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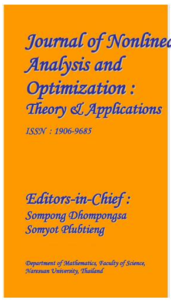

LOCALITY CONSTRAINED LINEAR CODING FOR IMAGE CLASSIFICATION

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ABSTRACT

The traditional SPM approach based on bag-of-features (BoF) requires nonlinear classifiers to achieve good image classification performance. This paper presents a simple but effective coding scheme called Locality-constrained Linear Coding (LLC) in place of the VQ coding in traditional SPM. LLC utilizes the locality constraints to project each descriptor into its local-coordinate system, and the projected coordinates are integrated by max pooling to generate the final representation. With linear classifier, the proposed approach performs remarkably better than the traditional nonlinear SPM, achieving state-of-the-art performance on several benchmarks. Compared with the sparse coding strategy [22], the objective function used by LLC has an analytical solution. In addition, the paper proposes a fast approximated LLC method by first performing a K-nearest-neighbor search and then solving a constrained least square fitting problem, bearing computational complexity of O(M + K2). Hence even with very large codebooks, our system can still process multiple frames per second. This efficiency significantly adds to the practical values of LLC for real applications

1. INTRODUCTION

The recent state-of-the-art image classification systems consist of two major parts: bag-of-features (BoF) [1] and spatial pyramid matching (SPM) [2]. The BoF method represents an image as a histogram of its local features. It is especially robust against spatial translations of features, and demonstrates decent performance in whole-image categorization tasks. However, the BoF method disregards the information about the spatial layout of features, hence it is incapable of capturing shapes or locating an object. Of the many extensions of the BoF method, including the generative part models [3], geometric correspondence search [4] and discriminative codebook learning, the most successful results were reported

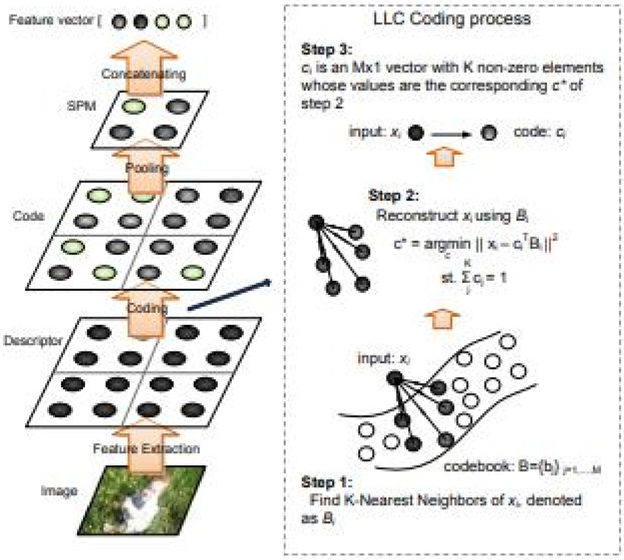


Figure 1. Left: flowchart of the spatial pyramid structure for pooling features for image classification. Right: the proposed LLC coding process.

by using SPM [5]. Motivated by [6], the SPM method partitions the image into increasingly finer spatial subregions and computes histograms of local features from each sub-region. Typically, 2l × 2l subregions, l = 0, 1, 2 are used. Other partitions such as 3 × 1 has also been attempted to incorporate domain knowledge for images with "sky" on top and/or "ground" on bottom. The resulted "spatial pyramid" is a computationally efficient extension of the orderless BoF representation, and has shown very promising performance on many image classification tasks. A typical flowchart of the SPM approach based on BoF is illustrated on the left of Figure 1. First, feature points are detected or densely located on the input image, and descriptors such as "SIFT" or "color moment" are extracted from each feature point (highlighted in blue circle in Figure 1). This obtains the "Descriptor" layer. Then, a codebook with M entries is applied to quantize each descriptor and gen erate the "Code" layer, where each descriptor is converted into an RM code (highlighted in green circle). If hard vector quantization (VQ) is used, each code has only one non-zero element, while for soft-VQ, a small group of elements can be non-zero. Next in the "SPM" layer, multiple codes from inside each sub-region are pooled together by averaging and normalizing into a histogram. Finally, the histograms from all sub-regions are concatenated together to generate the final representation of the image for classification. Although the traditional SPM approach works well for image classification, people empirically found that, to achieve good performance, traditional SPM has to use classifiers with nonlinear Mercer kernels, e.g., Chi-square kernel [7]. Accordingly, the nonlinear classifier has to afford additional computational complexity, bearing O(n3) in training and O(n) for testing in SVM, where n is the number of support vectors. This implies a poor scalability of the SPM approach for real applications.

