# Multi-Label Classification for Images with Labels for Image Annotation

## Swati Jain<sup>1</sup>, Md Rashid Mahmood<sup>2</sup>, Rohit Raja<sup>3</sup>, K.Ramya Laxmi<sup>4</sup>, Akanksha Gupta<sup>5</sup>

<sup>1</sup> Govt. J.Y. Chhattisgarh College, Raipur, India; e-mail : sjcscghed@gmail.com

<sup>2</sup> ECE department, Guru Nanak Institutions Technical Campus, Hyderabad, India, e-mail : er.mrashid@gmail.com

<sup>3</sup> IT Department, GGV Central University, Bilaspur Central University India, e-mail : drrohitraja1982@gmail.com

<sup>4</sup> SIET Hyderabad, India; e-mail : kunt.ramya@gmail.com

<sup>5</sup> IT Department, GGV Central University, Bilaspur Central University India; e-mail : akanksha.me2011@gmail.com

# ABSTRACT

Images and videos are increasing due to advancement in digital technologies. Annotate the given image for efficient image retrieval and processing it is required identifying a set of objects present in each image. Manual text-based image annotation is very time consuming and expensive and it becomes infeasible with such exponential increase in visual data. Multi-label classification problemgeneralizes the standard multiclass classification by allowing each instance to be simultaneously assigned into multiple label categories. A key challenge for multi-label classification is label sparsity that is many labels lacks sufficient training instances for building efficient classifiers. Hence, exploiting label dependency can significantly boost classification performance. Most of multi-label method uses binary decomposition of multi-label datasets but uses the same features for training the classifiers which may contain redundant features.

Keywords: Visual Data, Classification, Neural Network.

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# INTRODUCTION

he collection of digital images is useful if a user can find the images of desired content from it. The content management of pictorial data is an organized way to store and search the images from the database. The objective of the automated system is by using the features of the image contents understand the image [1]. In some cases, the dataset contains the extracted features from images and so the methods perform relatively better compared to datasets from which extraction has to be done. Feature extraction is important as it dominates the rest of the functionality of automatic image annotation [2].

# LITERATURE REVIEW

Automatic Image Annotation techniques have been discovered to label the entities present in the image.

#### **Corresponding Author :**

Swati Jain, Govt. J.Y. Chhattisgarh College, Raipur, India; e-mail : sjcscghed@gmail.com

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There have been various techniques used for AIA which can be best implemented using multi-label classification. Hence in order to perform AIA we have to perform multi-label classification of images [3].

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Figure 1: Categorization of representative Mutli-label learning algorithm

Multi-Label Classification can be implemented using various methods. Annotation system performs three basic operations one to segment the images, build the feature vector and the last is learning along with tagging. Training is essential because here a database of tagged images is used. The trained system then works on raw data to output annotated images and the entities contained in the image [4].

The literature survey of various multi-label classification techniques has been briefly studied. Over the last few years, several research works have been done for multi-label classification of images. All the researches have proposed different methods for multi-label classification of images [5].

# **PROBLEM IDENTIFICATION**

Automatic image annotation is important but highly challenging problem for researchers in computer vision and content-based image retrieval. Though automatic image annotation presents a particularly complex problem for machine learning, here by using machine learning, intelligence can be incorporated to improve the performance of the annotation system. The text-based search is more difficult if text is not present. The task of assigning semantic words to images can solve this difficulty. The overall objective is to develop an effective automatic image annotation system by using appropriate machine learning technique/s. The accuracy of annotation and speed of the system are targeted to be improved [6].

The system will take an image as input, uses various techniques of machine learning and use the training dataset and identify the elements present in the image[7]. There are various methods proposed on this but the accuracy needs to be improved. In case of multi-label classification, many labels have to be identified simultaneously. In MLC the output cannot be just correct or wrong it can be partially correct also[8].

- To organize the images semantically by tagging the images accurately with words so to improve performance of image retrieval.
- For automatic image annotation feature extraction and feature selection.
- Model Generation for image annotation by training.
- Image annotation using generated annotation model and learning.

# METHODOLOGY

In this section the methodology is used features extraction from images and then perform image annotation using the training dataset.Methodology of image annotation is categorized into number of steps which are as follows:

- a) Input image and preprocessing.
- b) CNN is used for extracting feature form Images.
- c) PCA is used for feature selection.

d) First Stage SVM is used for Classificationand BinaryRelevance.

e) Label Dependency Modeling using MutualInformation.

f) Second Stage Classification using Support VectorMachine.

# **Experimental Setup**

The model is implemented using MATLAB 2013a under Windows platform. The experiments are performed over the machine with the hardware configurations of given specifications. The images used in the study is Pascal VOC2012. The dataset contained 11540 images. 10,000 images are used to train the model and remaining 1540 are used for testing[9].





Figure 2 shows the overall description of process of automatic image annotation. The classification ability of the classifier used for features extracted hence to get better features for classifiers CNN is used[10]. CNN is a multi-layered perceptron inspired from biological process of different layers is used to form the architecture of CNN namely[11]

- a. ConvolutionalLayer.
- b. PoolingLayer.
- c. Rectified Linear UnitsLayer.
- d. Fully ConnectedLayer.
- e. LossLayer.

