Relevant Label Identification for Multi-Label Image Classification

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***Abstract*— Area of an image multi-label classification is increase rapidly in recent years, in machine learning and computer vision. Multi-label classification has attracted significant attention from researchers and has been applied to an image annotation. In multi-label classification, each instance is assigned to multiple labels, is a common problem in data analysis. In image classification, images are classified into multi-label classes using multi-label classification approach. However most of the multi-label classification approaches are incapable to explore the inter-label correlation between multiple labels effectively. Inter-label correlation analysis is important in multi-label classification. Using inter-label correlation, images can be classified into multiple classes very effectively. To address inter-label correlation problem in multi-label classification, label graph learning with support vector machine technique is used.**

***IndexTerms*—Multi-label classification, image annotation, inter-label correlation, support vector machine.**

I. Introduction

Multi-label classification for images is a task of great significance in the field of computer vision and machine learning. Nowadays, great amount of digital images present in the world. Today images are important way for information gaining, appearing and transmitting because of its visual foundation for recognizing the world. Image classification provides great support for image retrieval and also indexing because both of them require accurately label images. Based on the label association to the input samples, the classification methods can be categorized into single-label classification and multi-label classification [4], [26]. In single label image classification, each image have single label, but there are multiple label are available in images .The single-label classification problem can be further divided into two categories: Binary and multi-class classification. When the input data samples are categorized into one of two classes, it is called binary classification. When the input samples correspond to one among a pool of target labels, it is called multi-class classification. Use single-label classification framework for label the given image. Refer fig. 1, using single label classification user can label it as sea. But there are multiple objects present in it like, 'tree', 'beach', etc. but in single label classification only single label is for one image. User can search or retrieve this image using only one label i.e. 'sea'.

Fig.1. Example image

As opposed to single-label classification, each input sample is associated with a set of target labels in multi-label classification. The number of target labels corresponding to each input is not fixed and varies dynamically. This results in increased complexity in the implementation of multi-label classifier. Use multi-label classification framework for label the above image. Refer fig. 1, using multi-label classification user can label it as set of labels like, 'sea', 'tree', 'beach', and etc. user can label single image with multiple labels. If user wants to search or retrieve this he or she can use one of the above mentioned labels.

But is multi-label classification there is an issue of inter-label correlation [18]. Inter-label correlation is a relationship between two labels. Each image contain various instances and according to instances image get labels, these have relationship between them. These relationships are quite necessary to be considered to improve the accuracy in label propagation. Thus it is very attractive to develop new algorithms for characterizing the inter-concept similarity contexts more precisely and determining the inter-label correlation learning tasks automatically.

In this paper, first section will be review of literature where discuss some multi-label classification method and related work, and then in second section explain system architecture then in third section result analysis is done.

II. LITERATURE SURVEY

Recent decades have witnessed great progress in multi-label classification algorithms. Nowadays, multi-label classification algorithms [11, 1] are used in image classification. The focus of this work is more on labels of images. Multiple labels are usually associated with an image in many image analysis applications and there are several kinds of methods for addressing multi-label problem.

Multi-label Classification Techniques

1. ML-kNN

ML-kNN is derived from the popular k-Nearest Neighbor (kNN) algorithm. First, for each test instance, its k nearest neighbors in the training set is identified. Then, according to statistical information gained from the label sets of these neighboring instances, i.e. the number of neighboring instances belonging to each possible class, maximum a posteriori (MAP) principle is utilized to determine the label set for the test instance.

2. Multi-label Decision Tree

The basic idea of this algorithm is to adopt decision tree techniques to deal with multi-label data, where an information gain criterion based on multi-label entropy is utilized to build the decision tree recursively. Some algorithms of decision tree have developed such as ID3, C4.5 and CART. ID3 and C4.5 are only used for classification; where CART is used for classification and numerical prediction also.

3. Ranking SVM

The basic idea of this algorithm is to adapt maximum margin strategy to deal with multi-label data, where a set of linear classifiers are optimized to minimize the empirical ranking loss. Using hyper-plane, RankSVM classify the label pair into relevant and irrelevant label pairs.

