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Image Tagging using Modified Association Rule based on Semantic Neighbors

Mrs. Anupama Ganesh Phakatkar[1], Mr. Balwant A. Sonkamble[2]
[1]Computer Engineering Department
SCTR'S Pune Institute of Computer Technology
Pune, India
agphakatkar@pict.edu
[2]Computer Engineering Department
SCTR'S Pune Institute of Computer Technology
Pune, India
basonkamble@pict.edu

Abstract— With the rapid development of the internet, mobiles, and social image-sharing websites, a large number of images are generated daily. The huge repository of the images poses challenges for an image retrieval system. On image-sharing social websites such as Flickr, the users can assign keywords/tags to the images which can describe the content of the images. These tags play important role in an image retrieval system. However, the user-assigned tags are highly personalized which brings many challenges for retrieval of the images. Thus, it is necessary to suggest appropriate tags to the images.

Existing methods for tag recommendation based on nearest neighbors ignore the relationship between tags. In this paper, the method is proposed for tag recommendations for the images based on semantic neighbors using modified association rule. Given an image, the method identifies the semantic neighbors using random forest based on the weight assigned to each category. The tags associated with the semantic neighbors are used as candidate tags. The candidate tags are expanded by mining tags using modified association rules where each semantic neighbor is considered a transaction. In modified association rules, the probability of each tag is calculated using TF-IDF and confidence value.

The experimentation is done on Flickr, NUS-WIDE, and Corel-5k datasets. The result obtained using the proposed method gives better performance as compared to the existing tag recommendation methods.

Keywords- Modified Association Rule, Random Forest Semantic Neighbors, Tag Recommendation.

I. INTRODUCTION

With the rapid development of multimedia technology and the vast usage of the internet, the number of images is increasing exponentially. On many social websites, people share multimedia objects such as audio, video, and images. According to the survey, 3.5 billion photos are uploaded on the Flickr image-sharing website daily by registered users to connect the people with the same interest [1]. As the huge number of images are uploaded daily, indexing and retrieval of images become challenging. Therefore, it is necessary to create an index for images based on tags.

On Flickr image sharing websites, each photo is associated with the tags provided by the users which describe visual content, geolocation. These tags are used for the classification, retrieval, and indexing of the images. As per the study, 65% of Flickr images are associated with a fewer number of tags. Also, the user-assigned tags are most of the time are not relevant to the images. As shown in fig. 1(a), tag piknic is not related to the image. In such a scenario, it is very difficult to retrieve images using tags. Therefore, it is important to develop an algorithm that suggests tags to the users.

(a)

Tags:

TCoakley, Clover, Picnik

(b)

Tags:

Grumtine, Nature

Fig. 1 Tagged Images

The advantages of tag recommendation are: reduce typing or spelling mistakes and the cost of manual annotation. Also, it

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helps the user to select appropriate tags. In this paper, the work is done as follows:

1. The semantic neighbors are identified based on the random forest by assigning weight to each category.
2. The relationship between tags associated with the semantic neighbors are determined using a modified association rule.

The random forest is used because it has a very good classification capability. In [2], the fourteen types of classifiers were compared and conclude that random forest perform better than the other thirteen classifiers such as kNN and SVM.

II. RELATED WORK

In this section, we will discuss different approaches that have been adopted by various researchers for an image tag recommendation. These approaches are divided into various categories.

1) Methods based on Tag Co-occurrence

In this method, the tags are recommended based on the relationship between the tags associated with the images which are determined using different measures such as association rules, term frequency, etc.

In [3], the method is proposed for tag recommendation for Flickr images based on tag co-occurrence using symmetric and asymmetric measures. The method for tag suggestion is proposed in [4] using the GENIO algorithm by exploring the tag relationship at different levels of abstraction. The tags are stored in the transaction database and a hierarchy is created over the transaction database. The rules are selected with given support and confidence. Finally, the tags are ranked using the Borda count method. In [5], the method is proposed for tag suggestion using social and textual features of the images. The method has extracted tags from surrounding text associated with the images such as comments, title, and description. The social features are determined based on favorite topics. Finally, tags are recommended using the Naïve Bayes classifier.

