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Plant Species Identification using SIFT and SURF Technique

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Abstract: ***This research investigates the performance of plant species identification scheme using support vector regression (SVR) with different classification method. The classification involved combination of features derived from shape, shape+texture, shape+color+texture, correlation coefficient, color, and texture and cosine feature of plant species. The present paper introduces support vector regression (SVR) procedure to image based identification of species of plant. Visual contents of images are applied and three usual phases in computer vision are done: (a) feature discovery, (b) feature explanation, (c) image depiction. Three dissimilar approaches are castoff on digital databases of plants. The proposed approach is done by scale invariant feature transform (SIFT) method and two combined method, SURF and features from accelerated segment test-SIFT and also clustering of data done by F-Dbscan. Vision comparison is investigated for four different species. Some quantitative results are measured and compared.***

Keywords*:* Plant Species Identification System, SVR, SIFT, SURF, F-DBSCAN ***etc***

1. Introduction

Plants play important role in our life. Without plants there will be no presence of the earth's biology. In present days, various categories of plants are at the risk of destruction. To defend plants and to directory several kinds of flora varieties, a plant dataset (digital image) is an imperative stage in the direction of preservation of earth's biosphere. There is a large no. of plant species globally summarized in in existing work. To handle such volumes of evidence, growth of a rapid and effective classification technique has developed an area of active study. In adding to the maintenance feature, identification of species plants for leaf is also essential to use their medicinal properties and using them as foundations of alternate energy sources like bio-fuel. There are numerous methods to recognize a plant, like flower, root, leaf, fruit etc. In current times computer vision procedures and pattern recognition methods have been useful to automatic events of plant species recognition. The present paper proposes a system for automated recognition and identification of three types of plant species by evaluating shape features from digital images of their leaves. The association of the paper is as follows: section 2 provides an overview of related work, section 3 outlines the problem statement, section 4 provide the system model, section 5 give the proposed approach with discussions on overview, feature computation and classification schemes, section 6 provides details of the dataset and experimental results obtained and section 7 provides the overall conclusion and the scope for future research.

2. Literature Review

The literature studies have been lead in the past decade on mechanization of plant classification and recognition. Some studies absorbed on image based plant classification, while others focused on image-based plant recognition. Brendon J et al [1] proposed the image processing, and neural network classification approaches used for target of classifying the damaged to apple fruits and leaves in orchards. The objective of this was take benefit of taking images of the fruit/leaf without doing manual labour in terms of review and climbing trees and physically inspection the rats diseased.

L. Tang et al [2] presented low level features (texture features) to classify various kinds of grass weeds leaves. A pattern acknowledgment scheme collected of a Gabor wavelet feature extractor and a feed forward back broadcast ANN classifier was established to classify weeds into broadleaf and grass classes. Mostly, a Gabor wavelet filter bank was calculated to find joint space-frequency characteristics from a set of authentication images established the possible of the technique.

Stephen Gang Wu et al [3] specified a PNN (Probabilistic Neural Network) for classification of leaf images based on 12 leaf features. A principal component analysis (PCA) was used for dipping the 12 dimensions into five dimensions for faster dispensation. The 12 features used were functional length, physiological width, and leaf area, and leaf perimeter, horizontal feature. Feature fraction, form factor, rectangularity, fine factor, and border proportion of diameter, perimeter ratio of physiological length and physiological width, and vein features.

T. Satiohet al [4] deliberates an automatic method for recognition wild flowers. These recognition compulsory two images: a frontal flower image and a leaf image occupied through a digital camera. Seventeen features, eight from the flower and nine from the leaf, were fed to a neural network. This investigation produced an accuracy of 95% on 20 pairs of pictures from 16 wild flowers. These studies dealt with a single or group of comparable plant species only.

D. Warren et al [5] introduced an automatic computerized system that used as its input 10 images of each chrysanthemum species for testing the variation in the images. In this study, features such as shape, size and color of the flower, petal, and leaf were described mathematically. Different rose features was removed and used in the acknowledgment system for design appreciation. The training, though, was limited to chrysanthemum species only.

