requires huge training datasets, computing resources and processing time. There are many pre-trained models which are already trained on big datasets and model weights are shared for public use. Such pre-trained models can be used to transfer previously learned knowledge to a new situation or cross domain issues. Pre-trained models like VGGNet, ResNet, AlexNet and GoogleNet etc. are widely used.

This work focuses on investigating the feasibility of extracting important features learnt by a pre-trained CNN model and use these learnt representations for CBIR task. A frame work is created to use two leading pre-trained deep CNN models VGG16 and ResNet for extracting important features. A fusion of features from these two pre-trained models is used for image retrieval task in an unrelated domain, to fetch similar images from a satellite images dataset.

Our paper is organized as below: Section II explains the related work. Section III describes proposed methodology. Section IV lists experimental results, Section V summarizes results and Section VI presents the conclusion of this research work.

II. RELATED WORK

Image retrieval is an important research problem dealing with retrieval of similar images from a dataset which match to a given query image. Traditional text-based image retrieval methods used manually annotated keywords for searching the relevant images. This is labor-intensive, costly and a lengthy process. Also, it is a difficult task to describe semantics of every image and human perception impacts it [1] [2]. This led to development of content based image retrieval method [CBIR]. In this method, low level image representations are used to derive the similarity of images. These representations or features can be directly derived from the image data. A typical CBIR system works on query by example method, where low level content representations of query image are compared against database image content representations to extract top N similar images [1] [2]. Color, texture and shape are popularly used and accepted visual features in CBIR [1] [2].

Color feature is a prominent and widely used handcrafted feature in CBIR. Color is most distinguishing and dominant low level visual feature in CBIR [2]. Color is an effective feature since it is robust, simple to implement and requires lower storage. The global color feature performs well with variation in image position and scale. Hence color feature is most suitable for an effective image retrieval application [3]. Color histogram is the best method for representing color properties of an image [4]. Hue Saturation Value [HSV] color space representation works well with human perception of colors than Red Green Blue [RGB] color space [6]. Many CBIR systems have been designed by using Global color histogram color feature and achieved good image retrieval results [5] [7].

Gray level co-occurrence matrix method helps to represent texture properties in a compact manner [14]. Texture feature representations from GLCM like dissimilarity, correlation, angular second moment, homogeneity and energy are quite popular features in CBIR.

Hu Invariant Moments can be used as shape feature descriptors and are widely used in CBIR applications [17].

Extracting effective features is an important stage in object recognition and computer vision tasks [15]. Several researchers have focused on creating suitable image features for various of image classification applications [12]. There is a lot of interest developed about feature learning algorithms and CNNs [16]. Convolutional Neural Networks (CNNs) have gained much popularity in recent years. CNNs have achieved promising results in different image processing tasks including object recognition, image classification and clustering [8]. Hence CNNs are increasingly employed in various image processing applications like classification of objects, face recognition and gesture recognition [9] [10] [11]. Earlier research works show that it is possible to feed an image directly to a CNN network and utilize features for image classification [12] [13].

CNNs can derive high-level multi-scale features from image data which can perform better than handcrafted low level image features in representing an image. One major drawback of creating a new effective CNN model is the possibility of training it on huge image dataset with millions of images. This will need huge computing resources and processing time [18]. Collecting huge image data across various domains and tagging images can be quite challenging and expensive for real world problems. This has led to the use of features from well-established deep CNNs. Deep CNNs are found to gain good prediction results and Pre-trained deep CNN models are successfully applied in various image processing applications such as image classification, clustering and object detection etc. [19] [20] [21] [22] [23]. These CNNs are pre-trained on big-scale annotated natural image data collections (like ImageNet). One can build an inexpensive solution to address image processing issues in other domains by transferring learned knowledge from an existing pre-trained CNN model [27] [28]. There are various pre-trained deep CNNs like VGGNet, AlexNet, ResNet and GoogleNet are used in image processing related researches [29]. VGG16 pre-trained deep CNN model has shown good performance when used for image recognition, object detection, image classification and image compression tasks [24] [25] [26] [29]. Residual Neural Network (ResNet) is a recently introduced pre-trained deep CNN, they contain very deep layers and are able to handle the vanishing gradient problem very well. ResNet has established high prediction accuracy in various image classification tasks [31] [32] [33]. In our work, VGG16 and ResNet models are leveraged for image retrieval task by creating a fusion of learnt features from these models.