The method determines the semantic relationship between tags and recommends tags based on previous history. But this method may suffer from a cold start problem. Also, these user-assigned tags are highly personalized and may not reflect the visual content of the images.

2) Graph-based methods

In this method, the relationship between the user, image, and tag is represented as a folksonomy using a graph, and tags are recommended through a random walk of the folksonomy.

In [6], the method was proposed ranking of the tags. In the proposed method, a tag graph is created and the score of the tag is determined using kernel density estimation. But the probabilistic approach doesn't consider the relationship between tags which is further determined using a random walk over tag graph. But the proposed method is unable to consider semantic relation between the images. Image tagging using graph-based reinforcement is proposed in [7]. The method groups visually similar images using k means clustering algorithm and determines the semantic similarity using cosine similarity. The graph representing the image, tags, and users are created and the interrelationship between these objects are determined to recommend tags. Image annotation using a graph model is proposed in [8, 9]. Two types of graphs are created: images and word. The kNN sparse graph-based approach is proposed for the annotation of labelled and unlabelled images in [10]. The method is proposed in [11] for tagging and prediction of geolocation of the images using a hypergraph model.

The graph-based methods achieve good results and are less affected as compared to the tag co-occurrence method. However, retraining is needed every time a new image is added.

3) Matrix factorization methods

In this method, the image tagging problem is represented as a matrix and uses decomposition methods for the reduction of features.

In [12], the method for image tag recommendation is proposed using a heterogeneous network. The heterogeneous network consists of three types of graphs: image, tag, and the graph connecting image and tag graph. The method for image annotation and recommendation is proposed using the parallel factor analysis2 (PARAFAC2) approach [13]. The PARAFAC2 approach captures the relationship between user, image, and tag matrices by multiplying these three matrices. In [14], the TFC (Tensor Factorization and Tag Clustering model) model was proposed for image tag recommendation. The single value decomposition is applied to capture the relationship between the user, image, and tags. The algorithm for image tag recommendation is proposed using tensor factorization [15]. The user, image, and tag matrices are integrated into one tensor and the factorization method is applied to the tensor for ranking of the tags.

The advantages of the method are: reduction of dimensions reduces the noise and computational complexity. However, the method is expensive to create the model and has a scalability issue.

4) Discriminative methods

In a discriminative method, the images are represented using feature vectors and the classifiers are trained using these

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feature vectors to predict the category. Tags are recommended for unlabelled images based on the semantics of the category.

The method is proposed in [16] for the annotation of images. The method identifies salient and non-salient regions and used particle swarm optimization for labelling regions of the images. In [17], the method is proposed for image annotation using multiple Support Vector Machine (SVM) classification algorithms. The SVM is trained using different features and predicts the class label of an image based on probability. The method that selects positive and negative examples found most relevant for the given tag from database-annotated images is proposed in [18]. The SVM is trained per tag enabled fast classification.

The discriminative methods reduce the dimensionality since they explore the relationship between the object's groups but not direct objects. The method assigns tags which are not specific to the content of images. So, these tags are very general to describe an image and even to distinguish them from other tags.

5) Generative methods

In the generative method, the tags are recommended by correlating the visual and tag features. The multimodal method is presented in [19] for image tagging which utilizes both visual and tag features using deep learning techniques. In [20] the method was proposed for annotation of labelled and unlabelled images using the kernel canonical correlation analysis approach. The approach constructs a semantic space where the textual and visual features are integrated. The method for social image tagging with diverse semantics is presented in [21]. The method creates a uniform framework to cover the diversity and relevance of the tag and applied a greedy strategy to determine optimal tags. In [22] the method is presented for tag recommendation for geo images by creating a unified subspace where the visual and tag features are correlated. The method is presented in [23] for retrieval of images using hypergraph which uses both image and tag features.

The generative methods are good in capturing the relationship between tag and image features but have some limitations. The model is complicated as it needs more parameters and assumes features are independent.

6) Deep Learning methods

Given an input image, the deep learning methods extract features automatically without depending on the human crafted features. The models are trained in offline mode and used to extract features or tag suggestions for a new image.

