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# An Efficient Object Classification Based On ELM

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***Abstract-*** *Object classification important task in image processing. The image processing techniques greatly help to classify object. The goal of object classification is to accurately predict the target. Classification includes image sensor, object preprocessing, object detection, feature extraction from a image and object classification. Feature extraction is useful technique for efficient object classification. This paper presents Extreme Learning Machines classification techniques with feature fusion function. Extreme learning machine (ELM) is an emerging learning algorithm for the generalized single hidden layer feedforward neural networks, of which the hidden node parameters are randomly generated and the output weights are analytically computed*

***Key words****: Object Classifications, Image Processing*

## 1. Introduction

An Image is a square pixels array, or a matrix, arranged in columns and rows. The pixel is a picture element. Image processing is process image data for storage and transmission, which is used enhance the image for improve the image quality and reduce the noise. The enhancement is a process which is used to extracting image feature information. Image classification is easy task for human but it has to be a complex problem for digital devices. The raise of high-capacity computers, the availability of high quality scanning devices and low –priced cameras and the increasing need for automatic object analysis has generated an interest in object classification algorithm.

A simple object classification system consists of a camera fixed high above the interested zone in image processing, where objects are detected and consequently processed. Object Classification system consists of extracted feature database that contains predefined patterns that compares with detected object to classify in to proper category. Object classification is an important and challenging task in various application domains, including biomedical imaging, biometry, vehicle tracking, industrial visual inspection, robot tracking and image remote sensing. Image classification represents group pixels to define land cover features. Land cover may be forested, urban, agricultural and other types of features.Object classification uses the reflectance information for individual pixels. Pixels are the smallest unit represent in an image. Unsupervised and Supervised techniques are the most common classification approaches. There are three main object classification techniques in remote sensing.

A. Object Classification Techniques:

- Unsupervised image classification
- Supervised image classification
- Object-based image classification

Pixels are clustered based on the reflectance properties of pixel. Clustering process define the pixel grouping. The user physically specifies each cluster with land cover classes. Multiple clusters characterize a single land cover class.In supervised classification the user selects delegated samples for each land cover class in the digital image. These sample land cover classes are acknowledged as “training sets”. The training set compared with the land cover classes in the entire image by using the image classification software. The Supervised classification of land cover is based on the spectral signature distinct in the training set. The image classification software determines each class on what it resembles most in the training set.


Fig. 1: Object Classification Overview Diagram

## 2. Related Works

The system describes some textural features computations. Textural features based on the gray tone spatial dependencies. It illustrates their applications in category identification tasks of three different kinds of image feature information data sets. In each data set was divided into two parts, a training set and test set. Test set identification accuracy is 89% for photo micrographs, 82% for aerial photographs and 83% for the satellite photographs. These results indicate that the easily computable image textural (pattern) features probably have a general applicability for a wide variety of image-classification application. Additional processes are necessary to determine the size of the sub image region and the distances [1]. [2]This system presents UnECHO, a mechanism of integrating spatial and spectral information in an unsupervised classifier.

The techniques of unsupervised enhancement of pixel homogeneity features in a local neighborhood, This techniques will enable an unsupervised contextual classification of multispectral image feature that combine the spectral and spatial information producing results that are more meaningful to the human anylst. Its main advantages are that it simplifies image features by retrieval process of spatial structures. This Enhancement is specially, relevant for the new generation of airborn image process and space borne sensors with high spatial resolution. [2].

The spatial pyramid match kernel of measures distance between histograms of quantized SIFT descriptors, but within an SVM classifier. NBNN computes image to-class distances without descriptor quantization method. Their SVM feature learning phase compensates for some of the feature information loss due to quantization process, raising classification performance up to 64.6%. NBNN is extremely simple, efficient and requires no feature learning/training phase; However, comparison to the baseline performance of NBNN implies that the information loss incorrectly the descriptor quantization was larger than the gain obtained by using SVM classifier. [3]

The system proposes to image features classifcation and simultaneously to learn the unique image features in such high-dimensional scenarios. This learning method is based on the automatic feature optimization of a linear combination of kernels dedicated to different meaningful class sets of features, such class sets can be groups of bands, contextual or texture features or bands acquired by different sensors. System presents a kernel framework for combining and assessing the relevance of different sources of information multiple-kernel SVM image classification.