Related Work

Yunchao Wei et al. [7], propose Hypotheses-CNN-Pooling (HCP) for multi-label classification of images, where large single label image datasets are trained by CNN. Xuchun Li et al. [27], proposed a multi-label SVM active learning method and used it to solve multi-label image classification problem. Tao Zeng and Shuiwang Ji [10], resolve multi-task problem using multi-instance multi-task CNN. In CNN model, at image level transfer prior knowledge learned from large single label single task data sets. Xinmiao Ding et al.[5], proposed a context-aware multi-instance multi-label learning (CMIML) model consider instances and labels two cues. Using multiple graphs construct instance context cues and linearly combine labels are used to construct label context cues. These two context cues are integrated into a united framework.

Xin Li and Yuhong Guo[15], proposed multi-label classification strategy which is combination of label cardinality inconsistency and max-margin prediction uncertainty. Jian Wu et al. [12], represent selection technique for the most useful example-label pairs, but label correlation of an example is not consider. Jesse Read et al. [14], presented a single framework for multi-label classification using meta-labels. Jiang Wang et al. [3], proposed a combine CNN-RNN framework for multi-label classification for images. Advantages of CNN and RNN are use for joint image or label co-occurrence embedding. Yanwei Pang et al. [21], proposed an image classification technique which latent topic information and use multi-label multiple kernel learning to improve the image classification. Benhui Chen et al.[24], proposed multi-label classification technique based on delicate decision boundary SVM which improves the label ranking. Teng Li et al.[20], for label ranking and image annotation application developed contextual image decomposition method. Yong Luo et al.[17], semi-supervised multi-label classification for image use manifold regularized multitask learning (MRMTL) based algorithm.

Xiangyang Xue et al.[19], proposed a framework in which multiple labels are obtain by using feature label association and inter label correlation. Co-occurrence matrix and structured max margin framework is used. Yan Huang et al. [16], multi-label learning transform into multiple binary classification tasks, and used deep neural network architecture to handle multiple task problem. Ricardo Cabral et al. [6], proposed a method in which, low rank problem is formulated using weakly supervised learning and use transductive matrix to solve this. Aiwen Jiang et al.[25], proposed a calibrated RankSVM for multi-label classification. Using this technique multi-label classification and label ranking both problems are solved. Using RankSVM, a virtual label used as a calibrated scale, the rank algorithm has a natural zero-point. The optimal coefficient of the virtual label (threshold) is implanted in learning process, to obtain optimal position of the virtual labels adaptively. This makes difference between conventional RankSVM and calibrated Rank-SVM.

Gangadhara Rao Kommu et al.[13], proposed two probabilistic approaches partial and mutual information about labels to solve multi-label classification. Chen Ye et al. [8], proposed a method for multi-label active learning based on cosine similarity. Use cosine similarity to accurately evaluate the correlations between all labels. It reduces the labeling cost. But only positive correlation between all labels is considered not negative correlations. Jiwei Hu et al.[23], represented effective hierarchical image annotation system which use label propagation to the NBNN classifier. It effectively removes the irrelevant labels, and solves the multi-label problem. Wail Mustafa et al.[9], represented categorization technique for object to categorize into multiple and nested categories and it uses joint SVM to learn visual categories. Eva Gibaja et al. [22], presents a multi-label classification techniques based on decision tree by implementing J48 of C4.5.

In the following table 1, comparison of some of the methods used for multi-label classification is shown. The results are also provided in terms of accuracy, mAP and hamming loss of relevant label sets.

Table 1. Comparative study of Multi-label Classification

Authors	Method Used	Results
Jiang Wang et al.[3]	Combine CNN and RNN technique	mAP- 84.0%
Jian Wu et al.[12]	Example label based multi-label active learning method	Accuracy-8.7
Yong Luo, et al.[17]	Use manifold regularization for multi-label task	mAP-0.410
Xin Li et al.[15]	Use SVM classifier with max margin uncertainty and label cardinality inconsistency	Accuracy-0.33
Benhui Chen et al.[24]	Use probabilistic SVM classifier with delicate decision boundary	Accuracy-0.7263
Yan Huang et al.[16]	Use deep neural network for multiple label task	Hamming Loss- 0.157±0.008
Eva Gibaja et al.[22]	Use decision tree for multi-label classification	Accuracy- 0.595

III. MULTI-LABEL CLASSIFICATION SYSTEM

The multi-label classification system has multiple stages for finding the relevant labels for images. These stages are shown in figure no. 2. There are main two stages one is single-label classification and another is multi-label classification.

