International Journal of Computer Science and Applications,
©Technomathematics Research Foundation
Vol. 11, No. 2, pp. 38 – 49, 2014

AUTOMATIC IMAGE ANNOTATION USING DECISION TREES AND ROUGH SETS

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The process which attaches label to a digital image by understanding the contents of image is termed as Automatic Image Annotation (AIA). Color and texture are the prominent features of a digital image. The content based image understanding is possible by using the feature strength of color and texture of an image. A classifier is designed using Decision Trees (DT) and Rough Sets (RS) to tag untagged images. Rough Set Exploration System (RSES) is used to develop decision tree and rough set based classifiers for classification of Corel images. In this paper, the result obtained using these classifiers are presented and discussed. Using rough sets cent percent accuracy is achieved for dinosaur images while for flower, horses and mountain categories the results are improved.

Keywords: Automatic image categorization; color features; texture features; decision tree; rough sets.

1. Introduction

Nowadays, the management of digital data is becoming difficult but essential task. Since large amount of image data is increasing rapidly and due to easy internet photo sharing, storing these images with a well defined approach is requirement for searching them easily. Tagging images and storing them for retrieval can be a solution. The problem considered here is to classify images as per their category and then annotation using the tags available for that category. Though image classification and annotation are typically treated as two independent problems the motivating intuition, however is that these two tasks should be connected. For both the tasks automation is possible by understanding contents of the images. Content-based image retrieval (CBIR), is any technology where using the visual contents of the images, organization of digital picture archives is made easy [Datta *et al.* (2008)].

Hunt used decision trees for classification [Hunt *et al.* (1966)]. This idea can be used to tag the images by using Decision Tree Classifier (DTC). The multidimensional data can be handled by decision trees and the data acquired represented in the form of a binary tree which a human develops while taking decision. Image classification can be experimented for the purpose of tagging using decision trees.

Rough set theory is an extension to the set theory [Pawlak (1982)]. It is an effective mathematical tool used mostly for process uncertain and vague data. Set theory is extended for the study of intelligent systems when possessing information which is either incomplete or insufficient. Classification can be done by using rough sets and annotation of images can be done further.

In this paper automatic annotation of images using decision trees and rough sets techniques is discussed. A classifier using Rough Set (RS) is proposed that classifies images from Corel image dataset for annotation purpose. Color and texture features are extracted from the input images and then annotation is done. Decision tree generation, discretization and rule extraction for rough sets is carried out using RSES [Skowron *et al.* (2009)].

2. Related Work

The problem of automatic image tagging is closely related to that of image understanding and classification. Chang and Hsu presented a conceptual framework for image information systems and applications [Chang and Hsu (1992)]. A comprehensive survey of image retrieval up to 2000 is done by Smeulders [Smeulders *et al.* (2000)]. The problem of annotation is treated as a translation from a set of image segments to a set of words, in a way analogous to linguistic translation [Duygulu *et al.* (2002)]. A new learning technique, which extends Multiple-Instance Learning (MIL), is used for the problem of region-based image categorization [Chen and Wang (2004)]. Setia and Burkhardt presented a novel image annotation scheme which is fast and effective and scales well to a large number of keywords [Setia and Burkhardt (2006)]. The annotations can be automatically refined to improve annotation accuracy [Wang *et al.* (2006)]. A comprehensive survey of the field of image retrieval is given by Datta et al. where the initial work given by Smeulders et al. is summarized and the survey of the work after 2000 is reviewed [Datta *et al.* (2008)]. Semantic labeling by prototype images, which are defined as centroids of the training clusters [Piro *et al.* (2009)]. A method to automatically annotate image through the rules generated by support vector machines and decision trees improves annotations [Chen *et al.* (2009)]. Support vector machine is employed as a preprocessing technique to refine the input training data. It improves the rules generated by decision tree learning. Wu et al. represented the image-tag relation by a tag matrix, and search for the optimal tag matrix consistent with both the observed tags and the visual similarity. They have proposed a new algorithm for solving this optimization problem [Wu *et al.* (2013)].