The system proposed an efficient model selection procedure based on the kernel alignment. The result is a weight for the model ,experiments carried out in multi-and hyper spectral, contextual and multisource remote sensing image feature classification confirm the capability of the method in ranking the relevant image feature and show the computational efficient of the proposed strategy. It allows to automatically optimizing different kernel parameters and weights per dedicated kernel. Particularly when using kernel alignment for parameters estimation, computational costs is affordable for large –scale remote sensing applications.[4].[5]In this system proposed a logistic regression-based fusion (LRFF) method. and also design a new marginalized kernel by making use of the output of the regression model. Here the system compares proposed approaches with existing methods that combine color and shape on three datasets. The system proposed learning-based feature fusion process clearly out performs the state-of-the art fusion methods for image classification. In this paper, System presented a new approach to fuse multiple cues by adaptively a set of diverse and complementary visual words for s given class using a sparse logistic regression method and also a marginalized kernel used for better classification. Logistic Using regression here reduces multiple dictionaries the most specific discriminative words. Independent weighting for each cues is impossible in this system.[5].The system introduce the patch alignment framework to linearly integrate multiple image features in the optimal way and obtain a unified low-dimensional representation of these multiple image features for subsequent image classification.. This system want to focus on how to select optimal radius parameter for each image feature, respectively, contain the best low-dimensional for Multiple Feature Classification. [6].

The system presents a new hierarchical image segmentation method that applies graph laplacian energy as a generic measure for object segmentation. Which reduces the image pixel redundancy in the hierarchy by an order of magnitude with little or no loss of performance. The selected hierarchies using this laplacian energy, they can get a sensible semantic interpretation in terms of image and image features which used to get more robust image classification. In the classification stage, they apply local self-similarity (LSS) feature fusion method to capture the internal geometric region in an image. The system achieved better performance by using the combination of semantic hierarchical image segmentation and pixel local geometric region description. This technique provides satellite image analysis and classification that is better than those from alternative methods. Semi supervised learning method is not used in satellite image analysis. Furthermore, traditional spectral features will be incorporated into this system [7]. This paper presents a method to estimate the default rate using the non-linear model defined by standard Multilayer Perceptron (MLP) neural networks trained with a novel methodology called Extreme Learning Machine (ELM). The experimental results are promising, and show a good performance Extreme Learning Machine (ELM) is a competitively good solution for such complex tasks. The Extreme learning Machine (ELM), a recent second generation neural network algorithm, is identified as to achieve high quality performance in multifaceted problems and reduced computation time compared with other machine learning algorithms.ELM provides a very fast learning phase for relatively large data sets , that does not require iterative tuning which is dominant in other neural networks.

Due to the simplicity of their implementations, least square support vector machine (LS-SVM) and proximal support vector machine (PSVM) have been widely used in binary classification applications. The conventional LS-SVM and PSVM cannot be used in regression and multiclass classification applications directly, although variants of LS-SVM and PSVM have been proposed to handle such cases. This paper shows that both LS-SVM and PSVM can be simplified further and a unified learning framework of LS-SVM, PSVM, and other regularization algorithms referred to extreme learning machine (ELM) can be built. ELM works for the "generalized" single-hidden-layer feedforward networks (SLFNs), but the hidden layer (or called feature mapping) in ELM need not be tuned[8].

Feature learning using ELM may not be effective for natural signals(e.g., images/videos), even with a large number of hidden nodes.To address this issue, in this paper, a new ELM-based hierarchical learning framework is proposed for multilayer perceptron.