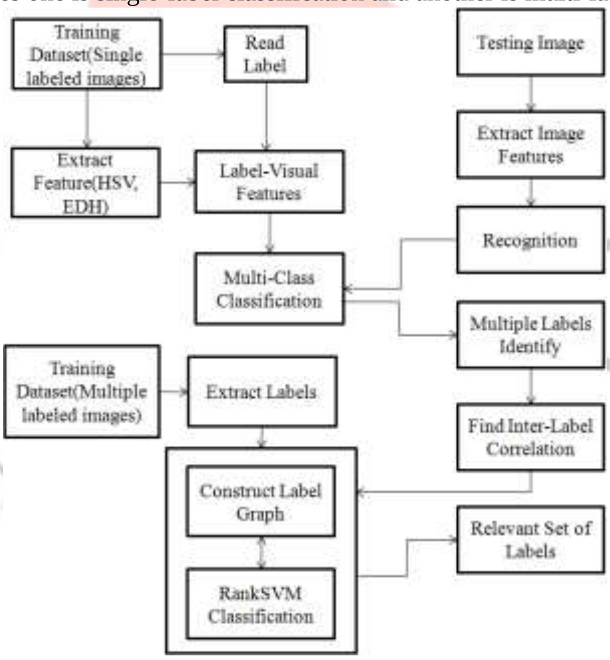

FIGURE 1. SYSTEM ARCHITECTURE

First in single label classification, takes the image dataset which contain single labels. Extract features from the image dataset and its labels. Store features of the images and labels of the images in database. HSV color, edges and texture these features are extract from images. Features are store in 66 size of feature vector. HSV color feature are in 18 real numbers of feature vector for each image. Canny edge detector is used to detect edges from images. To detect texture feature for images use edge map. Use co-occurrence matrix for texture extraction. Single label image dataset D is in the form of (xi, li) for i=1….n. Here xi is the number of images and li is the set of labels for image xi. In single label dataset each image contain single label i.e. li belong to {0, 1} is the set of labels li=l1,l2,…...ln where n is the number of labels, if label is present for image then l is denote with 1 else 0. Now, store these features and their labels of each image in database.

In second stage, i.e. in multi-label classification, multi-label image dataset is used to process. This dataset is used to find community for multiple labels. Each data samples contain multiple labels L(l1, l2,…., ln) where n is number of labels, and samples will be classified into classes using these labels. Using this community aware contextual information construct a graph [2] based on labels G(L, E) where Eij is the edge which connect ith label and the jth label. Using graph we can find the inter-label correlation. Inter-label correlation will help to classify an image into classes. Rank SVM will be used as classifier for labels. F(L, G) is the function for RankSVM classification, using label graph G(L, E) function will classified pairwise labels i.e. relevant labels and irrelevant labels for image. O(RL) is the output of the system and return images which are relevant set of labels RL to query image.

Now for testing phase, give the input image which has multiple objects. Unlabeled data sets U are used for testing phase. Extract HSV color, edge and texture features from testing image. Find relevant image to the query image based on these features. Using single label training module, take out single labels from relevant images. These labels are given to the multi-label classification module, to find inter-label correlated labels for retrieve labels. By this way we can find most relevant set of labels for image.

IV. RESULT

In single label image classification, the input images will consist of 10 classes each class contains 100 images. Hence total 1000 images are used for single label classification. The input images will have single instances. Identify visual features of images and their labels of each image. For multi-label image classification we use NUSWIDE dataset. Using this data set correlated labels are classified. For the testing phase, the input images will be given by users. Discover the visual features of testing image and find the labels. Find correlation between labels and more valid and accurate labels are taken out. For this implementation we are using Java platform on windows operating system. Precision is the fraction of true positive to true positive with false negative. Performance of the system will be measured by calculating the precision metrics. Precision for the image retrieval is shown in below table 2. Precision graph is shown in figure 2. Precision is calculated for 5 images from each class.