To improve the scalability, researchers aim at obtaining nonlinear feature representations that work better with linear classifiers, e.g. [7]. In particular, Yang et al. [7] proposed the ScSPM method where sparse coding (SC) was used instead of VQ to obtain nonlinear codes. The method achieved state-of-the-art performances on several benchmarks. Yu et al. [8] empirically observed that SC results tend to be local – nonzero coefficients are often assigned to bases nearby to the encoded data. They suggested a modification to SC, called Local Coordinate Coding (LCC), which explicitly encourages the coding to be local, and theoretically pointed out that under certain assumptions locality is more essential than sparsity, for successful nonlinear function learning using the obtained codes. Similar to SC, LCC requires to solve L1-norm optimization problem, which is however computationally expensive.

In this paper, we present a novel and practical coding scheme called Locality-constrained Linear Coding (LLC), which can be seem as a fast implementation of LCC that utilizes the locality constraint to project each descriptor into its local-coordinate system. Experimental results show that, the final representation (Figure 1) generated by using LLC code can achieve an impressive image classification accuracy even with a linear SVM classifier. In addition, the optimization problem used by LLC has an analytical solution, where the computational complexity is only $O(M + M)$ for each descriptor. We further propose an approximated LLC method by performing a K-nearest-neighbor (K-NN) search and then solving a constrained least square fitting problem. This further reduces the computational complexity to $O(M + K)$, where K is the number of nearest neighbors, and usually $K < 0.1 \times M$. As observed from our experiment, using a codebook with 2048 entries, a 300×300 image requires only 0.24 second on average for processing (including dense local descriptors extraction, LLC coding and SPM pooling to get the final representation). This efficiency significantly adds to the practical values of LLC for many real applications [8].

2. LITERATURE SURVEY

This seminal paper introduces the concept of LLC for image classification. It provides a comprehensive overview of the LLC algorithm, theoretical foundations, and experimental results demonstrating its effectiveness compared to other methods.

This paper proposes an extension of LLC called Linear Spatial Pyramid Matching (LSPM), which incorporates spatial information into the coding process. It presents experimental results showing improved performance in image classification tasks.

This paper provides a detailed analysis of the LLC algorithm, focusing on its theoretical properties and optimization techniques. It offers insights into the underlying mechanisms of LLC and its implications for image classification tasks.

This paper proposes an extension of LLC called Linear Spatial Pyramid Matching (LSPM), which incorporates spatial information into the coding process. It presents experimental results showing improved performance in image classification tasks.

This journal article provides a comprehensive overview of the Fisher Vector (FV)encoding method for image classification. The paper discusses the theoretical foundations of FV and provides practical guidelines for its implementation and application in real-world image classification tasks [9].

This classic paper proposes sparse coding as a model for understanding neural coding in the primary visual cortex (V1). Sparse coding with an overcomplete basis set is hypothesized to be a fundamental strategy employed by V1 neurons to efficiently represent natural images.

This paper introduces the Bag-of-Words (BoW) framework for object retrieval, where images are represented by histograms of visual words. The authors propose fast spatial matching techniques to efficiently compare BoW representations for image retrieval tasks.

This paper proposes Localized Soft Assignment (LSA) coding, a variant of sparse coding that incorporates soft assignment of local features to codewords. LSA coding improves the discriminative power of feature representations and enhances image classification performance.

This paper introduces the Pyramid Match Kernel (PMK) for discriminative classification with sets of image features. PMK measures the similarity between images based on the similarities of their feature sets, enabling effective image classification and retrieval.

3. PROBLEM STATEMENT

The traditional SPM approach based on bag-of-features (BoF) requires nonlinear classifiers to achieve good image classification performance. This project is a simple but effective coding scheme called Locality-constrained Linear Coding (LLC) in place of the VQ coding in traditional SPM.LLC utilizes the locality constraints to project each descriptor into its local-coordinate system, and the projected coordinates are integrated by max pooling to generate the final representation. With linear classifier, the proposed approach performs remarkably better than the traditional nonlinear SPM, achieving state-of-the-art performance on several benchmarks.

