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A Unique Class Prediction Classifier for Redundant Multi-Label Values to Support Efficient Clustering

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Abstract

The real-time applications have increased the need for heterogeneous data classification and clustering for the text, photo, music, film, and medical data sets. The complexity of the learning class for objects associated with the label set is a major problem for multi-label datasets. The current learning approach depends on the observed characteristic preference for a class of similar class labels, but the favorite property measures the object deviation label instead of the associated class for classification and also even certain features also affect clustering process. Few studies have attempted to target the complexity of associating multi-label that trains a multi-label dataset to support accurate labeling based on the feature selection but they fail to provide one single class which can support correct data record classification. The novelty of this paper is to provide a solution to the problem of associating redundant multi-labels values in the multi-label dataset. It presents a Unique Class Prediction (UCP) classifier for redundant multi-label datasets, which will predict a unique class for multi-label value for a data record which can support in effective clustering of multi-labeled data records. The key objective is to identify the most appropriate unique class value (UCV) interpreting the multi-value patterns by means of Learning Multi-label Association and Unique Class Prediction. Using a unique label density method the best multi-value pattern is generated and it is being used for unique class prediction. The experimental evaluation shows the effectiveness of the proposed classifier. The obtained result of Hamming loss shows a significant low and the accuracy shows higher in comparison to other classifiers that support multi-label dataset.

Keywords: Prediction, Unique class, Association Rules, Classifier, Multi-label, Clustering

INTRODUCTION

The heterogeneous data sources from the various domains in real world application are currently being described with multiple labels identified as multi-label entities. These data can be data from various fields such as "education, sports, multimedia, politics or medicine" [7], [23], [25]. Content and data can have multiple meanings, but they can also be associated with multiple classes for identification by multiple labels. Even high dimensional data usages can be used in the application of data processing [20] and machine learning [11], [17], [18], faced hurdles in the correct classification. In all cases, the cause of the problem is identified as multi-labeling. We handle this problems through one-to-multi-label classification by learning the multi-label association rules from a multi-label dataset that will get the betters accuracy of a multi-label classifier.

Efficient learning and constructing classifiers for heterogeneous datasets is a challenging task in data mining research, mainly the objects having duplicate or multi-label annotations. In the literature, most works constitute classifiers with the goal of "feature selection" [11],[12], "feature reduction" [8], [19] and "association classification" [2], and [22]. Classifiers typically predict data object classes based on a set of training data. However, the effect of duplicate labels on the structure of the classifier is not investigated to the extent that it does not have a significant impact on the predictive class label or even literature, this problem has not been explored so far to it extends.

In previous proposals “feature selection" and” feature reduction " methods [12], [8] have been used for multi-label classification. Most of these proposals are to reduce the ability to analyze the nature of the correlations between them and not to provide reinforcement information to predict the class. These reduced or selected features used by the classifier to train and organize support for on-the-fly. However, the complexity of the object is to translate these structures into multi-label and improvisation in classification. However, this selection method works well for some classifiers for multi-label learning [4], but may not be unique for each class label. For example, in a series of documents with word terms, text classification can relate to "entertainment", "politics", "sports", "stocks", and so on.

This paper aims to propose a "Unique Class Prediction" (UCP) classifier based on a multi-label learning data object characterized by utilizing a multi-valued association rule algorithm for the classification improvement. The unique label of a multi-label objects association is identified by calculating the label density and a multi-label association algorithm. In the data object class, we emphasize for finding a unique class value (UCV) that is very much suitable for the class suggestion. In the second step, we learn the multi-label binary association between multiple labels to construct the pattern for classification. This accurate prediction of classes for an object will support inaccurate clustering in a supervised manner.

The methods and algorithms are discussed in the following paper are organized as follows. Section-2 describes the related works performed in related to multi-label classifications, Section-3 discussed the multi-label association approach which describes the problem description and Multi-Label Association Learning, Section-4 presents the datasets and evaluation measures and section-5 presents experimental evaluation utilizing multi-label datasets. Finally, the conclusion of the paper is discussed in section-6.