Decision tree algorithm is a data mining induction techniques that recursively partition data set using depth first greedy or breadth-first approach [Hunt *et al.* (1966)]. Michie et al. compare alternative classifier-learning methodologies (including several based on decision trees) on applications in industry and commerce [Michie *et al.* (1994)].

Some of the earliest work is reported by Hunt et al. [Hunt et al. (1966)], and Russell et al. provide excellent tutorial overviews of inductive learning [Russell *et al.* (1995)].

Rough set theory was introduced by Pawlak in early eighties [Pawlak (1982)]. Some algorithms based on rough set theory, can be used for the problem of classification [Bazan *et al.* (2000)]. Rough set based image classification method which uses RGB color histogram as features to classify images of different themes [Singh (2009)]. Rough sets with formulation and approximation of boundary is the reason for better classification [Komorowski *et al.* (1999)][Skowron et al. (2002)]. Color image annotation using rough sets is proposed by Serata et al. Decision rules are constructed for each visual key and used for indexing and retrieval of images [Serata *et al.* (2006)]. Shape image classification and annotation using decision trees and rough sets was proposed [Patil and Kolhe (2012)].

3. Automatic Image Annotation System

We have used standard dataset Corel while developing the automatic image annotation system. The system has two phases namely, feature extraction and machine learning. These phases are explained in section 4 and 5 respectively.

3.1. *Data set*

Fig. 1. Sample images of Corel Dataset.

The Corel database consists of 600 image categories. Each category is manually labeled with descriptive keyword. Each category consists of 100 color images of size 384 × 256. For categorization, ten different categories Africa, beaches, buildings, bus, dinosaur, elephants, flower, horses, mountain and food are used. Sample images are as in Fig. 1 [Duygulu et al. (2002)].

3.2. *System Framework*

The images from standard Corel image dataset are input to the system. The annotation system extracts features from the images. The low level features extracted from feature vector. This feature vector is used to train the system. As shown in Fig. 2 the system assigns tag using annotation model generated for untagged images.

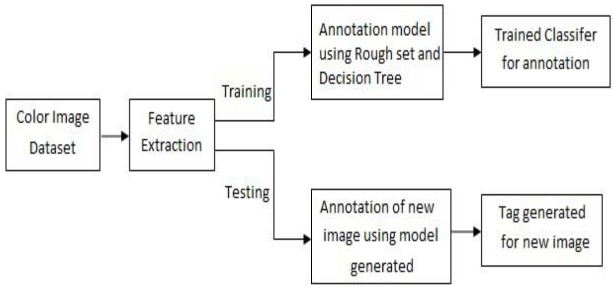

Fig. 2. Annotation system framework.

Features are extracted at global and local level from the images. These low level features formulate a feature vector which describes the image. The feature vector is used to build classifier using rough sets and decision trees. The output generated from the classifier is the tagged image.

4. Feature Extraction

Images are recognized easily by humans as high level concepts e.g. flower, dinosaur. System does not understand these high level concepts. These concepts are to be extracted at low level e.g. color and texture of image. The low level feature is a number which is understood by the system easily. Feature extraction is carried out to extract low-level image features from the images. These low-level image features represent a whole image or a specific region of image. Commonly extracted image features include color, texture and shape. The extracted image features are represented in a feature vector can be referred as the image signature. The process of extraction of features is demonstrated in Fig. 3.

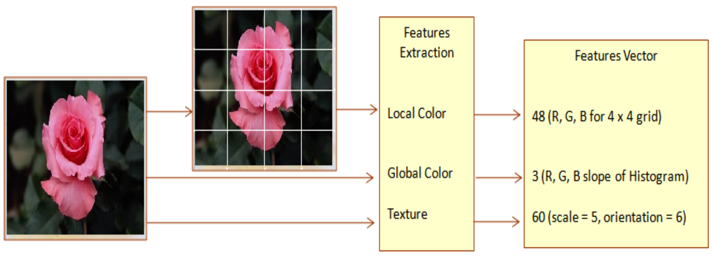

Fig. 3. Feature Extraction.