Convolutional network consists of set of filters whose output contains positive as well as negative values. The different values indicate the number obtained as a result of the CNN[12]. Figure 3 shows the matrix obtained as a result after giving image as input to CNN. The output can be an integer number generated as a result of various operations applied in CNN.

#### **Feature Selection**

In order to reduce the dimensionality Principal Component Analysis (PCA) is used. If there are some entities that contains some properties and it is required to combine the properties and derive new components which will produce a simpler description then PCA is used. Mathematically, PCA is an orthogonal linear transformation that transforms the data to a new coordinate system where coordinates are organized in the descending order of variance. After performing PCA top 200 features (out of total 4096) are selected and these features are given as input to the classifier model.

The eigen values in PCA tells how much variance can be explained by its associated eigen vector. Therefore, the highest eigen value indicates the highest variance in the data was observed in the direction of its eigen vector. Accordingly, if take all eigen vectors are taken together, variance can be explained in the in the data sample. Relative numbers can be obtained by first summing up all eigen values and then divide an eigen value by thissum.

Here  $\lambda_i$  denotes the eigen value for i<sup>th</sup> instance in the matrix after passing the input image through all the layers of CNN.

In PCA the top attributes are chosen based on the value of variance obtained. Experiments are done to find the optimal value of PCA so that the retrieved labels are correct. Experiments were conducted taking the top 50 and 200 principal components.

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Figure 4 shows the features obtained after performing PCA. The principal components are identified on the basis of the value ofvariance.

## **First StageClassification**

In First Stage Classification two methods are used namely - Binary Relevance and Support Vector Machine. Here the presence of particular elements of various classes is noted. There are total 20 classes and all the 1540 test images are tested whether they contain that particular class or not. In this case 1 indicates the presence of that class in that image whereas 0 indicates the absence of that class in thatimage.

# **Binary Relevance(BR)**

BR is aimportmant method in the multi-label learning which decomposes the multi-label dataset in binary datasets corresponding to each label. Classifiers are built for respective Though it is criticized for ignoring label-dependencies among different class labels.

# Support Vector Machines (SVM):

In SVM, First Stage Classification is shown. Here 1 implies presence of that class in that particular images and 0 implies absence of that class in that particular image.

# Label Dependency Modeling

The class labels in multi-label datasets are usually correlated and utilizing this information during classification will improve the classification ability. Here Mutual Information is used to find the correlation information. [Min-Ling Zhang, 2015]

# Mutual Information (MI)

MI is a measure of MI values the labels are selected from previous stage and it is then augmented with output.



Figure 5: Measurement of Information among labels

Figure 5 shows the dependency between various labels, labels can be mutually related, mutually exclusive or not related. Figure 6 shows Label Dependency Modeling using MI here 1 denotes mutually dependent labels whereas 0 denotes mutually exclusive labels.

### Second Stage Classification

The second stage classifiers are modeled using the new input features which also contains the output of classifiers from first stage whose labels are strongly dependent on this label. In second stage SVMs are used as base classifiers. The prediction from all other classifiers was concatenated to form the final prediction.







Figure 7: Second Stage Classification using SVM

Figure 7 shows Second Stage Classification, here 1 denotes presence of that particular class in the input images whereas 0 denotes absence of that particular class in input image.

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# **RESULT AND DISCUSSION**

For performance evaluation the evaluation metrics of multi-label classification methods are used because the prediction may and the metrics used are mentioned below.

PCA is performed for dimensionality reduction as well as selecting features with high variance. Results are reported after performing PCA with 50 and 200-dimensional input space. Mutual Information (MI) is used to exploit label correlation by selecting some labels as dependent based on some threshold value. The experiment is performed by choosing two threshold values MI score as 0.01 and 0.002 respectively.

 Table-1: Evaluation results for Pascal VOC dataset using different methods

Parameter	Binary Relevance (BR)	BrPCA(50)	BrPCA (200)	PM (t=0.01)	PM (t=0.002)
Accuracy	0.3187	0.3180	0.3498	0.3683	0.4030
Recall	0.3382	0.3355	0.3645	0.3831	0.4320
F1	0.3577	0.3595	0.3907	0.4118	0.4514
Hamming Loss	0.0630	0.0624	0.0598	0.0591	0.0423



Figure 8: Evaluation Scores for different methods on Pascal Dataset



Figure 9: Graphical representation of Hamming Loss for Pascal dataset

Figure 8 compares various methods on the basis of accuracy, recall and F1-Measure. The more the accuracy, recall and F1-Measure the better is the algorithm. Figure 9 compares the hamming loss for various methods on Pascal dataset. The less the hamming loss the better is the algorithm.

The Labels Returned Are Studied Here. The Correctly Predicted Labels And How They Differ From Ground Truth Is Studied.



Ground Truth:{bottle, dinningtable, person} Figure 10: The ground truth and obtained labels

Figure 10 depicts the output obtained from the proposed method.

# CONCLUSION

Multi-Label Classification methods improve the classification ability. First by using efficient features for decomposed binary dataset and second by modeling label dependencies by using pairwise mutual information among the class labels. For efficient classification convolutional neural network is employed for feature extraction. Binary relevance is used to ensure scalability of our method. For single-label images, it is practically easy to collect and annotate the images. However, the burden of collection and annotation for a large-scale multilabel image dataset is extremely high. In this research work the accuracy of image annotation is improved by using a training dataset. The results obtained are better than that of the methods in existence.

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