Sathwik, T. et al [6] uses a texture investigation of leaf image technique to identify and classify medicinal plants. The texture analysis makes a set feature which is used to query the image from the database.

Herdiyeni, Y. Kusmana, I [7] used Local Binary Patterns (LBP) which is one of texture feature method. It is use to identify the medicinal plant. The LBP is used in two ways, first is to calculate multiple histograms then links those collected. A second method is to classify medicinal plant based on LBP feature of each histogram.

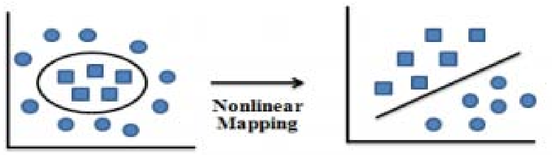
3. Problem Statement

This paper addresses this problem with the objective of developing plant species identification algorithms that can recognize problems in crops from images, based on colour, texture and shape to automatically detect or other conditions that capacity mark yields and provide the fast and precise explanations to the grower through the assistance of SVR classification and SIFT+SURF. After that, several techniques are used to classify the images according to the specific problem at hand.

4. System Model

4.1 Classification Using SVR

Support Vector Machines (SVR) is a controlled learning method frequently favored in classification and recognition because of their promising performance. Based on the selection of parameters and kernel strategy the performance can be enhanced. SVR multiclass classification can also explain real world problems capably with the well-defined theoretic model for multiclass data set. SVR can exploit the regular margin at the same time it can minimize the experiential classification error.
SVR classifier



Input feature space **New feature space**

Figure 1: SVR classifier of Mapping

SVR classifier maps the input vectors into a new high-dimensional feature space. The nonlinear mapping provides the solution for two class classification problem. It constructs an optima hyper plane to isolate the two classes through finding the largest margin. The two classes are signified by positive and negative class [11]. The figure 1 shows the two class classification.

5. Proposed Implementation

5.1 Support vector Regression

1) Support vector regressions are a moderately new machine-learning tool and have appeared as a dominant method for learning from data and in specific, for solving binary classification problems.
2) SVRs created from Vapnik's statistical learning theory [2], and they expressed the learning problem as a quadratic optimization issue whose fault surface is allowed of local minima and has worldwide finest, the goal is to discovery an optimal separating hyper plane (OSH) between the two data sets.
3) SVR finds the OSH by exploiting the margin among the classes. The main ideas of SVR is first transform input data into a higher dimensional space by means of a kernel function and then construct an OSH among the two classes in the transformed space.
4) Those data vectors near to the constructed line in the distorted space are called the support vectors [3].
5) The SVR estimates a function for categorizing data into two classes [2]. Using a nonlinear transformation that depends on a regularization parameter [3], the input vectors are located into a high-dimensional feature space, where a linear separation is active. Fig. 2 displays the linear separating hyper plane where support vector are bordered

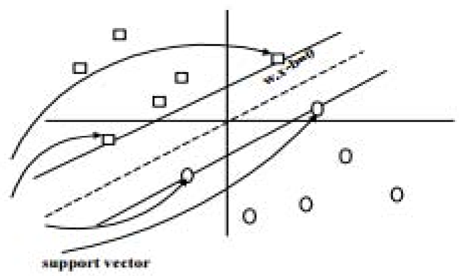


Figure 2: Linear separating hyper planes, the support vectors are circled.

To concept a nonlinear support vector classifier, the inner product (x, y) is substituted by a kernel function K (x ,y).

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{l} \alpha_i y_i K(x_i x) + b\right)$$

Where, f (x) controls the involvement of x. In this training part the typical subjects were considered as -1 and other subjects as +1. The SVR has two layers. During the learning procedure, the first layer chooses the base K (xi ,x), i=1,2,….N from the assumed set of kernels, while the second layer constructs a linear function in the space.