Table 2. Precision for the Image Retrieval

Class Name	Input Image	Total Number of Images Retrieve	Relevant Images	Precision (%)
Beach	1	15	10	66.00
	2	15	8	53.00
	3	15	8	53.00
	4	15	6	40.00
	5	15	8	53.00
Bear	1	15	11	73.00
	2	15	12	80.00
	3	15	11	73.00
	4	15	7	46.00
	5	15	7	46.00
Castle	1	15	7	46.00
	2	15	7	46.00
	3	15	8	53.00
	4	15	7	46.00
	5	15	6	40.00
Flower	1	15	9	60.00
	2	15	14	93.00
	3	15	8	53.00
	4	15	11	73.00
	5	15	9	60.00
Food	1	15	13	86.00
	2	15	11	73.00
	3	15	14	93.00
	4	15	10	66.00
	5	15	7	46.00
Horses	1	15	13	86.00
	2	15	6	40.00
	3	15	10	66.00
	4	15	14	93.00
	5	15	6	40.00
Mountain	1	15	12	80.00
	2	15	11	73.00
	3	15	12	80.00
	4	15	6	40.00
	5	15	10	66.00
Sunset	1	15	9	60.00
	2	15	8	53.00
	3	15	12	80.00

	4	15	10	66.00
	5	15	8	53.00
Vehicle	1	15	13	86.00
	2	15	11	73.00
	3	15	14	93.00
	4	15	9	60.00
	5	15	7	46.00
Zebra	1	15	8	53.00
	2	15	5	33.00
	3	15	8	53.00
	4	15	8	53.00
	5	15	11	73.00

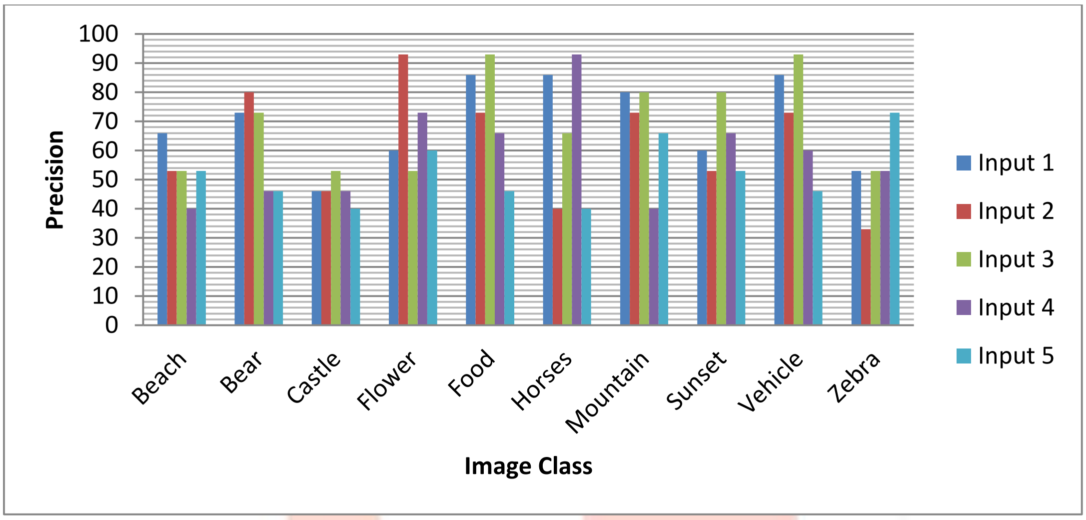

FIGURE 1. PRECISION GRAPH

Relevant labels are identifying for query image by using above mentioned system. Hence query image classify into these relevant labels. And these labels are correlated with each other. Table 3. Show the results for relevant labels for test images.

Table 3. Relevant Labels for Test Images

Input Images		
Relevant Labels	clouds sky horses	water reflection food

V. CONCLUSION

In this paper, discussion of the brief introduction of multi-label classification for images. And we also discuss well known multi-label classification techniques. We survey some multi-label classification algorithms for images. The above mentioned system will identify the multi-labels for a testing image. The system explicitly models the inter-label correlations by label graph learning, which is jointly optimized with multi-label classification. The system will help to achieve classification of the images into multi-label classes, reduce the problem of max-margin multi-label learning, and to find the intrinsic inter-label correlations.

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