RELATED WORKS

An accurate classification of data focuses on in-depth analysis of the data to provide the necessary information [1], [5], [9], [16]. Classification is performed mostly through the object's classifier test function and assigning a learning set for trained classes [21]. For example, a data set that contains a collection of records, and each record instance has a set of properties that are considered attributes of the set of identification classes. Classify data objects that are not noticed based on established class knowledge classifiers. The goal of classification is to build accurate classifiers that accurately support unknown data classification for real-time needs. Supervised learning is successfully used in many tasks of learning to identify undetected objects. However, in today's real-time data facilities, it is not suitable for multiple semantic meanings of data objects. The text of the article related to the news can be related policies, sports, economy, drawing, and so on. Creating multiple labels is a complex class of traditional supervised learning systems.

F. Charte et al. [1] present a multi-label classification technique that can work with multiple data label objects. The proposal has a large number of labels that will solve the traditional problem of high-dimensional data classification. Selection of feature selection utilizing examples of transforming data and association rules found based on label dependency. The label value identifies the selection function of a classification algorithm with multiple labels. This approach can be successful for linear transformations of data objects to represent labels of dependency, but it can be inaccurate for highly distributed data of multi-label data objects.

M. Zhang and Lei Wu [6] focused on the issue of "selecting features of multi-label learning". Utilizing a strategy to learn code-specific features to distinguish different label classes. Other name algorithms have been submitted to learn more about labels that build clusters based on specific characteristics of the LIFT label analysis application, mainly in clustering of positive and negative examples. Basic classification skills training examine the grouped results that are characteristic of the group. However, this approach presents a promising direction in the multi-label label of learning for classification, but the importance of association characteristics must be explored for other optimization.

Tsoumakas and I. Katakis [15] identify problems with classification labels and proposed solutions for data transformation and multi-label classification algorithm adaptation. Data conversion handles data problems with more label conversions from one label to another. Proposal to utilize a generic off-the-shelf label sorter to restrict classification requests. Classification algorithms are tailored to specific categories of disciplines to classify more labels in certain situations and achieve higher computational complexity.

K. Dembczynski et al. [24] discusses the formulation and description of labeling dependency in the classification of multiple labels. The focus is mainly on dependency labels through the difference between conditional labels and unconditional corrosion labels. Classification of more labels through unconditional dependency modeling has shown good results, such as in the case of conditional dependencies, with low efficiency in comparisons. X. Kong et al. [3] also explore the classification of more labels based on various types of dependence between the subject known as "PIPL", and its label. The proposals primarily focus on heterogeneous data to facilitate classification. This evaluation shows improvisation performance but is limited to heterogeneous network information data sets.

It is based on the above view and approach to understanding the importance of multiple labels in the field of classification and clustering. This emphasizes the importance of choosing a feature in classification accuracy. But learning the most characteristic features of a classification is a difficult question. In the configurations and limitations above, we propose a new approach to classifying more sets of label data utilizing Unique Class Prediction (UCP) classifiers in accordance with association rules for multi-label datasets. This learning algorithm generalizes the selective nature of dependency based on requirements and need areas. The details of the classification are described in the following sections.

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UNIQUE CLASS PREDICTION APPROACH

Problem

Traditional learning systems are mainly studied in supervised machine learning systems. In these systems, the data objects are associated with the labels of the supervised learning system, learning the set of data characteristics of the features used in the classification, as shown in Fig. 1.