This is comparable to discovery the best hyper plane in the equivalent space feature. The SVR procedures can theory a variability of learning machines using different kernel purposes.

5.2 SIFT (Scale Invariant Feature Transform)

The Scale Invariant Feature Transform descriptor which is effectively operated for object (species leaf) identification and image classification are designated as local features. Features removed using the SIFT procedure which invariant to image scale, rotation, and moderately strong to altering views and changes in clarification. The invariance and strength of the features mined using this process that makes it a particularly good applicant for object recognition and attaining one of the best performance facts from all present feature extraction methods [10]. In order to acquire SIFT descriptors, there are two steps, key point detection and feature extraction. In the first step, an image will be filtered with Gaussian functions at different scales and difference of Gaussian (DoG) is employed to sense key points which are the local extrema (maxima or minima). The more key points are coordinated between two images, the more similar the image. And the correspondence among two images is distinct like,

$$Dist_{SIFT} = 1 - \frac{SiftMatch(q,i)}{Keypoints(q)},$$

where Sift Match(q, i) is the no. of coordinated key points between images Iq and Ii, and Key-points (q) is the no. of key points accessible in image Iq so as to regularize the distance value to the assortment of [0, 1].

5.3 SURF (Speeded-Up Robust Features)

The SURF local feature descriptor was selected based on its abridged computational cost comparative to SIFT, wide usage, combined key-point detection machinery and compatibility with BoVW based image retrieval [11]. Firstly, SURF key-points are perceived then consistent descriptors are calculated. In our method, SURF key-point co-ordinates are used to contain the center of the plant species selection structure, then image pixel patches are tested centered on and about the key point. The consistent SURF and SIFT descriptor histograms are then joint. When all images have been handled, F-DBSCAN clustering is used to calculate a fixed-length for arbitrary images which resolute and enquired beside the dataset.

5.4 F-DBSCAN clustering Algorithm

The DBSCAN [8] is density based fundamental for cluster formation in huge data. The algorithm benefit is that it can determine clusters with arbitrary shapes and size. The procedure typically regards clusters as dense regions of objects in the data space that are divided through areas of low-density objects. The F-DBSCAN has two input parameters, radius (ε) and MinPts. For understanding the procedure of the algorithm has certain concepts and Descriptions has to be presented. The Description of dense objects is as follows.

Description 1: The area within a radius of a given object is called the ε - neighborhood of the object.
Description 2: If the ε -neighborhood of an object covers at least a minimum number σ of objects, then the object is called an σ -core object.
Description 3: Assumed a set of data objects, D, we say that an object p is openly density reachable from object q if p is within the ε -neighborhood of q and p is a σ -core object.
Description 4: An object p is density-reachable from object q with respect to ε and σ in a given set of data objects, D, if there is a chain of objects p1,p2,p3… Pn, p1=q and pn=p such that p_{n+1} is directly density-reachable from P_i w.r.t ε and σ , for $1 \leq i \leq n, pi \in D$.

Description 5: Any piece p is density-connected from object q with respect to ε and σ in a given set of data objects, D, if there is an object o ∈ D such that both p and q are density accessible from o with respect to ε and σ.

F-DBSCAN needs two parameters: radius epsilon (Eps) and minimum points (MinPts). It starts with an arbitrary preliminary point that has not been visited. After that it finds all the neighbor points within distance Eps of the preliminary point. If the no. of neighbors is greater than or equal to MinPts, a cluster is molded. The preliminary point and its neighbors are added to this cluster and the opening point is marked as visited. The procedure then recurrences the assessment procedure for all the neighbors' recursively. If the no. of neighbors is less than MinPts, the point is obvious as noise. If a cluster is completely prolonged (all points within reach are visited) then the procedure profits to iterate concluded the continuing unvisited points in the dataset.