4.1. *Color Feature*

Color features are commonly used for representation of digital image. Color is an informative feature for object understanding and classification of image. Color features can be extracted globally at full image or locally at patches of an image. The color features are computed for R,G,B channels of every image. For each of the three channels slope of the normalized histogram is computed. The color features are extracted at global level on full image results in three features. The resultant vector is Global Color Feature (GCF) vector of size 3. Local level extraction of features is done by plotting 4 X 4 grid. This grid results in 16 cells of an image and for every cell three features i.e. slope of normalized histogram are computed. These three features yields a vector of size 48 representing Local Color Feature (LCF).

4.2. *Texture Feature*

Human identify texture when sees it, but it is very difficult to define [Tuceryan and Jain (1998)]. Human understand texture as homogeneous visual patterns in images that manifest some kind of coherence or periodicity, such as wallpaper and bricks. The mean oriented energy is a texture feature descriptor. It is computed by applying oriented filters to the image. Texture features are extracted using discrete gabor wavelet transform [Manjunath and Ma (1966)]. An image I(x,y) with size P X Q, discrete gabor wavelet transform is given by a convolution [Zhang and Lu (2000)]:

$$G_{mn}(x,y) = \sum_s \sum_t I(x \quad s, y \quad t)\Psi^*_{mn}(s,t) \tag{1}$$

where, s and t are the filter mask size variables, and Ψ_{mn} is a class of self-similar functions generated from dilation and rotation of the mother wavelet.

An array of magnitudes is obtained by applying gabor filters on the image with different orientation at different scale, as given below

$$E(m,n) = \sum_x \sum_y |G_{mn}(x,y)| \tag{2}$$

These magnitudes represent the energy content i.e. mean oriented energy of the texture at different scale and orientation of the image. To find images or regions with homogenous texture mean μ_{mn} and standard deviation σ_{mn} are used to represent the homogenous texture feature of the region. These are magnitude of the transformed coefficients. Mean and standard deviation is computed as given in Eq. (3) and (4) respectively.

$$\mu_{mn} = \frac{E(m,n)}{P\ X\ Q} \tag{3}$$

$$\sigma_{mn} = \frac{\sqrt{\sum_x \sum_y (|G_{mn}(x,y)| - \mu_{mn})^2}}{P\ X\ Q} \tag{4}$$

A feature vector is created using μ_{mn} and σ_{mn} as the feature components. Five scales and six orientations are used in common implementation and the feature vector is given by: $\text{feature vector} = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \dots \mu_{45}, \sigma_{45})$

5. Classifier Design using Decision Trees and Rough Sets

A decision tree is formalism for expressing attribute values to class mappings [Quinlan (1993)]. A node of tree is either node tagged with category or intermediate node comprising decision rules linking to two sub trees. At each intermediate node some outcome based on the attribute values of an instance is computed, and is associated with one of the sub trees. The classification starts at the root node of the tree. The decision rule at root decides to go towards left or right sub tree. The process continues using the appropriate sub tree. If the node is leaf node, that means it's not rule and a decision that gives the predicted class [Podgorelec *et al.* (2002)].

A decision tree is generated using the training dataset of color and texture feature vector. The tree consists of rules for taking decision at every node. The tree is used when applied to test data for generating the object class for untagged images. Fig. 4 shows the process carried out on the feature vector using decision tree.

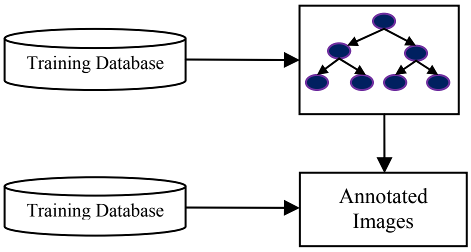

Fig. 4. Decision Tree based classier

To use rough set for classification, discretization of the data is essential to generate cut set and rule set. In discretization of a decision table A=(U, A U {d}) where Va==(va, wa) is an interval of real's, a partition Pa of Va is to be searched for any a€A. A partition of Va is defined by a sequence of the cuts v1<v2<v3<…vk from Va. Hence any family of partitions $\{P_a\}_{a \in A}$ can be identified with a set of cuts. The discretization process was targeted to search for a set of cuts satisfying some natural conditions [Singh (2009)]. The cut set comprises the set of rules that will be used to descretize the values in a range from the actual dataset. The descretized values of data are used to generate rules.