The novelties of this paper are as follows:

1)unsupervised multilayer encoding is conducted for feature extraction, and an ELM-based sparse autoencoder is developed via _1 constraint. By doing so, it achieves more compact and meaningful feature representations than the original ELM;

2) by exploiting the advantages of ELM random feature mapping, the hierarchically encoded outputs are randomly projected before final decision making, which leads to a better generalization with faster learning speed; and

3) unlike the greedy layerwise training of deep learning (DL), the hidden layers of the proposed framework are trained in a forward manner. Once the previous layer is established, the weights of the current layer are fixed without fine-tuning. Therefore, it has much better learning efficiency than the DL. Extensive experiments on various widely used classification data sets show that the proposed algorithm achieves better and faster convergence than the existing state of the art hierarchical learning methods[9].

## 3. Experiments

We test our method on a 4000 × 4000 high-resolution satellite image taken in Chengdu, China, in 2009, which consists of three bands (RGB) with 0.6-m resolution. Five classes of objects are identified based on visual appearance and spatial proximity. In total, 5009 objects of lands, lawns, residential areas, roads, and trees are collected after image segmentation by a commercial software eCognition (i.e., the shape parameter value is set to 0.5, the parameter scale is set to 50, and the other parameter values are set as default values). We randomly split the image data into a training set and a testing set for ten times and then calculate the average classification accuracy as the final result. Table I shows the size of the training and testing sets for each object class. To evaluate the performance of the proposed method, we choose the SVM classifiers with two types of kernels [linear and radial basis function (RBF)] and the LRFF method [11] as the baseline.Object classification is a division of image detection. It may be larger than object detection.

Object classification analyzes the numerical properties of different image feature and organizes data into categories .object classification algorithm normally employ two phases of processing :training and testing. Training set features are isolated, which is extremely important for object classification. Test set is used for testing process. Extreme learning machines (ELMs) have been confirmed to be efficient and effective learning techniques for pattern recognition and regression. However, ELMs primarily focus on the supervised, semisupervised, and unsupervised learning problems in single domain (i.e., source domain). To our best knowledge, ELM with cross-domain learning capability has never been studied.Extreme Learning Machine (ELM), proposed for solving a single-layer feed-forward network (SLFN)has been proven to be effective and efficient algorithm for pattern classification and regression in different fields. ELM can analytically determine the output weights between the hidden layer and the output layer using Moore–Penrose generalized inverse by adopting the square loss of prediction error, which then involves in solving a regularized least square problem efficiently in closed form. The hidden layer output is activated by an infinitely differentiable function with randomly selected input weights and biases of the hidden layer.

## 3.1 Feature Extraction

Four types of features are used in the experiment, which characterize the properties of the segmented regions in three aspects, namely, shape, spectral, and texture. For the shape information, we use the scale-invariant feature transform (SIFT) [12] and LSS [13]. In each segmented region, features are extracted in evenly sampled grid with 10 pixels apart in both
horizontal and vertical directions. The size of the patch is randomly sampled between a scale of 10 and 30 pixels. Moreover, we use the mean and standard deviations of three spectral bands (i.e., RGB) as the spectral feature. GLCM [14] is used to represent the texture feature.

## 3.2 Classification

Feature learning using ELM may not be effective for natural signals (e.g., images/videos), even with a large number of hidden nodes. To address this issue, in this paper, a new ELM-based hierarchical learning framework is proposed for multilayer perceptron. The proposed architecture is divided into two main components:1) self-taught feature extraction followed by supervised feature classification and 2) they are bridged by random initialized hidden weights. The input weights and hidden layer biases can be randomly assigned if the activation function is infinitely differentiable, and also showed that single SLFN with randomly generated additive or RBF nodes with such activation functions can universally approximate any continuous function on any compact subspace of Euclidean space.
As the output weights are computed with predefined input weights and biases, a set of nonoptimal input weights and hidden biases may exist. Additionally, ELM may require more hidden neurons than conventional learning algorithms in some special applications.ELM more compact networks that speed the response of trained networks. In terms of the imbalanced number of classes, a weighted ELM was proposed for binary/multiclass classification tasks with both balanced and imbalanced data distribution. Because the solution of ELM is dense, which will require longer time for training in large-scale applications. a fast sparse approximation of ELM for sparse classifier training at a rather low complexity without reducing the generalization performance. For all the versions of ELM mentioned earlier, supervised learning framework was widely explored in application which limits its ability due to the difficulty in obtaining the labeled data. semisupervised ELM for classification, in which a manifold regularization with graph Laplacian was set, and an unsupervised ELM was also explored for clustering.