Due to increased human activity and civilization growth, there is a steady decline in forest areas. Remote sensing technology helps to create a low cost solution for analysis of land cover usage, forest destruction analysis etc. [34] The Brazilian Cerrado is a highly biodiverse savannah area but witnessing a considerable decline in forest cover area since last few decades. Many researchers have focused on measuring change in land use pattern in the area using modern techniques. Various noted work is done on applying image processing methods for remote sensing applications. The image classification and retrieval problems in detection of land usage changes is quite challenging due to the low availability of rich vast datasets. Hence pre-trained CNNs can help to great extent by transferring knowledge learnt from other established domains. Pre-trained CNN model features are applied for image classification and found good results with smaller dataset [30].

III. PROPOSED WORK

A typical CBIR system consists of an offline database indexing module and online query module as outlined in Fig. 1.

A. *Offline database indexing*

This is one time offline exercise to extract the required features of every image from the dataset. The extracted features are saved in a features database.

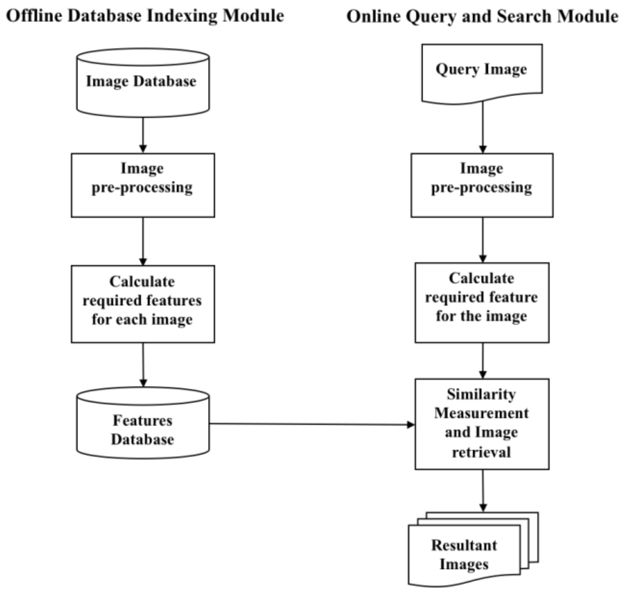


Fig. 1. Typical CBIR method

B. *Online query module*

In this online module, the retrieval of matching images for a given query image is performed. The features of the query image are calculated and compared against database features. The results are sorted based on similarity distances and top N images are returned.

In our work, a baseline CBIR and a proposed CBIR framework have been implemented. The baseline CBIR framework uses color, texture and shape as handcrafted features as depicted in Figure 2. Results from our proposed CBIR framework are compared with this baseline CBIR to gauge its effectiveness.

In proposed CBIR frame work, we extract learnt features from Pre-trained VGG16 and ResNet deep CNN models to create a fusion feature. This fusion feature is used for image retrieval task as outlined in Figure 3.

