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HYPER-SPECTRAL IMAGE CLASSIFICATION TASKS USING SPECTRAL IMAGING TECHNIQUES

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ABSTRACT: Hyperspectral image (HSI) classification is an important concern in remote sensing, but it is complex since few numbers of labelled training samples and the high-dimensional space with many spectral bands. Hence, it is essential to develop a more efficient neural network architecture to improve performance in the HSI classification task. Deep learning models are contemporary techniques for pixel-based hyperspectral image (HSI) classification. Deep feature extraction from both spatial and spectral channels has led to high classification accuracy.In this study, we propose an adaptive multi scale feature extraction approach tailored for hyper-spectral image classification tasks using spectral imaging techniques. Nowadays, rapid and effective searching for relevant images in large image databases has attained an arena of extensive awareness in many applications. Content-based image retrieval (CBIR) supports an efficient way to retrieve images depending on automatically derived image features. This project propose a two-stage CBIR algorithm in the concept.

INTRODUCTION

In this context, this paper presents a multi-scale hybrid spectral convolutional neural network (MS-HybSN) model that uses three distinct multi-scale spectral-spatial patches to pull out properties in spectral and spatial domains. The presented deep learning framework uses three patches of different sizes in spatial dimension to find these possible features. The process of Hybrid convolution operation (3D-2D) is done on each selected patch and is repeated throughout the image.This approach leverages the multi scale nature of hyper-spectral data to extract discriminative features across different spatial and spectral resolutions.

By dynamically adjusting the scale of feature extraction based on local image characteristics, the method effectively captures relevant information while minimizing the adverse effects of dimensionality. Central to this approach is the integration of advanced spectral imaging techniques, which enhance the representation of spectral signatures and spatial patterns inherent in hyper-spectral data.

PROPOSEDSYSTEM

Existing system Drawbacks

1. More processing time
2. less accuracy
3. less PSNR
4. Not fully automated
5. Limited Understanding of Context
6. Subjectivity in relevance
7. Scalability issues
8. Dependency on Metadata and Annotations
9. Difficulty in Handling Diverse Image Types
10. Semantic Gap

In many signal and image processing applications, it is necessary to smooth the noisy signals while at the same time preserving the edge information. The most commonly used smoothing techniques are linear filtering, averaging filtering, and median filtering. The linear filters smooth the noisy signals and also the sharp edges

Advantages

Localized Enhancement: By dividing the image into quadrants and applying histogram equalization independently to each quadrant, QDHE can enhance local contrast and details,leading to better visibility of features in different parts of the image.

Adaptive Processing: QDHE can adaptively adjust the enhancement process based on the characteristics of each quadrant, allowing for better preservation of image details and avoidance of over-enhancement or under-enhancement in specific regions.

Reduced Artefacts: Compared to global histogram equalization techniques, QDHE may produce fewer artifacts and unnatural-looking effects since it operates locally and preservesthe overall characteristics of the image while enhancing contrast.

Improved Visual Quality: The localized nature of QDHE can result in images that appear visually pleasing with enhanced details and better overall quality, making it suitable for various image processing applications such as medical imaging, surveillance, and photography.Overall, Quadrant Dynamic Histogram Equalization offers an effective approachfor enhancing image contrast and visibility by locally adjusting pixel intensity distributions within different regions of an image, leading to improved visual quality and better interpretation of image content.

LITERATURE SURVEY

Many Internet scale image search methods [11]–[17] are text- based and are limited by the fact that query keywords cannot describe image content accurately. Content-based image retrieval uses visual features to evaluate image similarity. Many visual features [5]–[9] were developed for image search in recent years. Some were global features such as GIST [5] and HOG [6].

Some quantized local features, such as SIFT [13], into visual words, and represented images as bags-of-visual-words (BoV) [8]. In order to preserve the geometry of visual words, spatial information was encoded into the BoV model in multiple ways. For example, Zhang et al. [9] proposed geometry-preserving visual phases which captured the local and long-range spatial layouts of visual words.

One of the major challenges of content-based image retrieval is to learn the visual similarities which well reflect the semantic relevance of images.

Image similarities can be learned from a large training set where the relevance of pairs of images is known [10]. Deng et al.

[11] learned visual similarities from a hierarchical structure defined on semantic attributes of training images. Since web images are highly diversified, defining a set of attributes with hierarchical relationships for them is challenging. In general, learning a universal visual similarity metric for generic images is still an open problem to be solved.

RELATED WORK

Feature Extraction: In this step, visual features are extracted from the images. These features can include color histograms, texture patterns, shape descriptors, or deep featuresextracted from convolutional neural networks (CNNs). These features capture the visual characteristics of the images in a numerical representation.