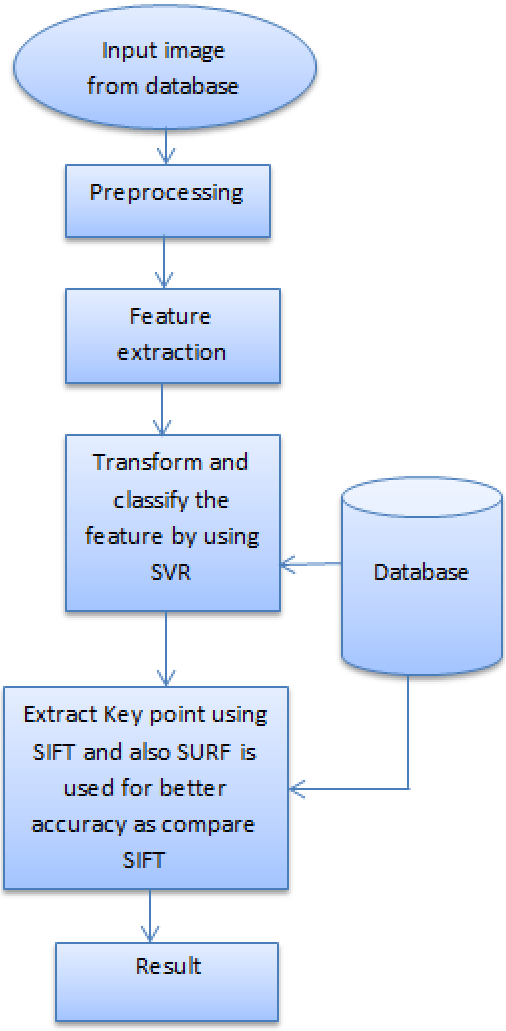


Figure 3: Proposed flow diagram

6. Result

The experiments were considered to organize each test image into a single class. Subsequently all the plant species images are occupied by us, their true classes are known. In our experiment, we identify the plant by the SVR classifier. Initially, we select ten of the samples as training samples, and the continuing is used as testing examples.

6.1 Development

In the improvement stage, above examined features will be investigated with different likely parameters to find best feature set and classifier. To implement some of these issues, it has monitored certain more basic stages before profitable into feature extraction and classification.

6.2 Image Acquisition

Proposed work is to classify leaf images taken through overall determination digital camera with specified minimum limits. One of the foremost issue originate in previous works are having quantity of extreme controls for obtaining image. In real setting, the images occupied may not be always leaf images or background of the image will not be strong. To avoid these developments, an object distinguishing procedure is projected to check before going into the procedure to remove those types of images. Previously implemented image cropping tools will be used to evade indistinct training. These will be applied as an additional feature of the scheme for used in real application.

6.3 Image Preprocessing

After image acquisition, image has to be preprocessed to excerpt requirement feature out from it. Most of the features absorbed are based on the morphological features of a species leaf. These features can be recognized once the leaf contour is acknowledged correctly. To mine leaf contour from the image, it should be improved to digital image. An image occupied through a digital camera is in RGB color format. In RGB design the image is saved as 3 dimensional vectors where Red, Green, and Green color intensity values are in the matrix for every pixel value. First RGB color image should converted to grayscale and then into binary image. In the alteration to grayscale image, following relative can be used.

$$G = 0.2989\ x\ R + 0.5870\ x\ G + 0.1140\ x\ B$$

Here G is the grayscale intensity value. So the 3 dimensional matrixes are converted into 2 dimensional matrixes where only grayscale intensity is available. Then this grayscale value has to be regulated for 1s and 0s to change into binary image. For this normalization, a threshold value should be specified. 0.95 is used as the threshold in this training.

6.4 Feature Extraction

After preprocessing of images, structures have to extract using the preprocessed images. As deliberated above in previous sub heading about feature exploration, all the selected features going to be removed. This procedure should be automatic where this will be used in training classifier as well as in test images.