Consider $X \subseteq U$ be a set that is represented using subset of attribute P. It is to be expressed with an arbitrary set of objects X comprising a single class, and this class is equivalent class of subset P. In general, X cannot be expressed exactly, because the set may include and exclude objects which are indistinguishable on the basis of attributes P. However, the target set X can be approximated using only the information contained within P by constructing the P-lower and P-upper approximations of X:

$\underline{P}X = \{x \mid [x]_P \subseteq X\}$ and $\overline{P}X = \{x \mid [x]_P \cap X \neq \emptyset\}$

The tuple $\langle \underline{P}X \mid \overline{P}X \rangle$ gives the lower and upper approximation boundaries defining rough set. thus, a rough set is composed of two crisp sets. The training dataset of features is used to find cut set for generating discretize dataset of training and testing data. From the training dataset rule set is generated and applied to test data for generating the object class.

Consider a sample rule given below:
attr0="(0.01769,0.02567)")&(attr1="(0.9261589,0.9594910)")&(attr2="(-Inf,0.6281610)") => (attr3=elephant)

The rule is for three color features. These attr0, attr1 and attr2 are the red, green and blueness feature generating output value attr3 that is category of the image. Fig. 5 shows the process carried out on feature vector using rough sets.

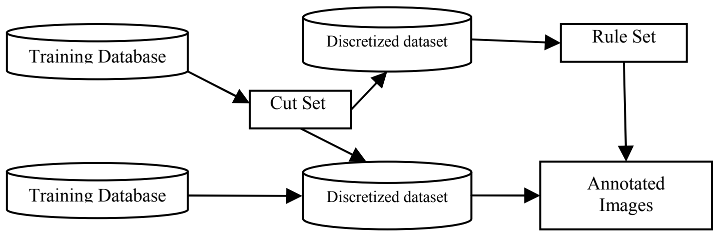

Fig. 5. Rough Set based classier

6. Experimental Results and Observations

Out of 1000 Corel images, 500 images are used for training purpose whereas remaining 500 images are used for testing. Two types of experiments are carried out on color images. Color features are extracted globally and locally gives Global Color Feature (GCF) vector of size 3 and Local Color Feature (LCF) vector of size 48. Gabor filter is used to extract texture gives Texture Feature (TXF) vector of size 60. In combination of local and global color with texture gives two vectors Global Color Texture Feature (GCTXF) vector of size 63 and Local Color Texture Feature (LCTXF) vector of size 108.

6.1. *Decision Trees (DT) Classifier*

A predefined size decision trees that split data set into fragments are used. These fragments are further decomposed representing a category. The parameters like maximal size of leaf, discretization in leaf, shortening ratio are set for decomposition algorithm.

The next task is test image dataset classification and annotation using generated decomposition tree. Experiments are conducted using all five combinations of feature vectors. Table 1 gives performance of decision trees.

Table 1. Analysis of Categorization and Tagging Accuracy of DT.

Features	Correctly Classified	Accuracy (%)	Coverage (%)
Global Color (GCF)	111	22.2	67.2
Local Color (LCF)	156	31.2	72.2
Texture(TXF)	102	20.4	65
Global Color Texture (GCTXF)	133	26.6	67.6
Local Texture Color(LCTXF)	167	33.4	64.2

Performance of texture features is poor as compared to other four combinations of features. Global color features (slope of RGB histogram) individually gives lower performance but it is improved when combined with texture. Color features extracted locally (grid based) gives better results as compared to global color and texture features. Combining local colors with texture features gives the best results and performance is further improved up to 33.4%. The term 'coverage' is used to represent the number of classified (either correct or wrong) images. It is observed that if only global color is considered flower, mountain, beaches categories gives better results since the images in this categories have dominating color features. The best results are obtained using local color feature in combination with texture feature (LCTX). Confusion matrix gives category wise classification accuracy with respect to other categories. Table 2 gives confusion matrix using LCTX features.