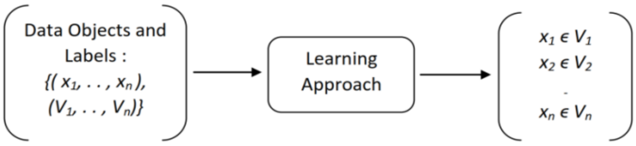

Figure 1: Traditional Supervised Learning

While this learning is well suited for a single term, complexity arises when there are multiple labels in an object. In the literature [4], [20], and [12], the improvisation of traditional supervised learning for applying multi-label data objects has been found. However, most of the proposed solutions are based on the functionality of dependency learning or peer labels and calculate the number of co-occurrences. However, this kind of information label may not be relevant for domains that are not available. In some cases, it is identified by the association rules algorithm and the underlying dependencies of the correlation label, but it does not facilitate changes to different sets of data labels and other domains. Our goal is to build classifiers based on new multi-label associations that can be implemented in different domains of a multi-label dataset and to provide the necessary accurate and rapid classification and clustering.

Learning Multi-label Association

The classification depends on the accuracy of the character selection and identification labels. It was observed that there are two or more data labels in a particular object domain suggesting some level of organization among them. This research association can be very useful for multi-level classification of data. We propose a system that learns two steps to identify a unique class label (UCV) that is very suitable for class suggestions. The second step is to find various multi-labels that support UCV and create useful pattern based rules for various classes.

To learn the UCV for an object instance we calculate the associated unique label density by comparing it to the Unique Class-Table (UC-Tables) as presented in Table 1. The unique label density (ULD) is calculated utilizing Eq. (1). The range of ULD values is between 0 and 1, and the higher the label, the closer the association is to the class.

Table 1: Unique Class-Table

Class	**Associating Labels**
Scene	Beach, Sunset, FallFoliage, Field, Mountain, Urban, etc.
Birds	Brown Creeper, Pacific Wren, Pacific-slope Flycatcher, Red-breasted Nuthatch, Dark-eyed, etc.
Bibtex	architecture, article, book, children, community, computer, dynamics, education, e-learning, games, social, social nets, etc.

The initial task of the multi-label learning system is now to find the UCV utilizing a vector, V consist of different object multi-labels. To do this, we create a UC-Table consisting of the parent class label of the domain, as shown in Table 1. Let's considered a training set D consists of n objects instances having k labels vectors which represented as, "D = {d_1,. . . , d_n}" and labels as. "V = {m_1, . . , m_k }".

$$UniqueValue\ Density\left(UVD\right) = \frac{\sum_{i=1}^{k}(v_k \in V)}{|V|} \quad (1)$$

The method for locating an instance of a UCV class utilizing UC-tables and UVD values is described in Algorithm-1.

Algorithim-1: Finding *UCV* Class for an instance

Input :

TD, *Training database*

UCT, *an Unique Class-Table*

Output: C_{Label}, *Identified Class Label of Instance*

Method:

for *i=0, i* < number of instance in *TD*

  d_i = *TD[i];*

  V[]=getLabels(d_i*);*

  for *t=0, t* < number of tuples in *UCT*

    C_t *= UCT[t][0]; // -- class label*

    A_t *[] = UCT[t][0]; // -- Association label*

    UVD = computeUVD (V[] , A_t *[]);*

    UVD-Label[t][] = [C_t *][UVD];*

  end for

  // -The highest *UVD* label from the *UVD-Label[ ][ ]*

  // -The class label which has the highest *UVD* label

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C_{Label} = *getUniqueClass (UVD-Label[ ][ ]);*

end for

Choosing a unique class for multi-label value results in a large loss of information [10], [20]. To overcome this problem, we extend a class that learns UCV with multiple label values to build association patterns through subscription rules to minimize hamming losses in data classification. The pattern generation process is illustrated in Fig. 2.

Fig. 2 illustrates the value of an instance in the association to find multiple values for the construction of a sample of classification.

Let's assume, the training datasets, "D = { (d_1,l_1), (d_2,l_2), . . . , (d_n ,l_k)}", where $d_i \in D$, $v_k \subseteq V$. To find the multi-labels which can be highly relevant to build the classifier class accuracy we consider a binary relevance of each instance labels, for example, the value "V = {v_1, v_2, v_3, v_4, v_5}" can have a binary equivalence as, "D = {(1,0,0,1,0), ... , (1,1,1,0,1)}". This learning mechanism will utilize all binary values, such that the list of labels set will be generated from D which supports the minimum number of support count required.