In [24], an image tag recommendation method is presented in which the random walk is performed on a graph constructed using user and image nearest neighbor. The features of the images are extracted using different layers of convolution neural networks. The SEM model is proposed in [25] for the annotation of images by extracting features of the images using the AlexNet convolution neural network. The method identifies the visual neighbors of a given image based on CNN features and predicts the tags using the Bayesian method.

The limitations of the deep learning methods are: does not work for the small size dataset and need a large dataset. It takes a very long time for training as requires more iteration for tuning the parameters.

7) Neighbor based methods

The neighbor-based methods find the k similar images based on the idea that the images similar to each other tend to have the same labels/tags.

In [26], the method is proposed for image labelling by modifying the classical k nearest neighbor classifier in which image and tag relationship is defined using a matrix. The method for image annotation is presented in [27] based on community which is identified from the tag graph. The tag graph is created from tags associated with visually similar images. In [28], the tags are recommended for the images using the user's history based on majority voting from the neighbors by creating a graph that captures the relationship between the user, image features, and ranked tags. The tag relevance method is presented in [29] based on weighted visual neighbors. The relevance of tags to the images is determined by determining a relationship between tags associated with visual neighbors. In [30], the labels are suggested for the images using two-pass kNN. The method determines label-based images from each category and images based on visual similarity. The visual and semantic based nearest neighbor method is presented for annotation of images using posterior probability [31]. The method is presented in [32] to identify relevant/irrelevant tags associated with the images using visually weighted nearest neighbors. The image tagging is presented in [33] based on geographical, time, and feature-based neighbors from the user's history. The tags are suggested by counting tags associated with these three neighbors. In [34], the tags are recommended to the labelled and unlabelled images by taking the difference between local and global tag counts. In [35], the images are annotated using distance and rank-based neighbors.

In this paper, tags are recommended based on an association between the tags associated with the semantic neighbors. The existing tag recommendation methods based on nearest neighbors assigns most frequent tags to an image and may be tagged with irrelevant tags. Also, they ignore the relations among the tags which motivate us to develop a method

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that explores association among the tags which helps to improve the performance of the tag recommendation system.

III. ASSOCIATION RULE MINING

Association rule mining is the most widely used data mining method to find patterns hidden in the data. It determines which items come together and the correlation among them [36]. It is used in many applications such as market bask analysis, bioinformatics, web mining, etc. Two measures are used to find the association between items: support and confidence.

E.g. pasta => olive oil (support = 40%, confidence = 75%)

40% of the support shows that pasta and olive oils are bought together. A confidence of 75% means that the customers who purchased pasta also purchased olive oil. The association between items are considered more interesting if they satisfy minimum support and confidence threshold value.

The support is the measurement of how two items frequently occur together and defined as follows:

$$support(x) = \frac{frequency(x)}{N} \quad (1)$$

Where N is the number of transactions in the database

The confidence is the measure of the percentage of transactions in the database containing x also contain y and defined as follows:

$$confidence(x \rightarrow y) = P(y|x) = \frac{frequency(x\ U\ y)}{frequency(x)} \quad (2)$$

Based on support and confidence, the association rules are generated as follows:

a. Generate non-empty subset of m
b. For each non-empty subset, list the rule $"n => m - n"$ if $\frac{frequency(xUy)}{frequency(x)}$ > minimum confidence

IV. RANDOM FOREST

Random forest classifier is an ensemble learning machine learning algorithm that consists of multiple decision trees [37]. For training, it uses the bagging method. In the bagging method, it selects N random samples and M features from the training data set with replacement and constructs a decision tree using random samples. The remaining data is used to determine the performance of classification. For a given test sample, each decision tree predicts the class label, and the random forest selects the class with the maximum vote. In a random forest, each tree is grown but does not prune. It is necessary to identify the proper attribute selection measure method as it maximizes the dissimilarity between the classes. The random forest used the Gini index attribute selection measure method for feature selection which is used for the construction of decision trees.