6.5 Classification

In the classification also, deliberated classification schemes will be applied to select a best classifiers from two classifiers SVR and Machine Learning. So the typical datasets will be verified using every classifier through giving above mined features to classify best execution scheme for this study. Image processing is carried out to extract the leaves from the background accurately

Figure 4: Input image

First we take the input from the database corresponding to data stored in input and output parameters and the training is carried out on the connection weights of the Support vector regression which is finally stored in the database in the place of connection weights. Training is completed equivalent to every of the data extant in the I/O factors board.

Figure 5: Gray scale image

6.6 Colour to Grayscale Conversion

Generally formula is used for converting RGB value of a pixel to its grayscale cost gray = 0.2989*R + 0.5870*G + 0.1140*B Though, an altered method is modified in this experiment considering the plant leaf domain. Most of the leaves are in different shades of green; very few are in shades of red, yellow and others. The green component is the least reflected and most absorbed. Since the leaf is captured on a white background, instead of converting the image into gray by the predefined formula, green band is processed further. This approach helped in separating the leaf from its background easily, as the leaf (green band) is in darkest shade and the background in lightest shade.

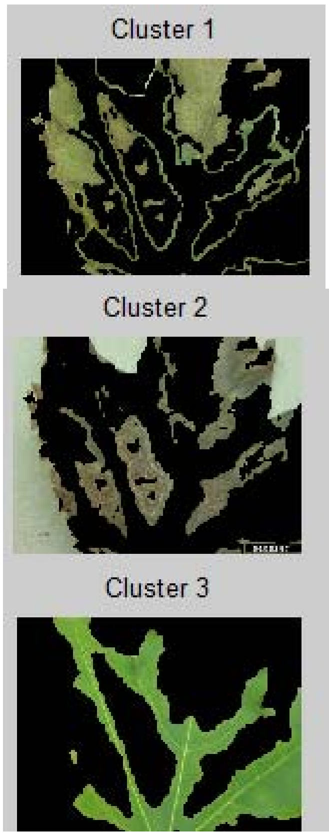


Figure 6: cluster formation using F-DBSCAN

These features were vital in identifying leaf shapes, number of parts and margin types. Leaves of 3 classes were used and a classifier was implemented and tested using multiple leaves of 3 different species. F-dbscan clustering was used to classify 15 leaf images into three clusters.

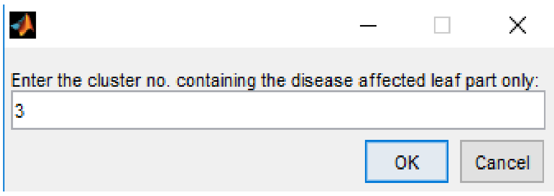


Figure 7: Cluster no. containing the disease affected leaf

Figure 8: SIFT-SURF key point matching

The output image filtered is assumed as the effort to Scale invariant feature transform algorithm to make it scale, rotation invariant. Keypoints/extremas are extracted from SIFT & Key point removal is complete using angle recognition method. Lastly Leaf images are recovered using Descriptor Ratio Matching. SURF approach, which is an effective alternative to SIFT. SURF pools its individual gradient location founded feature descriptor with a Hessian-Laplace area indicator. For the internal computations, it uses 2D box filters (Haar wavelets). These box filters estimated the properties of the derived filter seeds, and can be assessed using essential images.