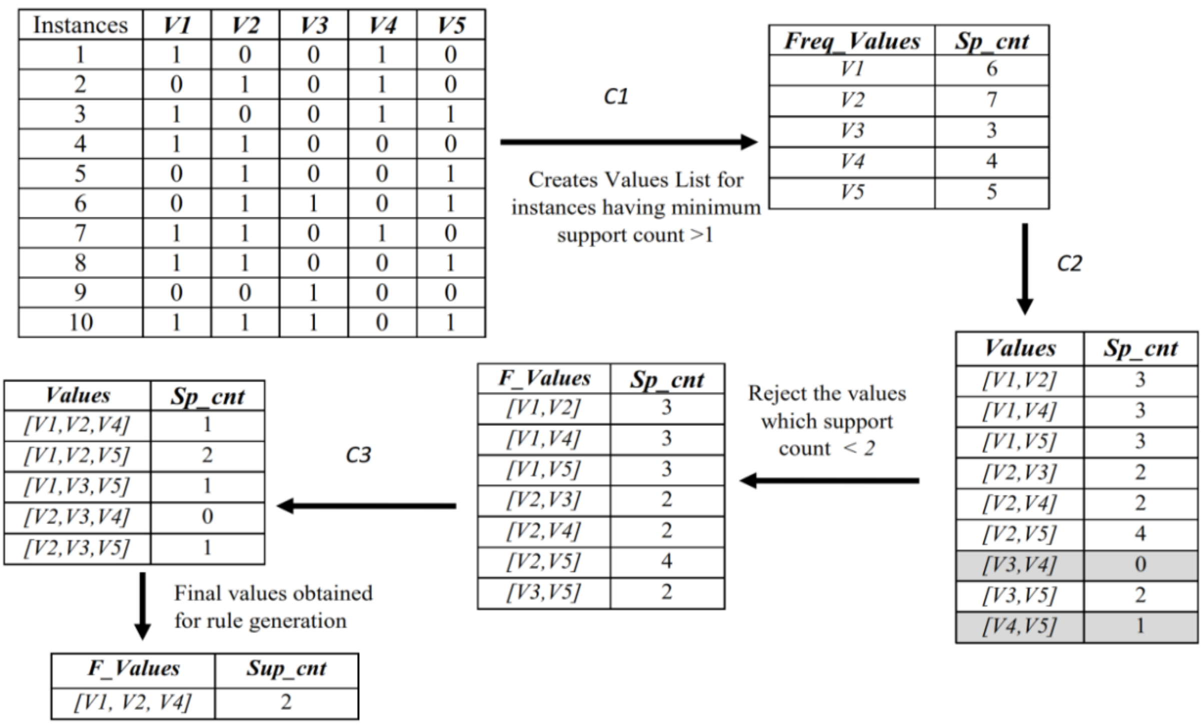


Figure 2: Pattern Generating from Multi-label values

In this case, since the absolute support count is 2, and the minimum relative support is 2/10 = 20%. The list obtained with C1 is configured as an item that meets minimum support, and the remaining items are ignored. Also, to identify the most frequent and associated label in C1 obtained, combine with C1 ⋈ C1 to construct C2 label with two labels and continue until one pattern value is obtained. This iteration continues until it has multiple labels that satisfy the minimum support. The final multi-label is considered the most relevant and relevant. It now utilizes the UCV Class, C, and multi-label entries to create classification rules for the classifiers as shown in Table 2.