Table 2. Confusion matrix for LCTX using decision tree classifier.

	Africa	**beaches**	**building**	**bus**	**dinosaur**	**elephant**	**flower**	**food**	**horses**	**mountain**
Africa	11	2	1	3	2	6	3	6	1	0
beaches	2	8	5	2	0	0	1	1	3	6
building	7	2	6	6	1	1	0	1	1	3
bus	2	3	4	6	2	1	0	2	1	4
dinosaur	1	0	0	3	40	1	0	0	0	0
elephant	5	1	4	2	1	15	0	1	2	2
flower	0	1	3	2	0	0	22	7	0	1
food	5	1	2	2	0	4	7	12	1	1
horses	0	0	1	0	0	8	0	2	18	0
mountain	2	7	0	2	1	1	0	0	1	13

After studying all confusion matrices generated using five types of features, it is observed that in five categories Africa, bus, dinosaur, elephant, horses local color along with texture outperforms other four types. Global color features along with texture for building, food categories gives better results since images from these categories have high color strength in full image. Fig. 6 shows graph demonstrating category wise performance with respect to features.

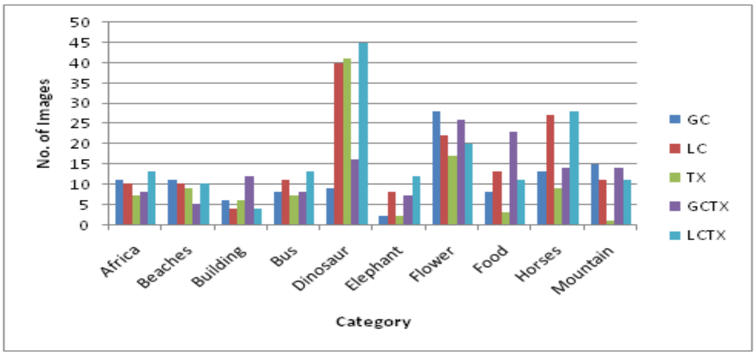

Fig. 6. Category wise performance of Decision tree classifier

6.2. *Rough Sets (RS) classifier*

Rough set works with the help of rules generated from the features vector. Decision rules classify objects by assigning the value of decision attribute. The data is discretized using cut set before generating the rules. The cut set is generated on train data by selecting method of cut generation. Once a cut set is generated training and testing datasets are discretized. Rules are generated from discretized training vector. The rule generation is carried out using four methods viz. exhaustive, genetic, covering and LEM2 algorithms. All these algorithms are implemented and it is observed that genetic algorithm gives better results as compared to other algorithms. Medium speed is selected for genetic algorithms. Cover parameter is set only for LEM2 algorithm. All five combinations of feature vectors are experimented using rules generated. Table 3 gives performance of classification using rough sets. It is observed that the coverage is improved 100% as compared to the decision trees except for global color features.

Table 3. Analysis of Tagging Performance of Rough Set classifier

Features	Correctly Classified	Performance (%)	Coverage (%)
Global Color(GCF)	131	26.5	79.4
Local Color(LCF)	270	54	100
Texture(TXF)	151	30.2	100
Global Color Texture (GCTXF)	242	48.4	100
Local Texture Color(LCTXF)	286	57.2	100

Though global color features (slope of RGB histogram) individually gives poor performance but it is improved as combined with texture features. Color features extracted locally which represent regions in an image. Therefore local feature improved the tagging performance. The results are improved up to 57.8% by combining local color with texture features.

Category Africa gives better result if global color features are considered. The results are improved using local color in combination with texture (LCTX) for six categories i.e. beaches, dinosaur, elephant, flower, food and mountain. Table 4 gives confusion matrix for LCTX features.