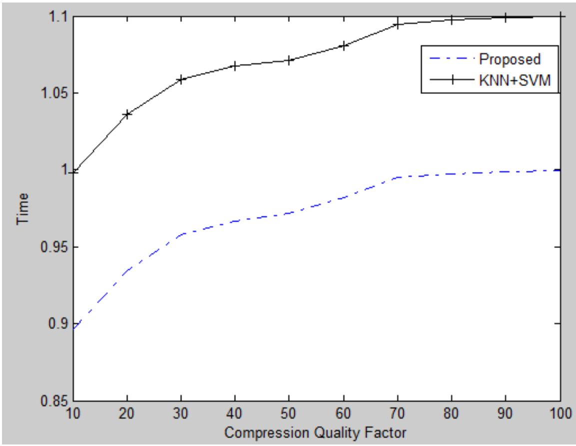


Figure 9: Compression quality factor for KNN-SVM vs. Proposed (SIFT-SURF)

compression quality ratio	KNN+SVM (Time)	Proposed(SIFT-SURF) ((Time))
10	0.89	0.99
20	0.93	1.03
30	0.95	1.06
40	0.96	1.07
50	0.97	1.08
60	0.97	1.088
70	0.98	1.89
80	0.98	1.094
90	0.98	1.1
100	0.98	1.1

The two main stages are training and query part. Images are first fed into the SIFT-SURF function from training set. This will extract the interest points from each image. These points will then cluster into clusters by F-DBSCAN algorithm, Euclidean distance, with respect to their descriptors. In query part when a user submitted a query image, using SIFT-SURF algorithm interest points and descriptors will be extracted.

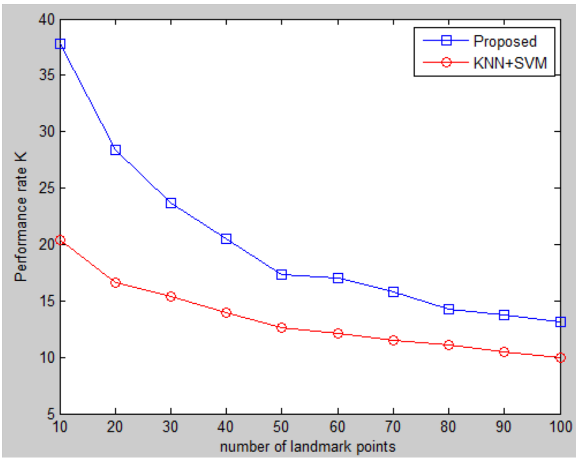


Figure 10: Number of landmark points for KNN-SVM vs. Proposed (SIFT-SURF)

Number of landmark points	KNN+SVM (Performance rate)	Proposed(SIFT-SURF) (Performance rate)
10	21	39
20	17	28
30	16	24
40	14	22
50	13	18
60	12	17
70	11	17
80	10	16
90	90	15.2
100	100	15

0 14.5000 85.5000 99.5000 142.0000 112.0000
0 164.5000 162.0000 168.0000 98.5000 218.0000

Matrix generation of image

species_disease = 'BLACKSPOT'

Different species own leaf characteristics with large and small inter-class variations, even if the study focuses on a single genus, it may contain many species, each of which encompasses greatly difference among essential populations. Therefore, we exactly excellent the species, which have similar leaf character and observe the classification performance of the proposed method. To validate the show of our projected technique, we built, as an image dataset, a total of leaf images from plant species. For each species, there are leaf images with variations in lighting, scale and background.

7. Conclusion

In this paper, SVR method and two combined methods are taken into consideration for plant species recognition and classification. Accuracy measurement and efficiency of each method are described. The methods were tested on digital dataset. Experimental results are also compared with some quantitative results and discussed allowing to human visualization for four different species. Investigates on the dataset, validate that SIFT-SURF method has the best performance between proposed methods. The proposed work will be useful for further procedure, SURF. Particular other groupings of dissimilar approaches of recognition and extraction of features can be used for next steps.

