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IMAGE CLASSIFICATION

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ABSTRACT

In pursuance of the formalizing the methodology of the present work, a substantial amount of the literature was surveyed. Besides, some survey papers regarding image classification. Literature related to the topic, having contributed to the present methodology has been categorized into the subtopics of supervised classification, unsupervised classification.

KEYWORDS: Image classification.

INTRODUCTION

Classification

Current subsection contains the literature related to core classification issues of pattern classification, classification models, feature mining approach for image classification and for knowledge transfer between images and text, by improving a heterogeneous transfer learning framework are studied.

Pal *et al.* (1998) attempted to apply the GA for pattern classification in N-dimensional data space. They asserted that future space should be bound and descritized up to the sufficiently small interval for being classified by GA. They compared the results with Bayes classifier, K-NN, and MLP. GA outperformed the other classifier and yield performance comparable to the Bayes classifier. They described a method for finding decision boundaries approximated by piecewise linear segments, for classifying patterns in R^n, $N \geq 2$, using an elitist model of genetic algorithms. This method includes a scheme for the automatic deletion of redundant hyperplanes resulting from its conservative estimate. The paper further discusses the issue of generalization capability of the GA as well.

Majumdar and Jayas (2000) developed classification models by combining more than one feature sets (morphological, colour, textural). This model is used to classify individual kernels of grains like Canada Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, oats, and rye. The mean accuracies (the average of the classification accuracies of the above mentioned cereal grains) 98.6% and 99.3% were achieved when the morphology-texture model with the 15 most significant features was used to test on an independent data set (total number of kernels used was 10,500) and on the training data set (total number of kernels used was 31,500), respectively. The highest classification accuracies were achieved when the morphology-texture-colour model was used.

Krasnogor and Smith (2005) proposed a tutorial for competent memetic algorithms as well as issues related to model, taxonomy and design. **Moscato (1989)** assigned name memetic algorithms to the combination of evolutionary algorithms with local search. These methods are inspired by models of natural systems that combine the evolutionary adaptation of a population with individual learning within the lifetimes of its members. This framework is defined by a general syntactic model. This model provides us with a classification scheme based on a computable index, which facilitates algorithmic comparisons and suggest areas for future research. This model also suggests the existence of a novel class of metaheuristics in which four schedulers interact.

Dollar *et al*. (2005) gave a feature mining approach for image classification and compared several strategies of feature mining. An in-depth empirical study was made on dataset SYST, RAND and GOOD. A layout of a general framework is aimed on the basis of theory, and experiments supported it. A number of basic strategies were implemented. Theoretical results were confirmed and importance of feature mining was demonstrated. In SYST, features are systematically designed for face detection. In RAND, features are randomly sampled from parameterized feature space. In GOOD, mining is done on the space for informative features. Informative mining is done on the features in COMP for complementary.

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Zhu *et al.* (2009) gave an approach for knowledge transfer between images and text by improving a heterogeneous transfer learning framework. The semantic concepts were extracted and used to enhance the target image representation. Matrix factorization and latent semantic features generated by the auxiliary data were used to build a better image classifier. The effectiveness of algorithm was measured on the Caltech-256 image dataset.

SUPERVISED CLASSIFICATION

Supervised classification requires a priori labelling before testing process. Analyst identifies representative training sites for each informational class and generates decision boundaries. Literature surveyed about supervised Classification is briefly described in this section.

Vogel and Schiele (2004) suggested an image representation to access natural scenes using local semantic description. Spatial grid layout, which splits the image into regular sub-regions, was used by them. Both texture and colour features were used for landscape image retrieval and classification based on a two stage system. Image is partitioned into 10×10 sub-regions. Then, each sub-region is classified using SVM or K-NN. Concept Occurrence Vector (COV) was used to represent the image.

Kuniyoshi *et al*. (2009) uses local feature correlation to classify scene and improves the performance of features. Local features were extracted from the image. It includes two steps. First step is based on feature and grid description for a key point detection using SIFT descriptor. The second step is scene classification, which is based on Linear Discriminant Analysis (LDA).

Manshor and Ramachandram (2012) gave a novel method for increasing performance of object class recognition by aggregating various features with local features. They extracted boundary-based shape features and local features from the image. The first type of feature is selected on the basis of segmented objects and interior information of objects is basis for second type of features. Combination and concatenation of obtained features was made in a new single feature vector using fusion procedure. Support Vector Machine is used for classification of features.

