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Image Retrieval based on Structural Information using VGG16

Arepaga Srikanth¹, Sunkari Rohit², Vuppula Vamshi Krishna³, Yenna Danush⁴

Department of Electronics and Communication Engineering Hyderabad Institute of Technology and Management,

Hyderabad, Telangana, India^{1,2,3,4}

Mrs. V. Mosherani⁵

Assistant Professor, Department of Electronics and Communication Engineering Hyderabad Institute of Technology and

Management, Hyderabad, Telangana, India⁵

ABSTRACT: As the size of digital collections increase at an unprecedented rate, traditional retrieval methods of textbased querying image collections will be more difficult to establish. While there are traditional retrieval methods to find images, these involve traditional methods of using color histograms and distance measures that only ultimately result in comprehending the image using base visual features or manual tags as we will illustrate in this article. Instead, we will explain a more intelligent version of image retrieval relying on deep learning approaches. In the proposed state of the art approach we will explain and illustrate from our use of various deep learning architectures of mining images, such as VGG16, ResNet, MobileNet etc., and meaningful detail and pattern can be extracted from images. With this new intelligent image retrieval approach the only effort required by the user is to inquiries the provide the query image, with it the meaningful features are extracted and the system retrieves all the visually similar images from the database. As we illustrate, the intelligent approach is simple, significantly fast and a highly accurate retrieval system that can be used to process a large image database.

I. INTRODUCTION

As digital images are produced in ever-increasing volumes, Content Based Image Retrieval (CBIR) is becoming ever more relevant as a method to manage ever-growing quantities of visual content. It can begin to address the shortcomings of traditional image content management systems. CBIR is fundamentally based on the idea of describing visual images with visual features (e.g. color histograms, segmented images) and organizing them by describing them as multidimensional feature vectors. However, the challenge is in describing the low-level features that machines can detect into higher-level semantics that humans can interpret. Recent developments in deep learning, and in Computer Vision particularly with Convolutional Neural Networks (CNN), have enhanced the performance of retrieval systems. CNNs have well-defined performance in tasks for Computer Vision. Moreover, CNNs help understand the meaningful features of an image that CNNs can learn by focussing on abstract features. The aim is not only to extract the

features of an image that CNNs can learn by focussing on abstract features. The aim is not only to extract the meaningful features and classify the images, but also to help the user understand the features of an image that led to a particular classification. This process of applying deep learning to this problem has capitalized on many of the benefits of other methods of retrieval, and mitigated some of the problems with previous approaches to retrieval.

II. LITERATURE SURVEY

Image Retrieval System.

Liu Y and others reported a significant advancement by putting deep convolutional neural networks to work in image retrieval. They achieved substantially better accuracy for retrieval based on learned visual "patterns" (rather than hand-crafted features). In part because the system can track and capture far more meaningful semantics, it produced better accuracy than traditional systems

Neural Codes for Image Retrieval.

Babenko A et. al, introduced a technique for retrieving images using convolutional neural networks (CNNs) that offered a compact representation of image features called neural codes. The neural codes creates a compact

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representation that is much more efficient for image retrieval than older techniques like SIFT. It also offers significant advantages over SIFT in terms of repeatability and accuracy

Deep Learning for Image Retrieval

Wan J and colleagues developed a model which built on a CNN pretrained model that added an aggregation method to the process of image retrieval. The multi-scale feature extraction model is effective at capturing low-level and high-level image information to better improve the accuracy of more complicated datasets. This model is valuable in situations when there are many complications due to depth of images.

CNN Features Off the Shelf

Razavian and colleagues, illustrated that pretrained CNNs could perform extremely well with image retrieval without having to think about re-training the model from scratch. The author trained part of the models such as the VGG16 model to extract the real image features from each image provided for search retrieval. Overall this method does not have the costs of training but for the time being as well provides reliable feature generation.

Integrating Local Descriptors

Jegou H, along with his collaborators studied various ways to combine conventional visual descriptors such as VLAD and Bag-of-Words effectively. However, instead of deep learning, they studied non-deep approaches designed to create simple representations of images. Their method is efficient in performance and speed and could be used in situations where computing power is limited. This work provides a strong foundation for minimal retrieval.

III. METHODOLOGY

Content-Based Image Retrieval (CBIR)

Typically, we find images using search engines like Google through text (or keywords) search. However, a text-based approach to defining (and retrieving) images often falls short because there are some images that cannot be captured or conveyed in a text-based manner. For example, it isn't possible to assign all images in a large or dynamic database (e.g., social media) descriptive tags without challenging efficiency. To solve for those limitations, content-based image retrieval (CBIR) systems have been created. CBIR systems look at the visual content of an image (i.e., color, shape, texture) rather than textual or key descriptors to locate similar images.