Given a number of trees, the algorithm constructs each tree as follows[38]: The algorithm selects a bootstrap sample randomly from the training dataset. The random forest tree F is constructed using bootstrapped samples. For the creation of a random forest tree, the algorithm applies repeatedly the next steps for the last node of the tree until the minimum node size is reached. i) It selects n variables out of m variables randomly ii) Use the Gini index to identify n variables iii) It then split the node into left and right subtree nodes.
The advantages of random forest are:

- It can work on high dimensional data.
- It can handle missing values.
- Less overfitting of data.

V. RESEARCH METHODOLOGY

The method is proposed for an image tag recommendation based on semantic neighbors and association rules. The semantic neighbors are identified using a random forest. The relationship between tags is determined using post-weighted association rules. Fig. 2 shows the proposed method framework. It consists of three processes: feature extraction, identification of semantic neighbors, and modified association rule mining.

1) Feature Extraction

In an image retrieval system, feature extraction is an important block. Many authors have proposed different feature representation methods using shape, color, and texture features. It is necessary to extract discriminative features and represent them effectively. Color features are commonly used in many image retrieval applications as the human eyes are sensitive to colors. Color is a robust feature because it doesn't get affected due to translation, rotation, and scaling. The texture is another important feature that represents visual patterns such as direction, brightness, smoothness, coarseness of an image.

In the proposed system, two types of features are extracted: color and texture [39, 40]. For color features extraction, an image is converted into L*a*b* color space and is divided into blocks. The first, second, and third order moment is calculated for each block as color features resulting in nine features. The wavelet packet is used to extract texture features of an image. For this purpose, Daubechies wavelet is applied up to level three to decompose an image into bands. The mean and standard deviation is calculated for each band presenting at the last level. For texture features are extraction using wavelet packet transform, an image is decomposed into sub-bands up to level three using Daubechies wavelet. The energy and standard

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deviation of each band of the last level are determined as texture features using eq.1 and 2.

$$Mean_i = \frac{1}{H*W} \sum_{h=1}^{H} \sum_{w=1}^{W} |F_i(h,w)| \quad (3)$$

$$Std_i = \sqrt{\frac{1}{H*W} \sum_{h=1}^{H} \sum_{w=1}^{W} (|F_i(h,w)| - Mean_i)^2} \quad (4)$$

$F_i(h,w)$ represents the coefficient matrices of i^{th} sub-band. W and H represent the width and height of the decomposed sub-band F_i. The features are combined using the early fusion method and normalized using the min-max normalization method to avoid the variation in feature range values.

2) Finding semantic neighbours using Random Forest

During the training phase, weight is assigned to each category depending on the accuracy of the classification. Given a test image I, it passes through each tree. It starts from the root and passes through each branch of the tree according to the split node function until it reaches the leaf node. It determines the samples which are present at the last level. Count the number of images stored at the last level for each category. Based on the probability and weight of each category, it identifies the semantic neighbors. The probability of each category is obtained as the fraction of samples of the same class in a leaf. The weight is calculated as the number of images correctly classified by a classifier. Figure 3 shows the example for the same.