In the past, the contributions to ELM theories and applications have been made substantially by researchers from various fields. However, with the rising of big data, the data distribution obtained in different stages with different experimental conditions may change, i.e., from different domains. It is also well known that electronic nose (E-nose) data collection and data labeling are tedious and labor ineffective, while the classifiers trained by a small number of labeled data are not robust and therefore lead to weak generalization, in particular for large-scale applications.

Although ELM provides better generalization when a number of labeled data from source domain is used in learning, the transferring capability of Domain- adaptation methods have been proposed for robust classifier learning by leveraging a few labeled instances from target domainin machine learning community and computer vision. It is worth noticing that domain adaptation is different from semisupervised learning, which assumes that the labeled and unlabeled data are from the same domain in classifier training.

In this paper, we extend ELMs to handle domain adaptation problems for improving the transferring capability of ELM between multiple domains with very few labeled guide instances in target domain, and overcome the generalization disadvantages of ELM in multidomain application.

### 3.3 Influence Of Size Of Training Set

The changes of the OA(Overall Accuracy) as a function of the percentage of training samples. The performance of the two kernel methods both increase as the number of training samples increases. However, our method maintains an advantage of 3%–6% over the LRFF method. These results show that, by using softmax regression model and class-to-class similarity,more effective kernel machines can be constructed for encoding the relationships of the observed data. Moreover, to evaluate the significance of the proposed method, the classification results are then processed by the resampled paired *t* test, where the number of resampled times is 10. All the tests are performed using two-side tests with a confidence level of 0.05.The *p*-values are less than 0.05 in most cases, indicating that the performances of our method and LRFF are significantly different.

In the training stage, for each cluster,we set the threshold as the maximum distance between its center and the patches in it. If the distance between one patch and its closest codeword is smaller than the chosen threshold, the patch will be assigned to this codeword. Otherwise, we assign the patch to a single virtual codeword.

In this way, the virtual codeword occurs more frequently in the outliers than others, which is helpful to detect the outliers. To evaluate the robustness of our method against outliers, we include 50 objects from undefined classes in the classification experiments.Fig 2 shows overall classification process.

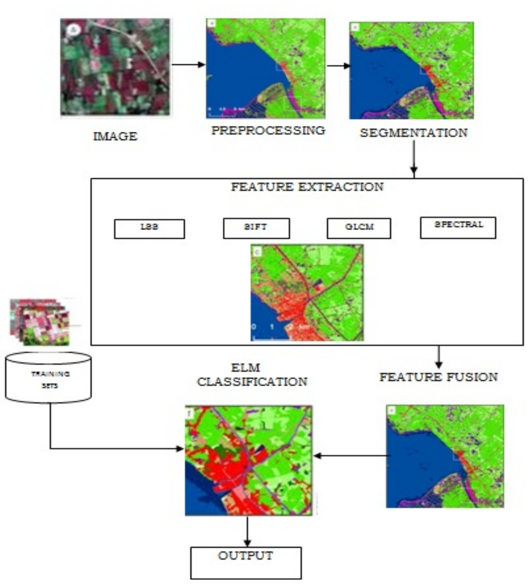


Fig.2 ELM Classification

## 4. Conclusion

In this letter, we have introduced a softmax regression based feature fusion method for object classification. This method takes into account the information about object-to-class similarities and the conditional probabilities that one object sample belongs to different classes. Moreover, an approximate method has been developed for measuring the similarity between different classes, and the information between features and classes could be thus better modeled. All the obtained information has been integrated for the ELM classification.ELM has witnessed a number of improved versions in models, algorithms, and real-world applications. ELM shows a comparable or even higher prediction accuracy than SVMs, which solve a quadratic programming problem.

ELM is reduced with a limited number of labeled training instances from target domains.

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