3.1 LIMITATION OF SYSTEM

However, LLC also has some disadvantages.one issue is that requires careful parameter tuning, as the performance can be sensitive to the choice of codebook size and other parameters. Another disadvantage is that it may not be well-suited for certain types of images,such as those with highly variable lighting conditions or complex textures.

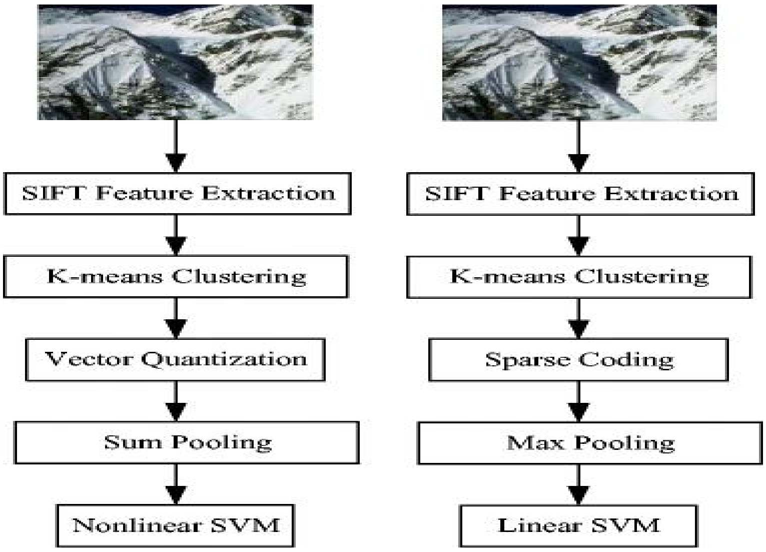
4. PROPOSED SYSTEM

In this project we apply locality constrained linear coding to identify object from images and this technique will extract features from images and then apply HOG descriptor to extract local pattern from images and generate a vector.Pattern vector will be applied on KNN algorithm to build image classification model and in this we experimenting KMEANS and KNN algorithm. Existing technique such as Bag of Features (BoF) and Spatial Pyramid Matching (SPM) is good at extracting features from images but its object classification accuracy is not satisfactory. In propose work author has describe an algorithm to extract features and then normalize and then apply HOG descriptor extract local pattern from images.Extracted pattern will be input to KNN and KMEANS to build classification model [10].

4.1 ADVANTAGES

LLC has several advantages over other methods of image classification. For one, it is computationally efficient, making it wee-suited for large-scale datasets. Additionally, it is robust to noise and other forms of corruption, making it useful in real-world applications.

5. SYSTEM ARCHITECUTE



6. IMPLMENTATION

1. **Upload Dataset**:

   Allows the user to select a directory containing the PASCAL VOC dataset.
2. **Run Normalize LLC Optimization**:

   Performs feature extraction using the HOG descriptor, normalizes the extracted features, applies PCA for dimensionality reduction, and splits the dataset into training and testing sets.
3. **Run KNN Algorithm**:

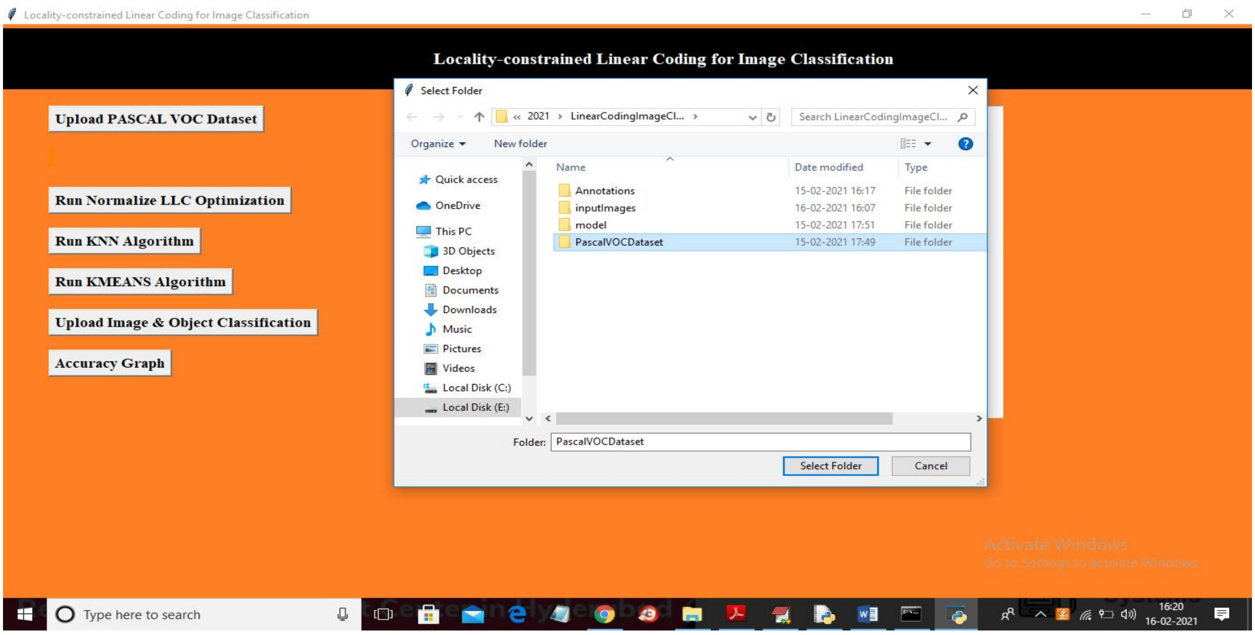
   Executes the K-nearest neighbors (KNN) algorithm on the dataset with different numbers of neighbors (k) and displays the accuracy of classification.
4. **Run KMEANS Algorithm**:

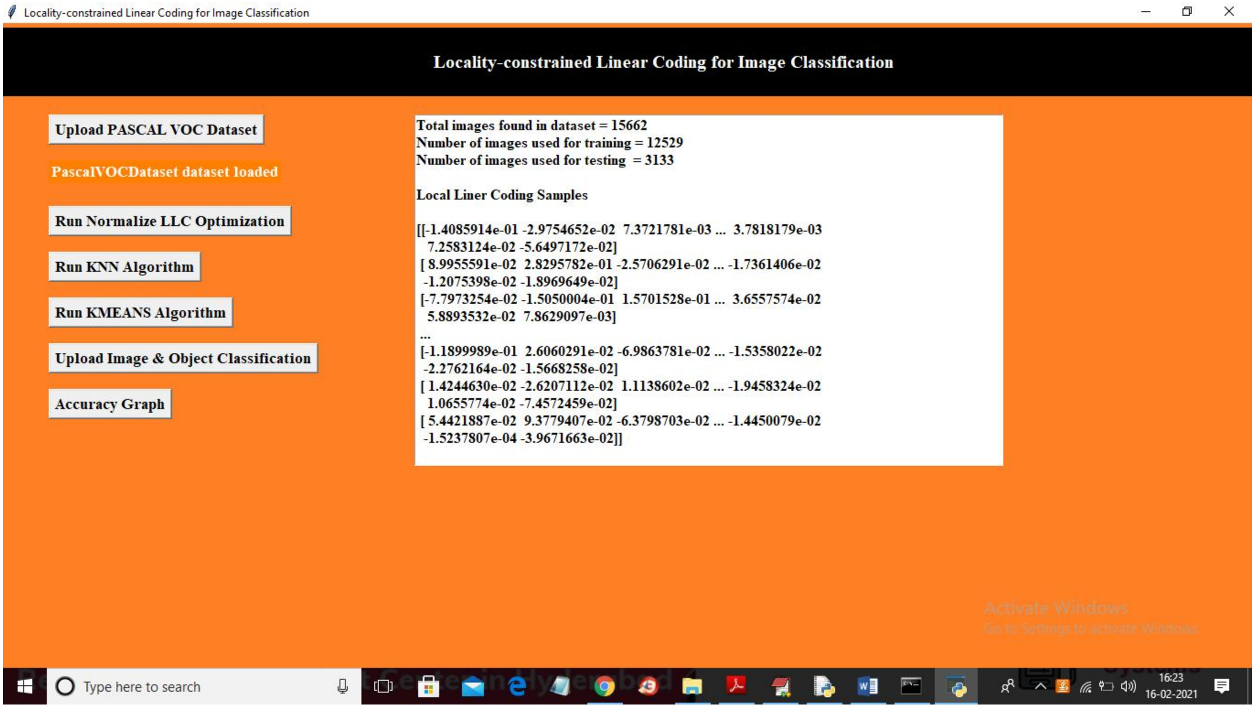
   Runs the K-means algorithm on the dataset with varying numbers of clusters and displays the accuracy of clustering.
5. **Upload Image & Object Classification**:

   Allows the user to upload an image, extract features using the HOG descriptor, apply PCA transformation and normalization, and classify the object in the image using the trained classifier.
6. **Accuracy Graph**:

   Plots a graph comparing the accuracy of KNN and K-means algorithms with different parameters.