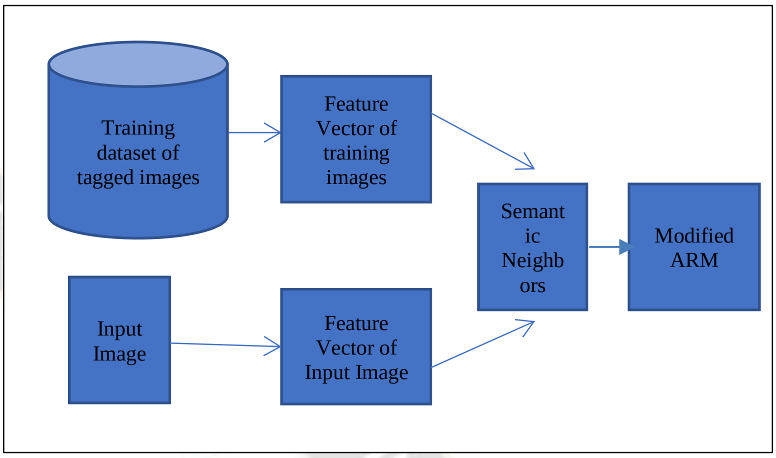

Fig. 2 Proposed System

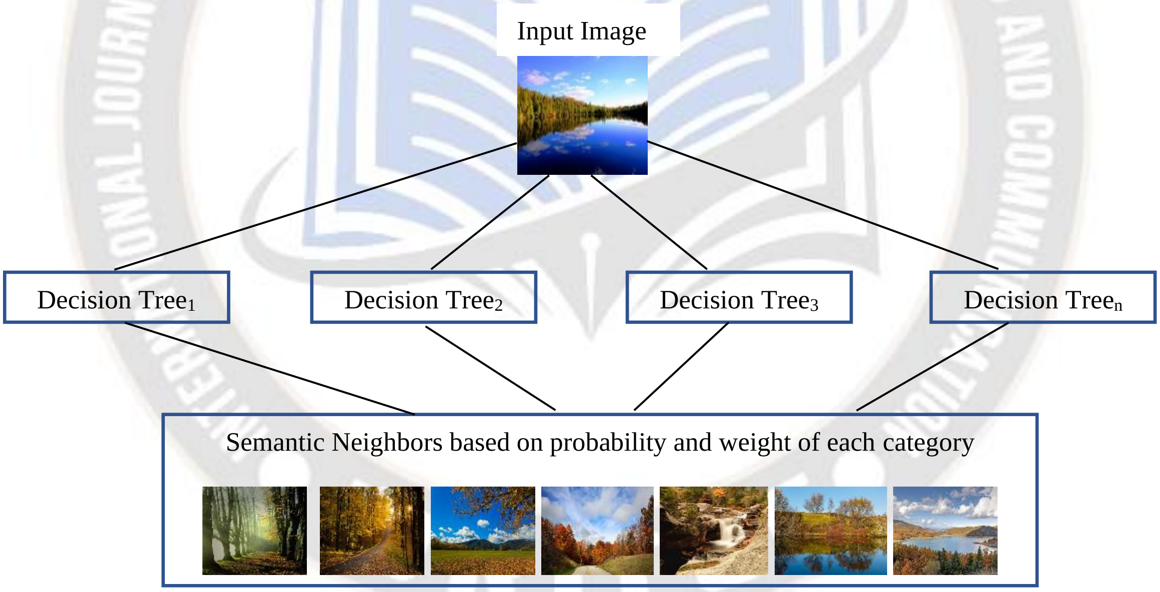

Fig. 3 Flow Diagram of Identification of Semantic Neighbors

Algorithm 1: To find Semantic Nearest Neighbors
Input: Training Images along with category number Output: Semantic Nearest Neighbors

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Steps:
1. For each $category_i$
   1.1. Initialize $weight_i$ to zero
   End For
2. For each $Image_j$ in training set do
   2.1 If $Image_j$ can be recognized correctly by classifier then
   2.1.1 $weight_i$= $weight_i$+1;
   End If
   2.2 imglist[$category_i$]= $image_j$
   End For
3. Given an input image I_q do
   3.1. Obtain category probability $p_1, \ldots, p_n$;
   3.2. For each $category_i$
   3.2.1. $classwt_i$= $weight_i$ * p_i
   End For
   3.3. set =argmax{$classwt_i$,..............,$classwt_m$}
   3.4. Get neighbors from imglist with maximum weight from the set

3) Modified association rule mining

The main purpose of the image tag recommendation is to find proper keywords which describe the images. The tf-idf of the tags associated with semantic neighbors are calculated and used as a weighting function in association rule mining to get more relevant tags for the images. The tf-idf of each tag is determined using following equation:

$$tf - idf(t) = \log\left(\frac{N_t}{SN_x}\right) \quad (5)$$

Where N_t is the number of images that are associated with tag t and SN_x is the number of semantic neighbours of an input image x

Given minimum support and confidence, the traditional association rule mining identifies a strong association between items. It considers each item equally. But in real word, each item may have different importance resulting in different weights. In the modified association rule mining, weight is assigned to each tag so that the related tag will get more importance over other tags.

To determine rules using association rule mining, we need to define transactions and item set to determine association rules. The semantic neighbors represent the transactions and tags represent the item sets. Given minimum support and confidence, the association rule mining algorithm performs over defined transaction and item set to generate rules $x \rightarrow y$ where x and y represent tags. The sample rules on three different datasets are shown in table 1.