Indexing: Once the features are extracted, they are organized and indexed in a way that facilitates efficient searching. Various indexing techniques such as hash tables, inverted files,or tree-based structures are

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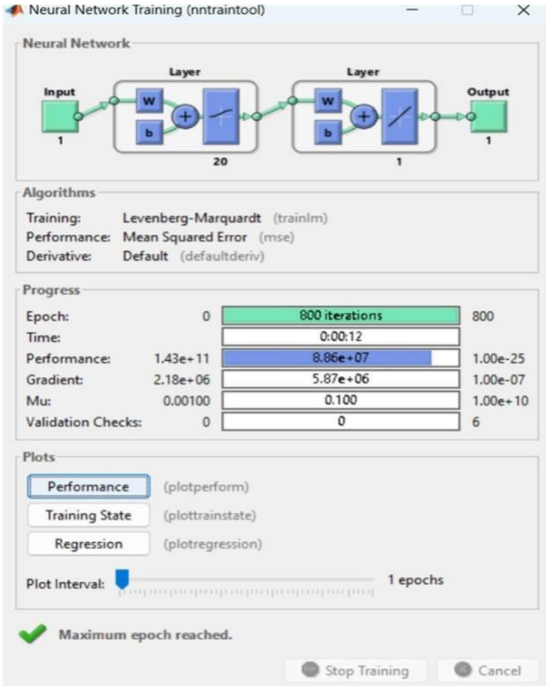
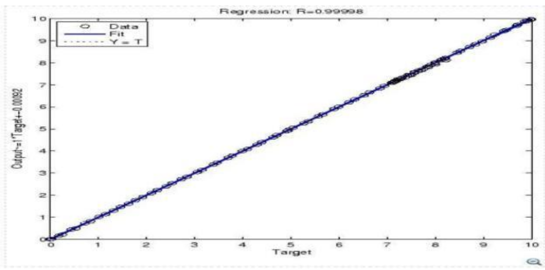
used to speed up the retrieval process.

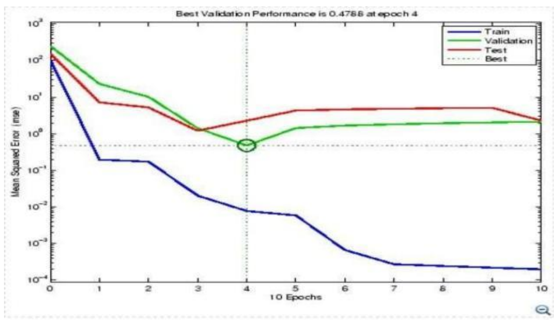
Querying: Users provide a query image or a description of the desired image. The system then compares the features of the query image with those of the images in the database usingsimilarity measures such as Euclidean distance, cosine similarity, or correlation coefficient.

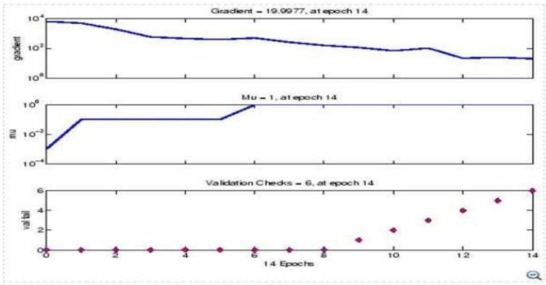
Retrieval: Based on the similarity scores obtained from the comparison, images in the database are ranked according to their relevance to the query. The most relevant images arethen retrieved and presented to the user.