7. EXPECTED RESULTS




Locality-constrained Linear Coding for Image Classification
Locality-constrained Linear Coding for Image Classification
Upload PASCAL VOC Dataset
PascalVOCDataset dataset loaded
Run Normalize LLC Optimization
Run KNN Algorithm
Run KMEANS Algorithm
Upload Image & Object Classification
Accuracy Graph
Total images found in dataset = 15662
Number of images used for training = 12529
Number of images used for testing = 3133
Local Liner Coding Samples
[[-1.4085914e-01 -2.9754652e-02 7.3721781e-03 ... 3.7818179e-03
7.2583124e-02 -5.6497172e-02]
[8.9955591e-02 2.8295782e-01 -2.5706291e-02 ... -1.7361406e-02
-1.2075398e-02 -1.8969649e-02]
[-7.7973254e-02 -1.5050004e-01 1.5701528e-01 ... 3.6557574e-02
5.8893532e-02 7.8629097e-03]
...
[-1.1899989e-01 2.6060291e-02 -6.9863781e-02 ... -1.5358022e-02
-2.2762164e-02 -1.5668258e-02]
[1.4244630e-02 -2.6207112e-02 1.1138602e-02 ... -1.9458324e-02
1.0655774e-02 -7.4572459e-02]
[5.4421887e-02 9.3779407e-02 -6.3798703e-02 ... -1.4450079e-02
-1.5237807e-04 -3.9671663e-02]]
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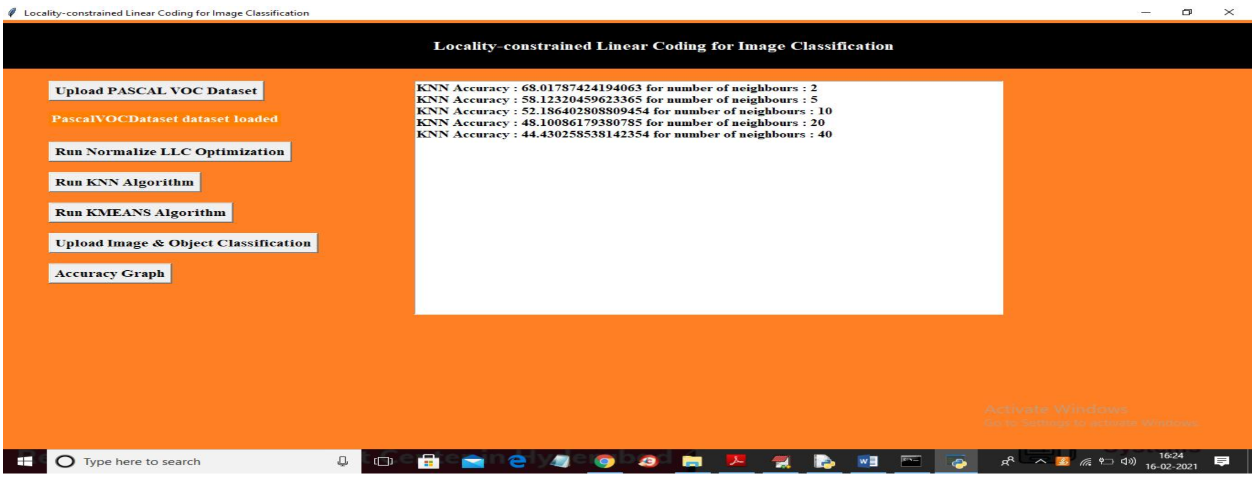
Locality-constrained Linear Coding for Image Classification
Locality-constrained Linear Coding for Image Classification
Upload PASCAL VOC Dataset