Table 2: Rules obtain Utilizing Multi-Label Association

Generated Multi-Values	*Classifier Rules*	*Class*
{V1,V2,V4}	• *{V1},{V2},{V4}* • *{V1,V2}, {V1,V4}, {V2,V4}* • *{V1,V2,V4}*	C_{Label}

In this case, since the absolute support count is 2, and the minimum relative support is 2/10 = 20%. The list obtained with C1 is configured as an item that meets minimum support, and the remaining items are ignored. Also, to identify the most frequent and associated label in C1 obtained, combine with C1 ⋈ C1 to construct C2 label with two labels and continue until one pattern value is obtained. This iteration continues until it has multiple labels that satisfy the minimum support. The final multi-label is considered the most relevant and relevant. It now utilizes the UCV Class, C, and multi-label entries to create classification rules for the classifiers as shown in Table 2.

Acquired rules can be used for accurate classification of multi-label objects. The accuracy of the classification is also supported by effective clustering of data objects. In the next section, we will perform an experimental evaluation of a multi-label dataset to analyze the accuracy and hamming loss compared to traditional multi-label classification methods.

DATASETS AND EVALUATION MEASURES

To evaluate the effectiveness of the proposal, we used Tsoumakas [14] Hamming loss (HL) and accuracy methods. The dataset is used to download the analysis from the MULAN [26] data store as shown in Table 3.

Table 3: Datasets Used for Experiment Evaluation

Datasets	**Domain**	**Instances**	**Attributes**	**Values**	L_{Card}
Scenes	images	2407	294	6	1.074
Birds	audio	645	260	19	1.014
Bibtext	text	7395	1836	159	2.402

Multi-Label Datasets

Multiple label classification complexity arises from an extensive variety of real-world circumstances and domain applications. For the data set related to the experiment setup, the multi-label data "Multimedia Classification", "Text Classification" and "Bioinformatics" are dealt with three main application areas are often observed. All data sets are primarily obtained from the MULAN [26] data store as summarized in Table 4. It displays domain data set properties in terms of "number of instance", "attributes", "Values" and "L_{Card}".

The "L_{Card} " represents the label which determines the average number of labels per test data. The L_{Card} measured are discussed in [1], [6] for each datasets as, $D = \{ (d_n, V_k) \mid 1 \le n \le k\}$ is the denoted as in Eq. (2),

$$L_{Card} = \frac{1}{N}\sum_{i=1}^{n} |V_k| \qquad (2)$$

where N is the total data records and V consist of k object multi-labels values.

Evaluation Measures

Hamming Loss (HL)

This is the most widely accepted measure of further labeling measures for misclassification of data labels. It evaluates misclassification of the instance and pairs in terms of labels that are not related to being expected and relevant labels. The performance is considered perfect if HL = 0.

$$Hamming\ Loss(HL) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{V}|h(d_i)\delta l_i| \qquad (3)$$

where δ defines the "symmetrical dissimilarity between two datasets instances", $h(d_i)$ is the hamming loss for the data record d_i, N is "the number of testing datasets", l is the instance label, and V is "the total class labels which are likely to the datasets".

Accuracy

Accuracy measures the percentage of the label actually measured predicted correctly within a given data set. It is the proportion of the correctly predicted labels from the total number of test datasets, which is the number of hamming value of a label intersecting with the number of labels, and with the actual total number of label instances which is the total union of hamming of labels. It computed as given in Eq. (4),

$$Accuracy(A) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{V}\left|\frac{h(d_i)\cap l_i}{h(d_i)\cup l_i}\right| \qquad (4)$$

where $h(d_i)$ is the hamming loss for the data record d_i, N is "total number of testing datasets", l is the instance label and V is "the total number of class labels which are likely to the datasets".

Algorithm Evaluated

The proposed method is implemented with "Weka Tool" and MULAN [26] data sets and open-source Java library. We applied multi-label classification utilizing the proposed Unique Class Prediction (UCP) approach on standard multi-label classification methods, those are, "Binary Relevance" (BR), "Label Powerset" (LP), "Calibration Label Ranking" (CLR) and "Random-k-Labelset" (RAkEL) [15], [13]. The experiment was conducted with "Weka" and "MULAN Libraries" utilizing 10-fold cross-validation methodology over different data sets.