Table 4. Confusion matrix for LCTX using Rough Set classifier

	Africa	**beaches**	**building**	**bus**	**dinosaur**	**elephant**	**flower**	**food**	**horses**	**mountain**
Africa	15	2	2	4	3	4	2	14	4	0
beaches	1	12	12	4	2	2	0	2	9	6
building	1	1	9	13	5	4	4	5	4	4
bus	5	4	10	19	2	1	1	3	2	3
dinosaur	0	0	0	0	50	0	0	0	0	0
elephant	4	1	2	5	1	27	0	2	3	5
flower	0	0	1	1	0	0	44	3	1	0
food	2	0	0	5	5	2	5	29	2	0
horses	0	1	1	0	0	2	0	0	46	0
mountain	0	3	2	3	2	4	1	0	0	35

Considering all confusion matrices generated using five types of features it is observed that for category dinosaur, 100% performance is achieved by local color features, global color and texture features as well as local color and texture features. Flower images are classified with respect to the local color feature as its performance is same after adding texture features. Fig. 7 shows graph demonstrating category wise performance.

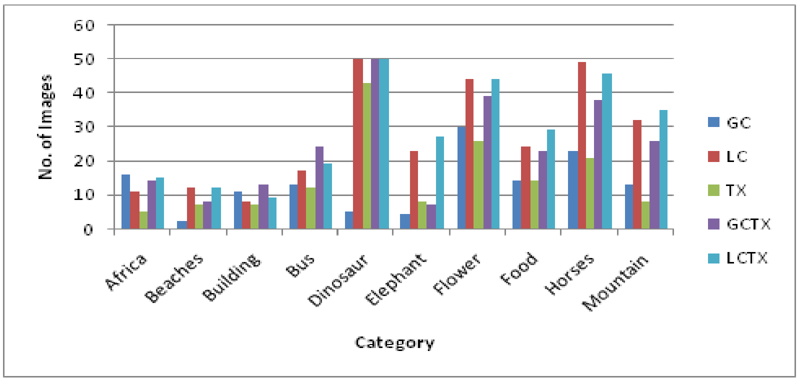

Fig. 7. Category wise performance of rough set classifier

The annotation using rough sets proposed by sereta et al. [Serata et al. (2006)] is improved for categories beaches, buildings, dinosaur, flower and horses. The results using rough sets are improved because of features used and the rules generated through descretization of the values.

Category wise accuracy comparison is given in Table 5. Category dinosaur contain single object image so it is easy to classify. Category food contains mix objects of other categories misleading classification. Africa is also a category containing mix types of textures and colors, due to which objects of other categories are misclassified as Africa. The improvement is achieved in categories dinosaur and mountain because the texture features extracted using gabor wavelet gives magnitude of energy of the regions which is similar for these categories.

The category label is assigned to classified image. These image categories may be semantically related. For example, category "beaches" and the "mountain" contain images of rocks, sky and trees. A lower bound for the annotation accuracy is computed for the evaluation of the system.

Table 5. Categorization Performance on Corel

Category	Categorization Performance (%)			
	[Chen and Wang (2004)]	**[Setia and Burkhardt (2006)]**	**[Piro et al. (2009)]**	**Proposed Approach**
Africa	67.7	66	74.8	30
beaches	68.4	32	56.4	24
building	74.3	76	74.0	18
bus	90.3	64	73.4	38
dinosaur	99.7	94	88.8	100
elephant	76.0	50	87.8	54
flower	88.3	78	89.0	88
horses	93.4	72	91.4	92
mountain	70.3	70	62.0	72
food	87.0	76	55.6	58

7. Conclusion

In this paper image annotation using rough sets and decision trees is proposed. The annotation accuracy using rough sets is improved as compared to decision trees. Decision trees are not able to discriminate images since the raw features generates if-else based binary tree to classify images. Comparatively rough sets give better results since during rule construction approximation boundaries plays the role. The cut set is generated on actual data to discretize the actual values from dataset. The rules generated are not restricted like decision tree. The result for category dinosaur using rough sets is 100% and for categories flower and horses results are further improved. In mountain category the images have different type of textures that matches with other categories like beaches. For this category, use of rough sets i.e. data approximation using cut sets has further improved the categorization performance.