PascalVOCDataset dataset loaded
Run Normalize LLC Optimization
Run KNN Algorithm
Run KMEANS Algorithm
Upload Image & Object Classification
Accuracy Graph
KNN Accuracy : 68.01787424194063 for number of neighbours : 2
KNN Accuracy : 58.12320459623365 for number of neighbours : 5
KNN Accuracy : 52.186402808809454 for number of neighbours : 10
KNN Accuracy : 48.10086179380785 for number of neighbours : 20
KNN Accuracy : 44.430258538142354 for number of neighbours : 40
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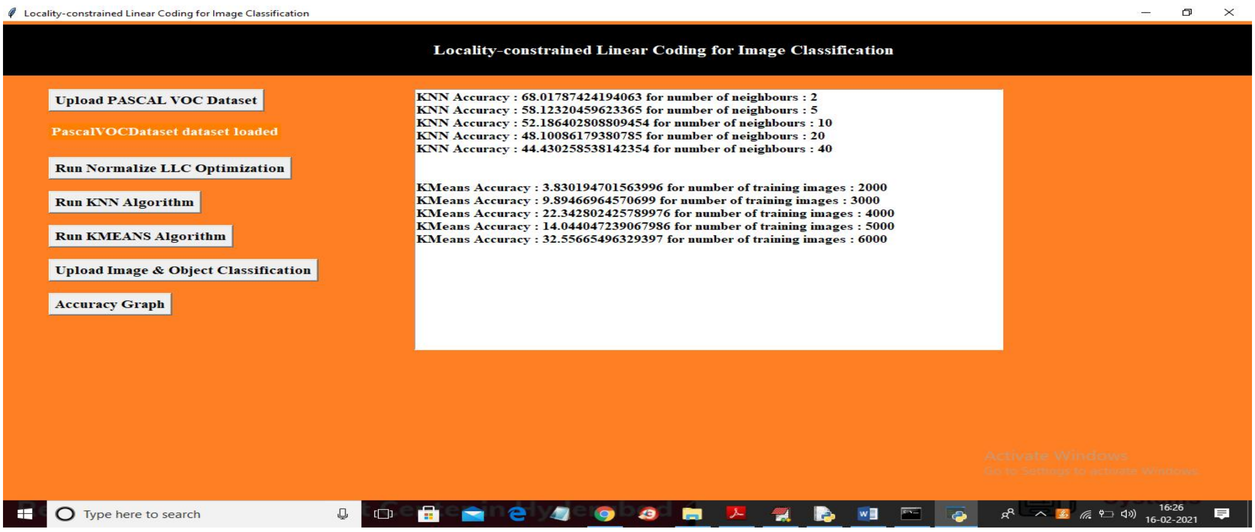
16:24
16-02-2021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KNN Accuracy : 52.186402808809454 for number of neighbours : 10
KNN Accuracy : 48.10086179380785 for number of neighbours : 20
KNN Accuracy : 44.430258538142354 for number of neighbours : 40
KMeans Accuracy : 3.830194701563996 for number of training images : 2000
KMeans Accuracy : 9.89466964570699 for number of training images : 3000
KMeans Accuracy : 22.342802425789976 for number of training images : 4000
KMeans Accuracy : 14.044047239067986 for number of training images : 5000
KMeans Accuracy : 32.55665496329397 for number of training images : 6000
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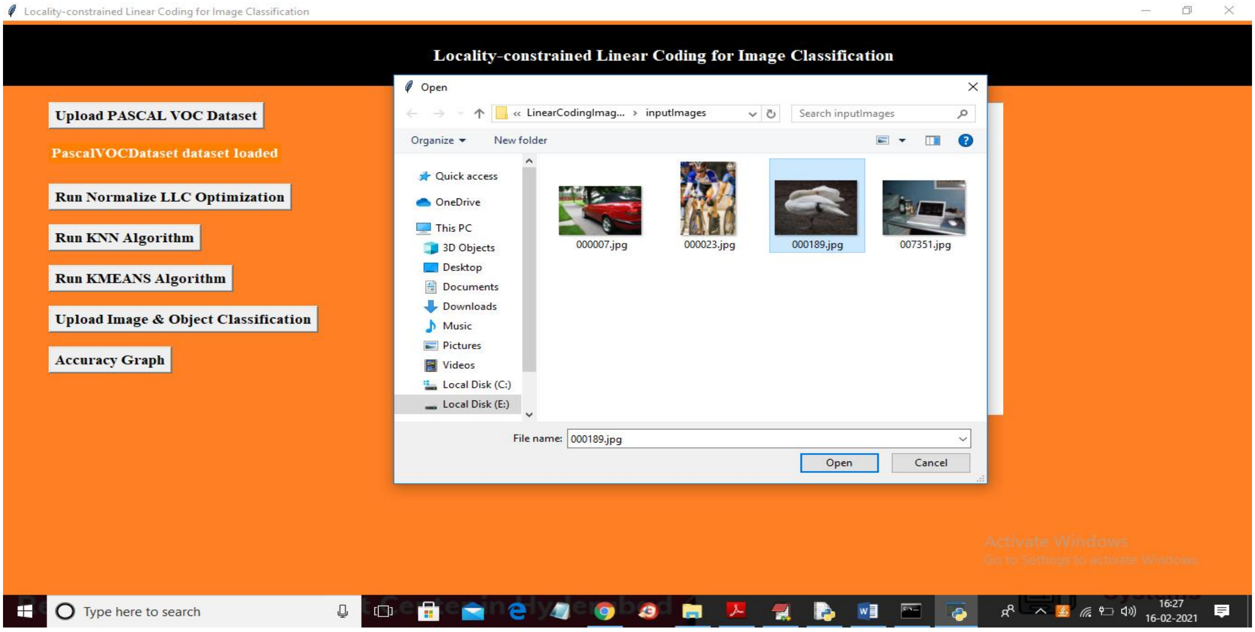
16-02-2021