If $x \rightarrow y$ rule is identified by association rule mining, it is necessary to identify how to recommend tag y, if tag x is recommended. Given support and confidence value of x and $x \rightarrow y$ respectively, tag y can be recommended as follow:

$$P(y|x) = confidence(x \rightarrow y) * tf - idf(x) \quad (6)$$

Table 1: Sample Association Rules Determined from Training Dataset

Flickr	NUS-WIDE	Corel-5k
{'flying'}, {'aircraft'}, 0.68	{'red'}, {'autumn'}, 1.0	{'polar'}, {'snow'}, 0.5
{'headshot'}, {'actor'}, 0.93	{'elephant'}, {'Africa'}, 0.46	{'people'}, {'swimmers'}, 1.0
{'headshot'}, {'portrait'}, 0.5	{'wildlife'}, {'zebra'}, 1.0	{'coast'}, {'water'}, 0.80
{'leaf'}, {'clover'}, 1.0	{'celebrity'}, {'actor'}, 1.0	{'jet'}, {'sky'}, 0.53

The algorithm 2 for image tag recommendation using modified association rule is outlined below:

Algorithm 2: Tag Recommendation using Modified Association Rule
Input: Semantic Neighbors (SN_x) along with tags, support, confidence Output: Ranked Tags
Steps: 1.1 For images in SN_x do

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1.2 For all tags associated with image do
1.2.1Calculate tf-idf using eq. 5
End for
End for
1.3 For images in SN_x do
1.4 For all tags associated with image do
1.5 For each association rule $x \rightarrow y$ do
1.5.1Calculate probability of y using eq. 6
End for
End for
End for
1.5.2Rank the tags according to probability value

VI. PERFORMANCE METRIC

The performance of the classifier is evaluated using a confusion matrix on test data. The confusion matrix analyses the test data to determine how the classifier identifies test samples of different categories. It consists of a count of predicted values and actual values. By using these counts of values, the accuracy are determined to estimate the performance score of the classifier.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (7)$$

Where

TP = Test Sample is positive and predicted positive.
TN = Test Sample is negative and predicted negative.
FP = Test Sample is negative and predicted positive.
FN = Test Sample is positive and predicted negative.

To evaluate the performance of tag recommendation algorithm, the normalized discounted cumulative gain (NDCG) metric is used. It measures relevance at different levels and assumes the tags which are relevant more useful if present in the ranked list. Given an image with ranked tag list T_1, T_2, T_N, the NDCG score is calculated per image tag list and finally averaged to get the performance of the tag recommendation.

$$NDCG@k = \frac{1}{z}\sum_{i=1}^{k}\frac{2^{r(i)}-1}{\log(1+i)} \quad (8)$$

Where z is a normalization constant so that NDCG@k=1 for the perfect ranking. The r(i) represents the relevance level of the i^{th} tag. r(i) is set to one if the i^{th} tag in the tag list is relevant to an input image, and otherwise set to zero.

VII. DATASET

The experimentation is done on Flickr, NUS-WIDE and Corel-5k datasets. For the Flickr dataset, the images are collected from the Flickr image-sharing website using public API. The images belong to different categories: actor, autumn, fish, clover, butterfly, and airplanes. The images are of medium size with maximum width or height fixed to 320 pixels.

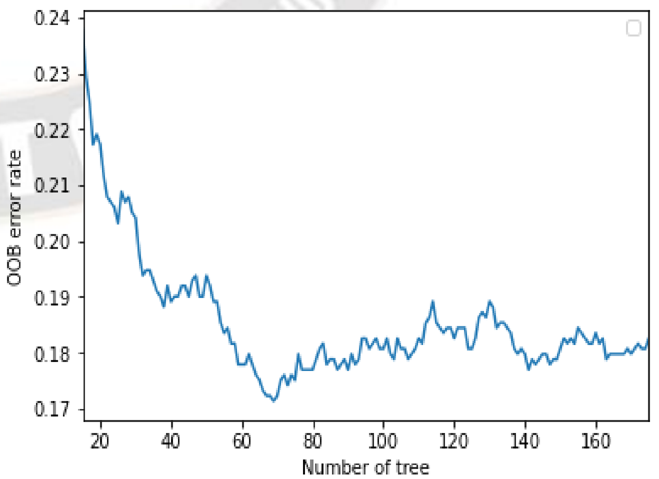
The NUS-WIDE dataset contains the images collected from Flickr and has been created by the National University of Singapore's media search lab [41]. The eight categories of images from the NUS-WIDE dataset are used for experimentation.