UNSUPERVISED CLASSIFICATION

Unsupervised classification does not require human annotation. The literature surveyed about unsupervised classification is given here.

Selim *et al.* (2005) gave a novel method for classifying outdoor scenes. Images are divided into regions using classification and patch-based clustering algorithms. The resulting region type codebook is obtained and clustered. Two models are constructed for scene representation: regions with same spatial relationships are considered together and regions with different relationships are considered separately. Classification was performed on these representations using Bayesian classifiers. The proposed model significantly outperforms the global feature-based methods.

Fei-Fei *et al*. (2007) gave a novel method for classifying events into static images by integrating scene and object categorization. An integrative model was a technique used to categorize object and scene. Local features were selected from the image and used to group objects. They identify the scene after dividing objects. Thereafter aggregating both object and scene recognition events are classified. The disadvantage of this approach is that the object and scene identification alone can't assess classification performance.

Jiang *et al*. (2012) gave a hierarchical classification of noisy images. Three strategic methods used are local pathway for highlight detection, global pathway for essential capture, and hierarchical classification. Features are extracted using Gabor filter. Principle Component Analysis (PCA) is applied to reduce dimensionality. Visual context is obtained by combining PCA and real part of Gabor image. Pseudo-restoration is done directly on noisy images. A set of local features were found, when pseudo-restored image highlight detection is done. Monte Carlo approach and log linear model are used to cluster the features. Classification was performed on clustered features using Self Organizing Tree Algorithm (SOTA).

CLASSIFICATION USING SUPPORT VECTOR MACHINES

Vapnik **(1979)** developed Support Vector Machines (SVM) for image classification. **Cortes and Vapnik (1995)** introduced the soft margin hyperplane for non-separable data. This development in SVM made it more applicable. SVM classifies data with different class labels by determining a set of support vectors. These support vectors are members of the set of training inputs that outline a hyperplane in the feature space.

Huang and Wang (2006) proposed a novel technique based on Support Vector Machines for pattern classification. In training process, classification accuracy is affected by kernel parameters setting for SVM. The feature subset and parameters are optimized without decreasing the accuracy of SVM classification. This approach is based on genetic algorithm for parameters optimization and feature

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selection. The Grid algorithm and proposed GA-based method are tried on several real world datasets and parameter searching is performed by traditional methods. Classification accuracy is improved by the GA based approach as compared with the Grid algorithm.

Min *et al.* (2006) presented a GA-SVM based model in which optimization of SVM parameters is performed using GA. The dataset was divided into the training set and validation set having ratio 0.7 and 0.3. Two sections were explained in which training data was divided for NN and GA-SVM. In this model NN is used to avoid over-fitting and GA-SVM is used in training of the model. They discussed three different methods to measure the effectiveness of the given model with given feature subset and selected values of parameters. The SVM-based model has been compared with other methods such as the logistic regression and neural network and this method has shown good results.

CLASSIFICATION USING NEURAL NETWORK

One of the primary means by which computers are endowed with human-like abilities is through the use of a neural network. Literature surveyed related to this topic is given in this section.

Sexton and Dorsey (1998) compared backpropagation (BP) with the GA for neural network training. This comparison is a variation of backpropogation and used to overcome the limitations of gradient algorithms. They discovered that a global search technique such as the GA outperforms the BP algorithm as an alternative NN training technique.

Park *et al.* (2009) proposed architecture of a granular neural network. They provided a comprehensive design methodology and elaborated it on an algorithmic setup supporting its development. They developed a design strategy for radial basis function, neural networks to reduce the dimensionality of input space over which receptive fields were formed. The main difference lies in the evolutionary optimization of input spaces where various fields were induced by different subsets of input variables with respect to the network design. Experimental results showed the benefits of the proposed design method. This method becomes viable and competitive tool that can be used in the design of the RBF-like networks.

Kabir *et al.* (2010) presented a novel feature selection method based on wrapper approach using neural network. It determined neural network architecture during the feature selection process. A compact NN architecture, i.e. Constructive Approach for Feature Selection (CAFS), was developed to reduce the redundancy in features. Correlation information is used to select less correlated features.

CONCLUSION

Hence, this is the related literature surveyed and used in formalizing the image classification efficiently. This study will be helpful for those working in the field of image processing.

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