EXPERIMENTAL EVALUATION

This section describes the outcomes of experiments conducted utilizing "Weka Tool" and "MULAN" [26]. At first, we learned UCV utilizing a unique class table, and later discovered multiple labels utilizing binary label association data sets instance. The learn knowledge of UCP classifier is compared with the traditional multi-label classifier methods. The results obtained on applying on each data set in Table-3 are presented in the following Tables-4.

Table 4: Number of UCP Pairs Identified for the Classification

Datasets	Labels	Associated multiple-values	Non-Associated	UCP Classification Pairs
Scenes	6	3	3	8
Birds	19	13	6	38
Bibtext	159	114	45	386

RESULTS

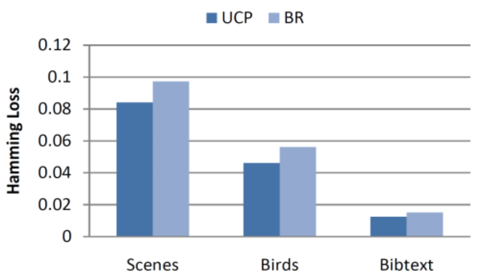
This section discusses the evaluation results obtained in form of Hamming Loss(HL) and Accuracy.

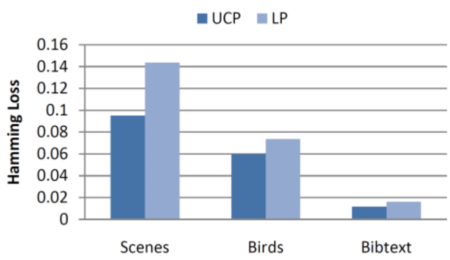
Hamming Loss Performance

Fig. 3, show the hamming loss performance in comparison to BR, LP, CLR and RAkEL and Table 6 shows its statistical values. The proposed UCP show a lower hamming loss in comparison to another classifier due to accurate association of label pattern generation and unique class label prediction. Even the difference of loss is minimum in comparison but it can be a good enhancement in the classification improvisation.

Table 5: Classifier HL Performance ("The Lower The Better")

Datasets	***UCP***	**BR**	***UCP***	**LP**	***UCP***	**CLR**	***UCP***	**RAkEL**
Scenes	***0.0841***	0.0973	*0.0951*	0.1437	*0.0994*	0.1121	*0.1012*	0.0962
Birds	*0.0462*	0.0561	*0.0599*	0.0735	*0.0452*	0.0506	***0.0437***	0.0489
Bibtext	*0.0125*	0.0151	***0.0117***	0.0161	*0.0098*	0.0144	*0.0132*	0.0151





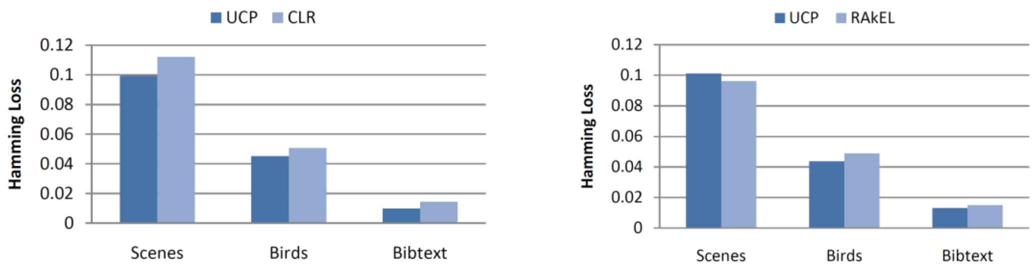


Figure 3: Hamming Loss Comparison

Accuracy Performance

Fig. 4 show the Accuracy performance in comparison to BR, LP, CLR and RAkEL and Table 6 shows its statistical values. The accuracy obtained by UCP is quite convincing in comparison to other classifiers, except in the case of “RAkEL" with "scene" datasets. This difference can be considered uncertain, but in comparison to other cases, it outperforms very significantly in comparison. The improvisation in classification accuracy helps to categorize the objects efficiently and also support in unclassified object clustering effectively.