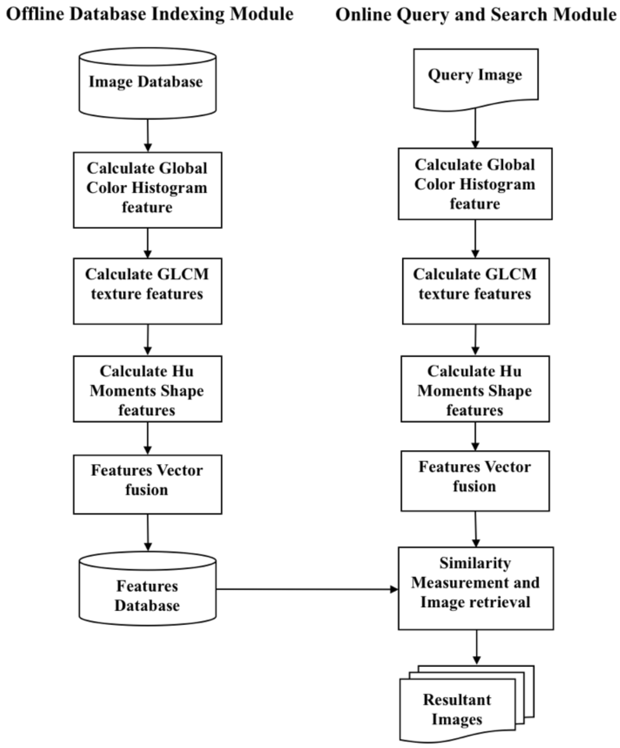


Fig. 2. Baseline CBIR using handcrafted features.

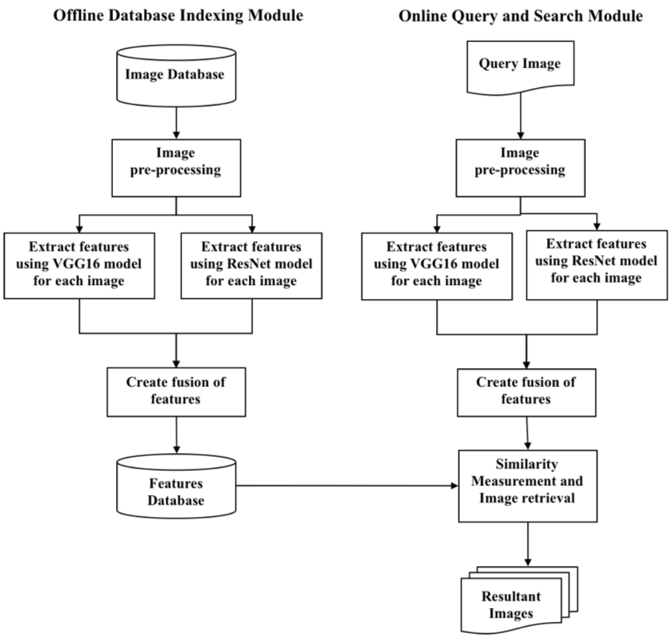
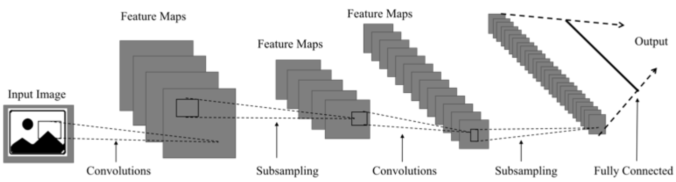


Fig. 3. Proposed CBIR using fusion of pre-trained CNN features.



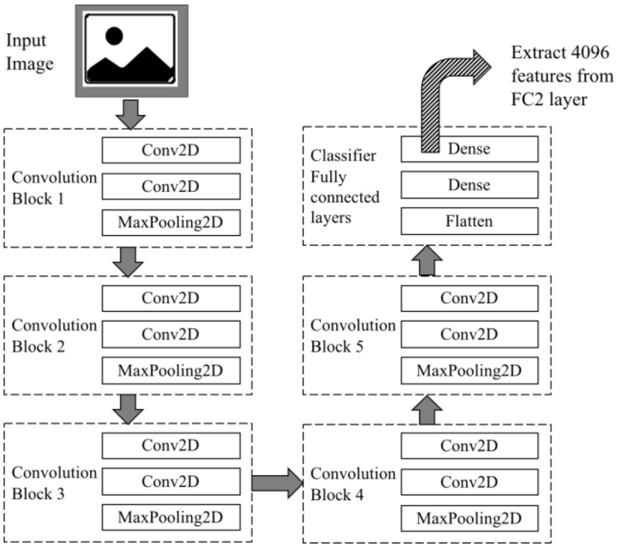


Fig. 4. Multi-layer CNN model architecture.