70 percent of the images for the self-generated and NUS-WIDE dataset are used for training and 30 percentages of the images are used for testing after 10-fold cross-validation.

Corel 5k dataset contains 4500 training images and 499 test images. Total 260 labels are available in the dictionary of the dataset. On average 3.4 labels are assigned to the images [42].

VIII.EXPERIMENTAL RESULTS

During the experimentation, we have extracted the L*a*b* and wavelet packet features of the images. The features are used for training the random forest classifier. The two parameters need to specify when the random forest classifier is used for generating a prediction model: the number of tree (mtree) and the number of features (f) used for the split in each node to make the tree grow. To classify the samples in the dataset, a constant number of mtree random predictive variables are used, and each sample of the dataset is classified by mtree number of trees defined by the user. The class is predicted based on the most frequent class predicted by mtree generated. According to the authors [43], a more number of trees may provide good results. Also, in [44] the authors stated that using more trees does not affect the model. The out-of-bag (OOB) is used to determine the prediction error of random forests. Figure 4 shows the out-of-bag (OOB) error for the number of trees ranging from 20 to 200 for three datasets.



Flickr Dataset

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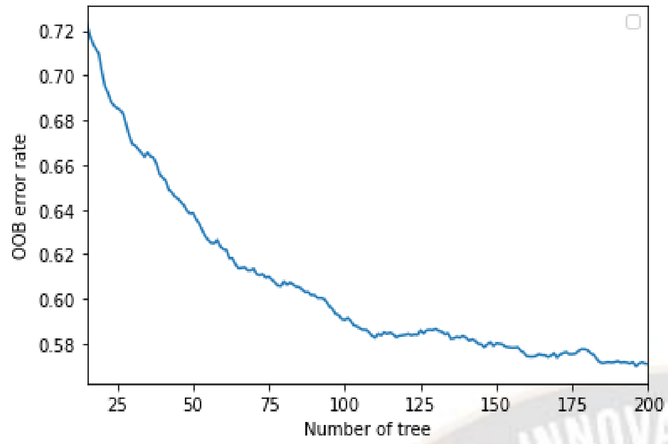
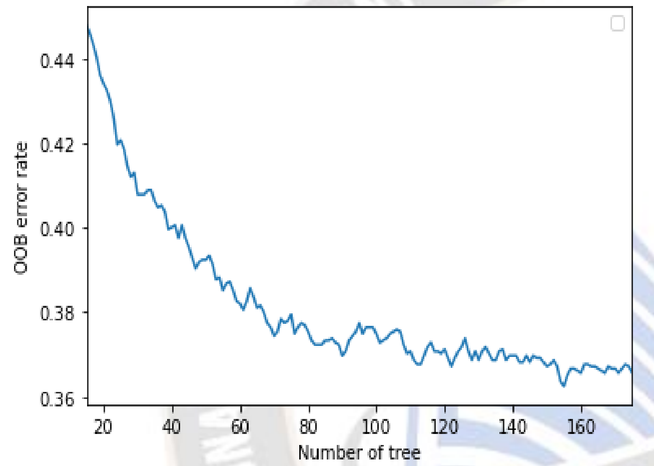


Corel-5k Dataset



NUS-WIDE Dataset

Fig. 4 Out-Of-Bag (OOB) Error

Figure 5 shows the performance of the random forest classifier obtained using eq. (7).