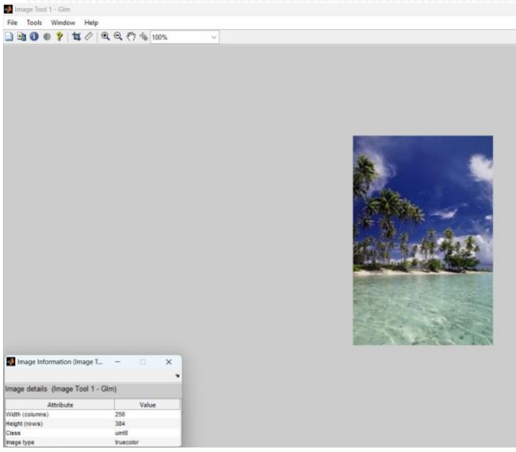
SAMPLE RESULTS

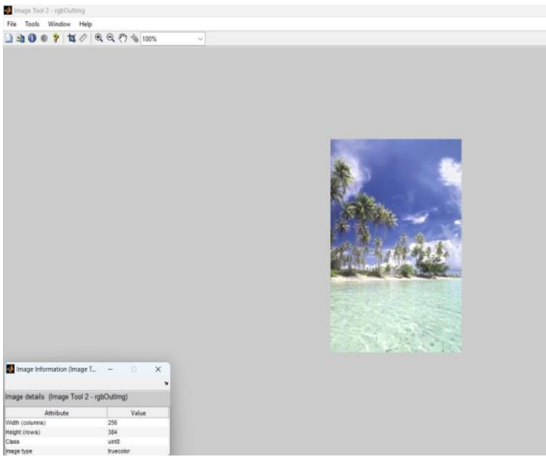


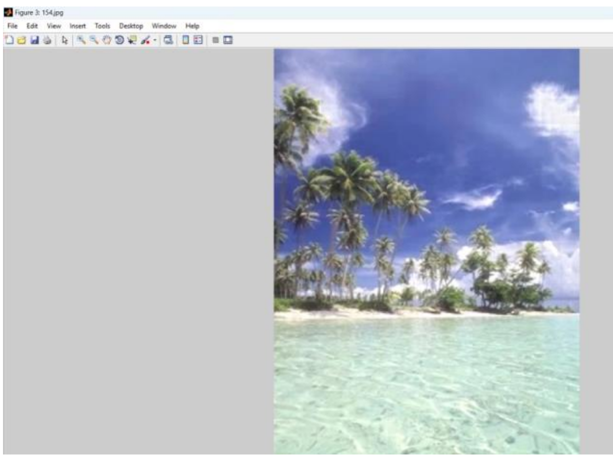


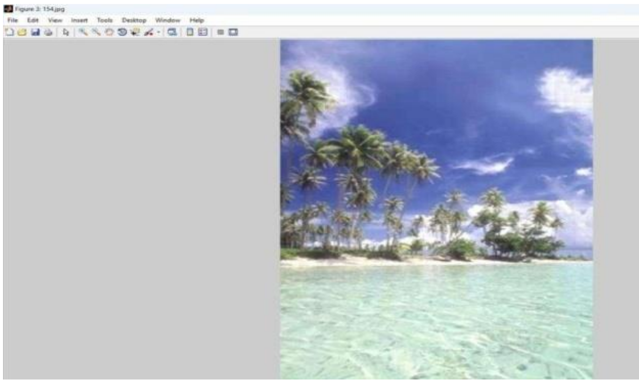












CONCLUSION

We have also shown that one of the major problems of conventional CBIR is the semantic gap, that exist between low level image representation and actual visual response. To bridge this gap, relevance feedback mechanism is used.

As a result, some of the important contributions of the lower valued feature components may be overshadowed by the higher valued features, resulting in an erroneous ranking of the images. Finally, image enhancement is done using CLAHE and QDHE along with feature extraction in

Firstly, our proposed method demonstrates significant improvements in classification accuracy compared to traditional approaches. By adaptively extracting features at multiple scales, we effectively capture both local and global spectral characteristics, thereby enhancing lassification performance.

REFERENCES

[1] R.Silvers.Digital Composition of a Mosaic Image, US Patent and Trademark Office, http://www.uspto.gov, 2000.

[2] K.I. Laws. Rapid Texture Identification. Proc. SPIE Conf. Image Processing for Missile Guidance, pp. 376- 380, 1980.

[3] L.G. Shapiro and G.C. Stockman. Computer Vision. Prentice Hall, 2001.

[4] R.C. Gonzalez and R.E. Woods. Digital Image Processing. Prentice Hall, 2002.

[5] X. Tai, C. Wu, F. Ren, and K, Kita, Image Retrieval Based on Color and Texture. Proceedings of the Fifth Mexican International Conference on Artificial Intelligence, 2006.

[6] M. Tkalcic and J.F. Tasic, Color Spaces: perceptual, historical and applicational background EUROCON 2003, Computer as a Tool, The IEEE Region 8, vol. 1, Sept. 2003, pp. 304-308.

[7] M.J. Swain and D.H. Ballard. Color Indexing. International Journal of Computer Vision, 7(1):11-32, 1991.

[8] M. Flickner, H.S. Sawhney, J. Ashley, Q. Huang, D. Dom, M. Gorkani, J. Hafner, D. Lee, D. Petkovic, D. Steele, and P. Yanker. Query by Image and Video Content: The QBIC System. IEEE Computer, 28(9):23-32, September 1995.

[9] M. Stricker and M. Orengo. Similarity of Color Images. Proceedings SPIE, vol 2420, pp. 381-392, 1995.

[10] M. Stricker and A. Dimai. Color Indexing with Weak Spatial Constraints. Proceedings SPIE, vol 2670, pp. 29-40, 1996.

[11] T. Mostafa, H.M. Abbas, and A.A. Wahdan. On the use of Hierarchical Color Moments for Image Indexing and Retrieval. IEEE International Conference on Systems, Man and Cybernetics, 2