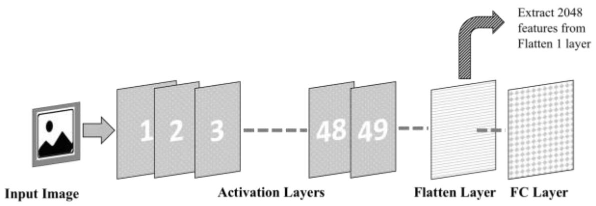


Fig. 5. Extraction features from VGG16 CNN model.

Fig. 6. Extraction features from ResNet50 CNN model.

A typical pre-trained CNN model usually consists of many layers that incrementally calculate features from a given in-put image data as shown in figure 4.

VGG16 deep CNN model is implemented from Python Keras package. It is a 16-layer deep CNN created by the Visual Geometry Group from University of Oxford [29]. VGG16 model is trained on ImageNet, which is a large dataset containing 3+ million digital images distributed across 5000+ categories. VGG16 model consists of 5 convolution blocks and each convolution block containing two convolution layers (size 3X3) and one maxpooling layer (size 2X2) as depicted in Figure 5. The final classification step of the model consists of fully connected (FC) layers.

ResNet50 CNN model is a 50 layer deep model and 2048 features learnt from this model are extracted by tapping flatten 1 layer as outlined in Figure 6. ResNet50 is implemented from Python Keras package.

4096 VGG16 features are clubbed with 2048 ResNet features to get final fusion features for image retrieval.

Image retrieval performance is measured by calculating precision values as defined in equation (1).

$$Precision = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ images\ retrieved} \quad (1)$$

Our proposed CBIR method is implemented using Python 3.6.5, Keras 2.2.2 module, TensorFlow 1.11 as backend on macOS High Sierra 10.13 operating system (64 bit) and 16GB RAM with Intel core i7 processor.

IV. EXPERIMENTAL WORK

Proposed CBIR method is subjected to experimental study on Brazilian Cerrado Savanna Scenes Dataset [30]. This dataset is created from multi-spectral scenes extracted from images acquired by the RapidEye satellite sensors over the Serra do Cipó region. The images are selected based on three bands near-infrared, green, and red bands. These bands help to differentiate vegetation scenes in an effective way. The dataset details are tabulated in Table 1.

TABLE 1: SATELLITE IMAGES DATASET

Sr. No#	Knot Class	Number of Images per class
1	Agriculture	47 Images
2	Arboreal	962 Images
3	Herbaceous	191 Images
4	Shrubby	111 Images

One image from each class which is not part of the training dataset is selected as input query for the experiment. For a selected image from a class, we can safely assume that the user is interested to fetch images from the same class. Hence, resultant images fetched from same class are marked as relevant images and images fetched from other classes as irrelevant. The precision rates are measured by varying the number of images retrieved.

Table 2 outlines the list of handcrafted features used in baseline CBIR frame work.

TABLE 2: BASELINE CBIR HANDCRAFTED FEATURES

Sr. No#	Category	Handcrafted Feature
1	Color	Global Color Histogram
2	Texture	Gray level co-occurrence matrix: Correlation, Homogeneity, Energy, Dissimilarity and Angular Second Moment (ASM)
3	Shape	Hu Moments

This baseline CBIR framework is used to measure performance of proposed method over it. GCH feature [H-8, S-12, V-3 bins] is calculated in HSV color space. Gray-level co-occurrence matrix (GLCM) is used to compute the texture properties Correlation, Homogeneity, Energy, Dissimilarity and ASM. Shape feature is calculated by using Hu Moments. These handcrafted features are calculated for each image in the dataset and a features fusion vector is created. The fusion feature vectors are stored in features database.