Locality-constrained Linear Coding for Image Classification
Upload PASCAL VOC Dataset
PascalVOCDataset dataset loaded
Run Normalize LLC Optimization
Run KNN Algorithm
Run KMEANS Algorithm
Upload Image & Object Classification
Accuracy Graph
Open
LinearCodingImag... › inputImages
Search inputImages
Organize
New folder
Quick access
OneDrive
This PC
3D Objects
Desktop
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Pictures
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Open
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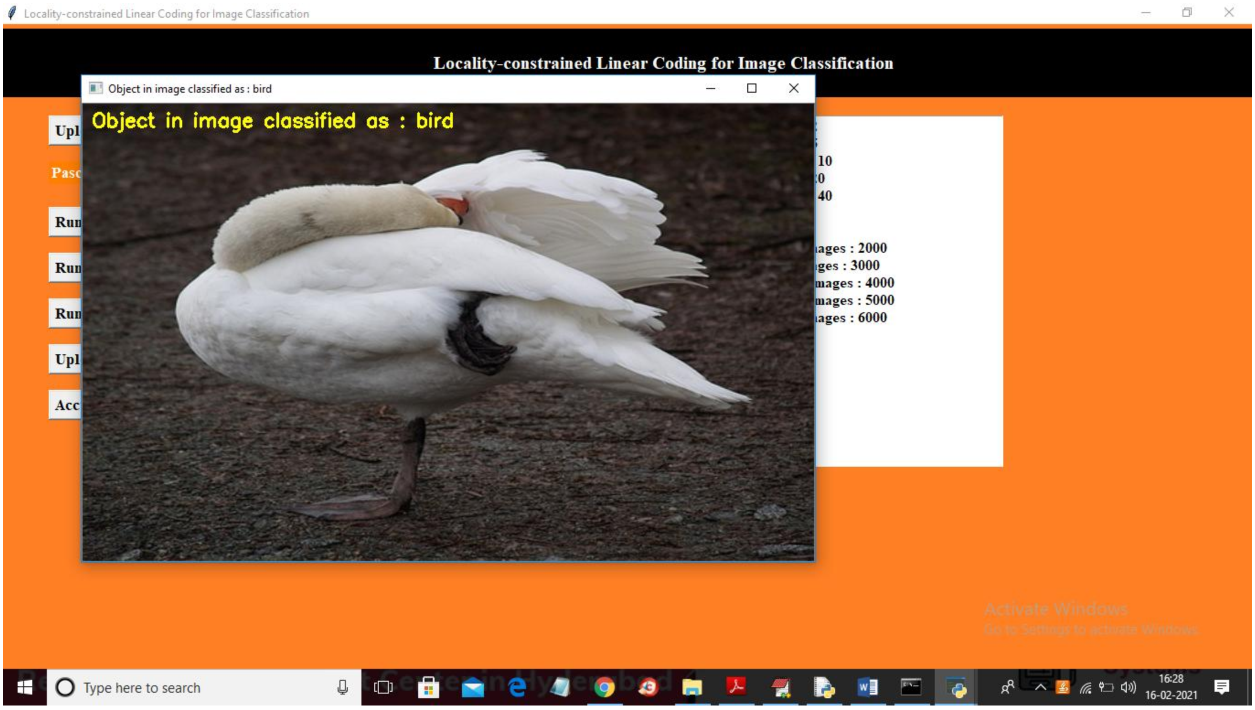
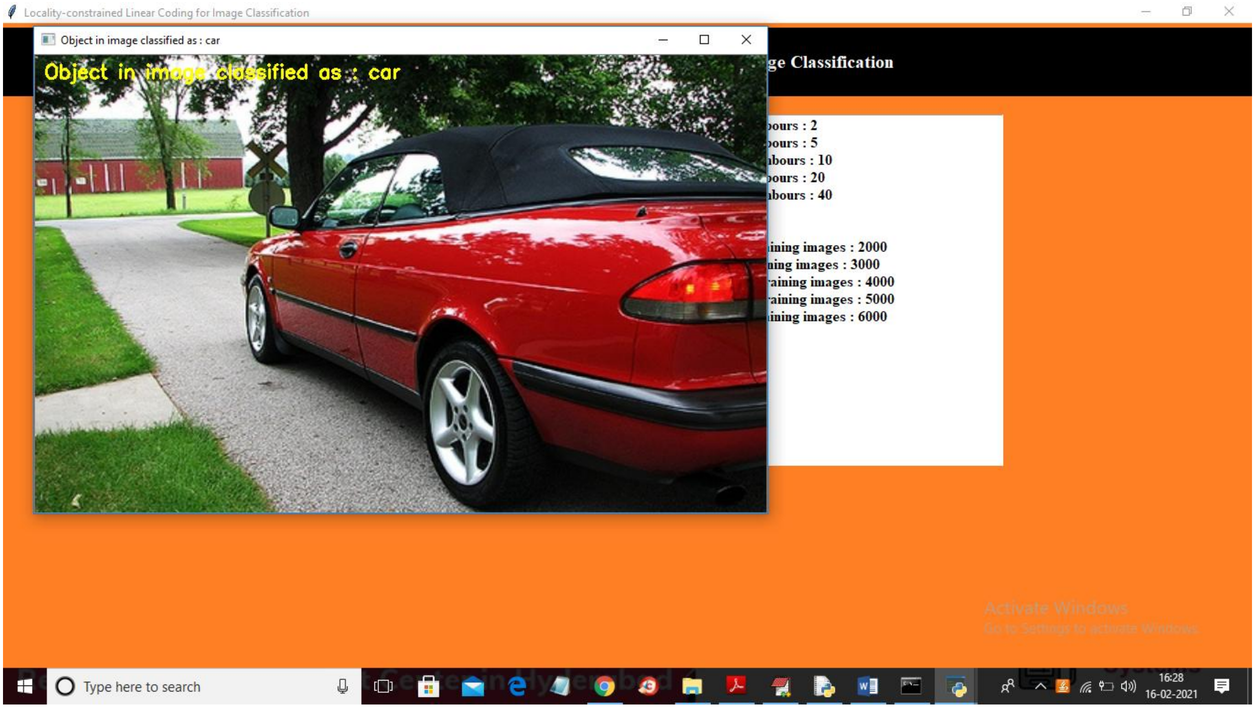