Table 6: Classifier Accuracy Performance ("The Higher the Better")

Datasets	***UCP***	**BR**	***UCP***	**LP**	***UCP***	**CLR**	***UCP***	**RAkEL**
Scenes	*0.799*	0.553	***0.839***	0.5893	*0.7918*	0.5265	*0.6247*	0.6841
Birds	*0.6708*	0.4666	*0.7189*	0.5295	***0.7319***	0.528	*0.727*	0.5452
Bibtext	***0.7204***	0.4187	*0.6437*	0.3869	*0.5015*	0.4089	*0.3854*	0.3657

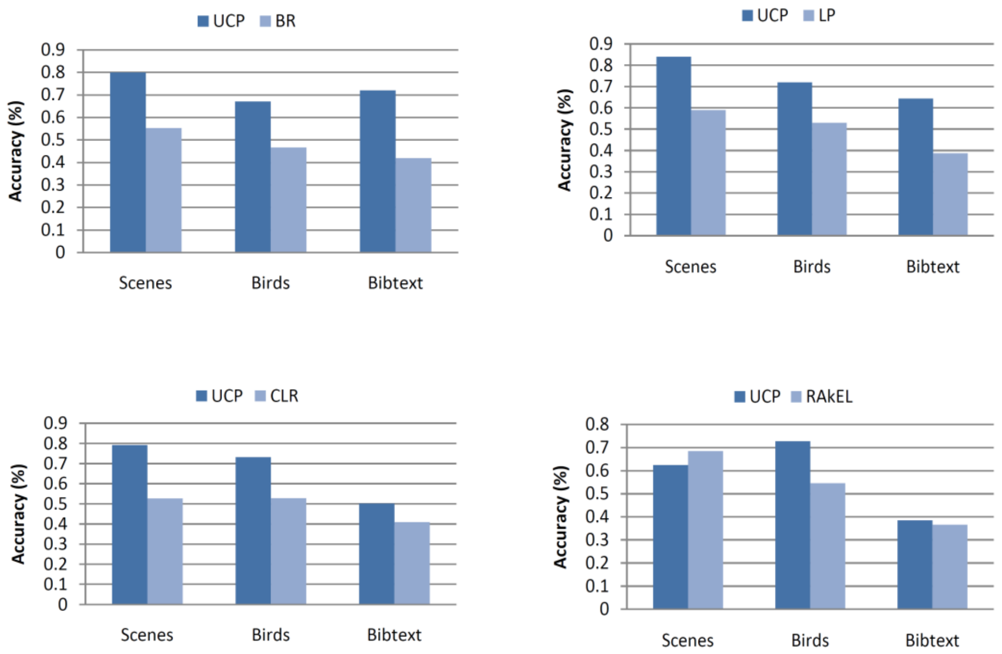


Figure 4: Accuracy Percentage Comparison

CONCLUSION

In this paper, we propose a unique class prediction (UCP) approach utilizing label association between multiple labels. The learning process initially identifies a unique class label (UCV) that is very well suited to class suggestion and in the second step finds another multiple labels supporting UCV to construct a class pattern useful for different object classifications. It calculates the associated label density by comparing it to the UC-Table to learn the UCV for instance. The contribution of this proposal will be used to learn a variety of multi-label datasets and the possible ways to learn multiple labels for efficient classification utilizing. Experimental evaluation measures the hamming loss and accuracy of the UCP in compare to existing classifiers. It shows a low hamming loss and high accuracy in comparison. Even the difference is minimal it makes a positive improvisation for efficient classification and support in effective clustering also. In the future, it can be further investigated to utilize association labels with fuzzy and Bayes elements to swiftness on multi-label classification.

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