References

[1] Brendon J. Woodford, Nikola K. Kasabov and C. Howard Wearing (1997) “Fruit Image Analysis using Wavelets” in Proc. 6th Int. Conf. Image Process. And It‟s Applicant, Duplin, Ireland.
[2] L.Tang, L. Tian, B. L. Steward (2003) “Classification of broadleaf and grass weeds usingGabor Wavelets and an artificial neural network” Transactions of the ASAE Vol. 46(4): 1247-1254 _ 2003 American Society of Agricultural Engineers ISSN 0001-2351.
[3] Stephen Gang wu, Forrest Sheng Bao, Eric You Xu, Yu-Xuan Wang, Yi-Fan Chang and Qiao-Liang Xiang (2007) “A Leaf Recognition Algorithm for Plant Classification Using Probabilistic Neural Network”, arXiv:0707.4289vl [cs.AI].
[4] T.Satiosh and T.kaneko (2000), “Automatic Recognition of Wild Flowers”, ICPR, Vol.2, pp. 2507-2510
[5] D.Warren (1997) “Automated leaf shape description for variety testing in chrysanthemums” in proc. 6th Int. Conf. Image Process and its Applicant. , Duplin, Ireland.
[6] Sathwik, T. Yasaswini, R. ; Venkatesh, R. ; Gopal, A."Classification of selected medicinal plant leaves using texture analysis", Chennai Centre, Central Electron. Eng. Res. Inst., Chennai, India ; Pages 1-6 July 2013
[7] Herdiyeni, Y. ; Kusmana, I. ; Dept. of Comput. Sci., Bogor Agric. Univ. (IPB), Bogor, Indonesia ; Kusmana, I."Fusion of Local Binary Patterns features for tropical medicinal plants identification" Advanced Computer Science and Information Systems (ICACSIS), 2013 International Conference Sept. Page 353 - 357, 2013
[8] D. Hsu and S. Johnson, "A Vibrating Method Based Cluster Reducing Strategy", Fifth International Conference on Fuzzy Systems and Knowledge Discovery, vol. 2, (2008), pp. 376-379.
[9] J. H. Peter and A. Antonysamy, “Heterogeneous Density Based Spatial Clustering of Application with Noise”, International Journal of Computer Science and Network Security, vol. 10, no. 8, (2010), pp. 210-214.
[10] K. Mikolajczyk and C. Schmid, “A performance evaluation of local descriptors,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 10, pp. 1615–1630, 2005.
[11] H. Bay, T. Tuytelaars, and L. Van Gool, “SURF: Speeded up robust features,” in *Proceedings of the 6th European Conference on Computer Vision (ECCV)*, pp. 404–417. Springer, 2006
[12] G. Csurka, C. Dance, L. Fan, J. Williamowski, and C. Bray. *Visual categorization with bags of keypoints*, in. ECCV’04 workshop on Statistical Learning in Computer Vision, 2004. pp. 59–74.
[13] Xin Chen, Xiaohua Hu1, Xiajiong Shen, *Spatial Weighting of Bag-of-Visual-Words*. Proceedings of the 13th pacific-Asia Conference on Advances in Knowledge Discovery and Data Mining, 2009. pp. 867-874.
[14] Yi Yang, Shawn Newsam, *Bag-of-visual-words and spatial extensions for land-use classification*. Proceedings of SIGSPATIAL International Conference on Advances in Geographic Information Systems, 2010. pp. 270-279.
[15] Michael Villamizar, Jorge Scandaliaris, Alberto Sanfeliu, and Juan Andrade-Cetto, *Combining Color-based Invariat Gradiet Detector with HoG Descriptors for Robust Image Detection in Scenes under Cast Shadows*. IEEE International Conference on Robotics and Automation, 2009. pp. 1997-2002.
[16] Jun Yang, Yu-gag Jiang, *Evaluating bag-of-Visual-words representations in scene classification*. Proceedings of the International Workshop on Multimedia Information Retrieval, 2007. pp. 197-206.
[17] David Picard, Nicolas Thome and Matthieu Cord, *An Efficient System for Combinig Complementary Kernels in Complex Visual Categorization Tasks*. Proceedings of IEEE International Conference of Image Processing (ICIP), 2010. pp. 3877-3880.
[18] C.-F. Tsai, *Bag-Of-Words Representation in Image Annotation: A Review*. International Scholarly Research Network, 2012. pp. 1-19.

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