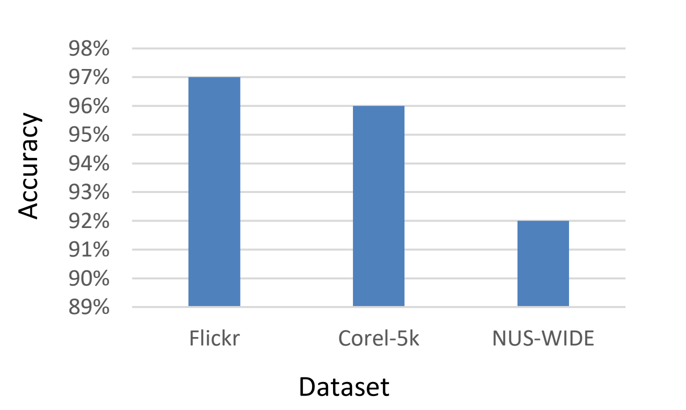


Fig. 5 Performance of Random Forest

Table 3 shows the performance of the existing and proposed tag recommendation algorithm. The performance of the proposed tag recommendation algorithm is better as it can recommend/suggest tags with higher NDCG scores.

Table 3: Performance of different tag recommendation algorithm

Method	Flickr dataset	Corel-5k dataset	NUS-WIDE dataset
NVote	92.07 %	58.44%	68.96 %
TagProp	89.67 %	81.25%	68.50 %
Tagvoting	84.45 %	85.34%	85.20 %
Proposed Method	97.15%	95.80%	96.65%

In Nvote method, the local and global frequency of each tag is determined, and tags are suggested by taking the difference between them. In the TagProp method, the rank and distance-based weight is assigned to each neighbor and recommends top k tags based on frequency.

In tagvoting method, top k similar images are determined based on visual features. The occurrence of each tag associated with visually similar images is counted and recommends top k tags. The method assigns the same importance to each image in the neighbor list. The existing methods for tag recommendation based on nearest neighbors ignore the relationship between the tags. The proposed method gives good results for tag recommendation by exploring tag correlation using modified association mining.

Table 4 shows the sample images with the tags suggested by the proposed system and the humans from the datasets: Flickr, NUS-WIDE, and Corel5k. It is observed that the relevant tags have been assigned to the images by the proposed system. As shown in image (1. c), only one relevant tag autumn is assigned by the human. But the proposed system adds more tags such as trees and leaves which describe the content of an image

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Table 4: Tag Recommendation Result

Flickr Images			
Image Number	(1. a)	(1. b)	(1. c)
Tags assigned by humans	vness clover	hugo von schreck fish fische tamron 28-300mm f/3.5-6.3 di vc pzd a010 canon eos 5d mark iii	laserenissimadesigns autumn
Recommended Tags	clover macro leaf nature green	Fish aquarium tropical water underwater	autumn trees netherland fall leaves
NUS-WIDE Images			
Image Number	(2. a)	(2. b)	(2. c)
Tags assigned by humans	wood autumn Ireland fall forest eire explore soe emeraldisle thekinks abigfave onlythebestare edwarddullard kilkenny1953 proudshopper	fish yellow swimming swim January 2006 greatyarmouth angelfish sealifecentre	d50 nikon elephants naturesfinest philazoo specanimal abigfave naturewatcher
Recommended Tags	autumn fall nature landscape leaves trees red	Angelfish fish aquarium underwater	elephants elephant africa wildlife nature
Corel_5k Images			
Image Number	(3. a)	(3. b)	(3. c)
Tags assigned by humans	Sky water pool	field horses mare foals	jet plane smoke
Recommended Tags	People water pool swimmers	horses foals mare field grass	plane jet sky smoke

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IX. CONCLUSION

The method is proposed for suggestion of the tags for the images based on semantic neighbors using modified association rules. The proposed method identifies the semantic neighbors using random forest based on weights assigned to each category. The tags associated with the semantic neighbors are mined using modified association rules to explore the relationship between the tags. The experimentation is done on Flickr, NUS-WIDE, and Corel-5k dataset. The performance of the proposed method is evaluated using the NDCG metric and the experimental result shows that the proposed method achieves good results as compared to the existing methods for tag recommendation.

In future we will focus on: i) exploring the information associated with the images such as user, description and comments, etc. ii) to develop hybrid approach to combine hand-crafted rules and deep learning iii) to develop a method to determine the correlation between tags using other frequent pattern mining methods iv) to develop optimized method for large datasets.

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