Locality-constrained Linear Coding for Image Classification
Object in image classified as : bird
Object in image classified as : bird
Type here to search
16:28
16-02-2021



8. CONCLUSION

This paper presents a promising image representation method called Locality-constrained Linear Coding (LLC). LLC is easy to compute and gives superior image classification performance than many existing approaches. LLC applies locality constraint to select similar basis of local image descriptors from a codebook, and learns a linear combination weight of these basis to reconstruct each descriptor. The paper also introduces an approximation method to further speed-up the LLC computation, and an optimization method to incrementally learn the LLC codebook using large-scale training descriptors. Experimental results based on several well-known dataset validate the good performance of LLC.

9. FUTURE SCOPE

Satellite imaging and military applications represent burgeoning frontiers in the realm of image classification, poised to significantly impact various sectors. With the increasing availability of high-resolution satellite imagery, there is a growing demand for sophisticated image classification techniques to analyze and interpret vast amounts of data obtained from space. In military contexts, image classification plays a pivotal role in intelligence gathering, reconnaissance, and surveillance, aiding in identifying potential threats, monitoring troop movements, and assessing terrain conditions. Moreover, advancements in broadband devices and mobile technology are poised to revolutionize image processing systems in handheld devices, enabling real-time analysis and classification of images directly on the device. These advancements open up new possibilities for applications such as augmented reality, remote sensing, and environmental monitoring, where rapid and accurate image classification is essential for decision-making and situational awareness. As satellite imaging and military applications continue to evolve, the need for robust and efficient image classification algorithms will remain paramount, driving innovation and advancements in the field.

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