Similarly, handcrafted features for every query image are computed and matched against entries in features database. Cosine distances method is used for features similarity measurement and top N matching images are retrieved. The image retrieval experiment is repeated for each query image by varying the number of images retrieved. Image retrieval results from baseline CBIR method are tabulated in Table 3.

In proposed CBIR method, fusion of learnt features from pre-trained VGG16 and ResNet50 CNN models are subjected to experimentation. 4096 features are extracted from VGG16 FC2 layer and 2048 features are extracted from ResNet50 flatten-1 layer. This gives us 6144 features per image. During offline database indexing module, these features are saved in the features database. In online query step, 6144 features obtained from each query image are compared with the features database. Cosine distances method is used for calculating the image similarity and retrieve top N results. The image retrieval experiment is repeated for each query image by varying the number of images retrieved. Image retrieval results from our proposed approach are tabulated in Table 3.

TABLE 3: AVERAGE PRECISION RATES FOR IMAGE RETRIEVAL.

Image Class	[Method 1] Baseline CBIR using handcrafted feature	[Method 2] Proposed CBIR method using fusion of VGG16 & ResNet 50 learnt features
Agriculture	12.87%	40.17%
Arboreal	66.43%	78.80%
Herbaceous	29.67%	57.70%
Shrubby	33.47%	55.47%
Overall Precision	35.61%	58.03%

V. RESULTS AND DISCUSSION

The experimental study shows that the baseline CBIR with handcrafted features (Color, texture and shape) yields an average precision of 35.61% across all classes of the satellite images dataset. The proposed CBIR method which uses fusion of features from VGG16 and ResNet50 pre-trained deep CNN achieves an average precision of 58.03% across all classes of the dataset. The improvement in precision rate is observed in all image classes and across different retrieval sizes as depicted in Figure 7. Experimental results show that our proposed CBIR frame work using pre-trained VGG16 and ResNet50 CNN model fusion learnt features performs better than baseline CBIR using handcrafted features (Color, texture and shape).

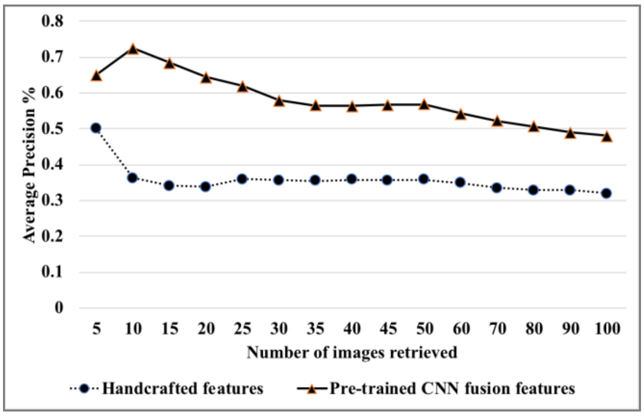


Fig. 7. Comparing of baseline and proposed CBIR for average precision vs number of images retrieved.

VI. CONCLUSIONS

In this work, it is demonstrated that learnt features from pre-trained deep CNN model are suitable for image retrieval task. A new CBIR framework is created by fusing features from pre-trained VGG16 and ResNet50 deep CNN models. The proposed CBIR framework is tested on a multiclass digital database of satellite remote sensing images. Proposed method achieved average retrieval precision of 58.03% for the proposed CBIR framework, which clearly outperforms the average retrieval precision of 35.61% from baseline CBIR framework using handcrafted feature (Color, texture and shape). Results show a 22.42% increase in the average precision in the proposed CBIR method. The improvement in average precision is seen in all classes of the dataset and number of images retrieved. From experimental results we conclude that learnt features from pre-trained deep CNN models can be successfully used for image retrieval task and perform better than handcrafted features..

Future Scope: The current work explored the usage of VGG16 and ResNet 50 pre-trained models. Other popular pre-trained models like AlexNet and GoogleNet etc. can be tried. Some of the layers of the pre-trained CNN model can be fine-tuned and retrained on a new dataset to achieve better results.

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