How CBIR Works

In CBIR, for a search to be completed the process typically begins with an image rather than text. The system examines the image's features (e.g., color patterns, textures, and shapes) and the features will be examined through the image data. The data provided by the features allow the system to examine a similar image or sets of images in the database. CBIR efficiently serves as a means of automatic image indexing and retrieval in large, changing databases of images. In addition, it bypasses the difficulties associated with a text- based approach by making searching for large amounts of images practical or possible. CBIR can also make accurate image search practical, which can otherwise be impossible in characterizing image content fully with textual descriptors. The current version of the LOA (Lower-part OR Adder) is viewed as an approximate adder in our design methodology.

Relevance Feedback (Human Interaction)

In content based image retrieval human feedback plays an important role when considering perceived searches. When the user submits an image query, the relevant visual matches are extracted by the system and the user states which results are considered useful or non-useful. Basedon the user feedback for preference, the systemcan learn from the users preference to enhance the user's experience of retrieving images for future queries. This process allows forreasonably better mapping of machine results to user's expectations.

Quantization for Performance/Computational Operation

It can be quite laborious to work with large colour images, which have millions of variations. Quantization reduces the set of colours to smaller workable set of colours. That processing of colour quantization can bring much better computational efficiency and storage efficiency whilst visually keeping the same level of detail. (So therefore, with colours broken like in the HSV colour space, with breaks akin.)





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Fig 1: Main page





Fig 2: Uploading Dataset

IV. DESIGN

VGG-16 is a deep convolutional neural network with 16 layers, and has been trained with over a million images from the popular ImageNet dataset. This kind of training allows VGG-16 to recognize and categorize images into 1000 categories that include familiar objects, like keyboards, and animals. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC), an annual competition focusing on computer vision tasks, is where VGG-16 catch fire as a famous image recognition architecture.

Resnet

A Residual Network (ResNet)[1] is a type of artificial neural network (ANN). It is very similar to Control Neural Networks as well. It is basically a gate-less version of the Highway Net[2], with Highway Nets being the first effective very deep feedforward neural network (hundreds of layers), one of many resonant differences in a later time.

Mobilenet

MobileNet is a convolutional neural network designed for mobile and embedded vision



Fig 3: Dataset Loadad





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V. RESULTS



Fig 3: Resnet Results



Fig 3: VGG16 Results



Fig 3: Mobilenet Results

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Algorithm Name	Precision	Recall	1	F1 SCORE				Accuracy		
Resnet	0.3875968992248062	6.25	0.72	99	270	07299	27	6.2015	50387	5969
VGG16	99.21875	99.10714285714286	99.1	02	564	10256	41	99.224	80620	15504
MobileNet	97.15007215007215	95.80853174603175	96.1	30	906	47098		96.899	224800	520154

Fig 3: Comparision table





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VI. CONCLUSION

The proliferation of image repositories has created a need for better image content retrieval methods. Recent review articles note traditional image retrieval methods have a number of shortcomings and call on researchers to test new approaches to remedy performance issues. A key issue is developing algorithms that produce very high levels of accuracy while maintaining a low computation cost since algorithms require exponentially more computation, time, and effort to process vast amounts of fundamental image- based content. Of course, there are other issues that foster overall performance of image retrieval.

REFERENCES

- Lecun, Y., Bottou, L., Bengio, Y., et al.: Gradient-based learning applied to document recognition. Proc. IEEE 86(11), 2278–2324 (2018)
- Wan, J., Wang, D., Hoi, S., Steven, C.H., et al.: Deep learning for content-based image retrieval: a comprehensive study. In: Proceedings of the 22nd ACM International Conference on Multimedia, pp. 157–166. ACM (2017)
- 3. Piras, L., Giacinto, G.: Information fusion in content-based image retrieval: a comprehensive overview. Inf. Fusion 37, 50–60 (2019)
- 4. Ren, J.: Investigation of convolutional neural network architectures for image- based feature learning and classification. Thesis (2019)
- Wang, H., Cai, Y., Zhang, Y., Pan, H., Lv, W., Han, H.: Deep learning for image retrieval: what works and what doesn't. In: IEEE International Conference on Data Mining Workshop (ICDMW), pp. 1576–1583 (2020)
- 6. Lin, K., Yang, H.F., Hsiao, J.H., Chen, C.S.: Deep learning of binary hash codes for fast image retrieval. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, pp. 27–35 (2021)
- 7. Tong, S., Chang, E.: Support vector machine active learning for image retrieval. In: Proceedings of the Ninth ACM International Conference on Multimedia, pp. 107–118. ACM (2021)









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