Acknowledgments

The authors gratefully acknowledge University Grants Commission, New Delhi for the support provided for the research work through UGC SAP at the level of DRS-I (No: F.3-52/2011(SAP-II).

References

Bazan, J.; Nguyen, H. S.; Nguyen, S.H.; Synak,P. ;Wr´oblewski, J.(2000): Rough Set Algorithms in Classification Problem. In: Polkowski, L., Tsumoto, S., Lin, T.Y. (eds.), Rough Set Methods and Applications, pp. 49–88.

Chang, S. K.; Hsu, A. (1992): Image information systems: where do we go from here? IEEE Transactions on Knowledge and Data Engineering, 5(5), pp. 431–442.

Chen, Y.; Wang, J. Z. (2004):Image categorization by learning and reasoning with regions. The Journal of Machine Learning Research, 5 , pp. 913-939.

Chen, Z.; Hou, J.; Zhang, D.; Qin, X. (2012): An annotation rule extraction algorithm for image retrieval. Pattern Recognition Letters, 33(10), pp. 1257-1268.

Datta, R.; Joshi, D.; Li, J. ; Wang, J. Z. (2008) : Image retrieval: Ideas, influences, and trends of the new age. ACM Computing Surveys, 40(2), pp. 1–60.

Duygulu, P.; Barnard, K.; de Freitas, N.; Forsyth, D.(2002): Object recognition as machine translation: Learning a lexicon for a fixed image vocabulary. In: The Seventh European Conference on Computer Vision, Denmark, Springer Berlin Heidelberg, pp. 97–112.

Hunt, E. B.; Marin, J. ; Stone, P. J. (1966). *Experiments in induction*. Academic Press, New York.

Komorowski, J. ; Pawlak, Z.; Polkowski, L. ; Skowron, A. (1999): Rough Sets: A Tutorial. In S.K. Pal, A. Skowron (Eds.), Rough Fuzzy Hybridization. A New Trend in Decision-Making, Springer-Verlag, Singapore, pp. 3-98.

Manjunath, B.S. ; Ma, W.Y. (1996): Texture features for browsing and retrieval of large image data, IEEE Transactions on Pattern Analysis and Machine Intelligence, 18(8), pp.837-842.

Michie, D.; Spiegelhalter, D. J.; Taylor, C. C. (1994) : *Machine Learning, Neural and Statistical Classification*, Ellis Horword.

Patil, M. P. ; Kolhe, S. R. (2012) :Automatic Shape Annotation Using Rough Sets and Decision Trees. IJEIR, 1(2), pp. 32-37.

Pawlak, Z. (1982): Rough sets. Int. J. Computer and Information Science, 11, pp.341-356.

Piro, P.; Anthoine, S.; Debreuve, E.; Barlaud, M. (2009): Sparse Multi scale Patches (SMP) for Image Categorization. Advances in Multimedia Modeling, LNCS 5371, pp. 227-238.

Podgorelec, V.; Kokol, P.; Stiglic, B.; Rozman, I. (2002): Decision trees: an overview and their use in medicine. Journal of Medical Systems, Kluwer Academic/Plenum Press, 26(5), pp. 445-463.

Quinlan, J. R.(1993): *C4.5: Programs for Machine Learning*, Morgan Kaufmann, San Mateo, CA.

Russell, S.; Norvig, P. (1995) :*Artificial Intelligence: A Modern Approach*. Prentice Hall, Englewood Cliffs, NJ.

Serata, M.; Hatakeyama, Y. ; Hirota, K.(2006) : Automatic Image Annotation based-on Rough Set Theory with Visual Keys. In: Intelligent Signal Processing and Communications, 2006. International Symposium ISPACS'06. pp. 530-533

Setia, L.; Burkhardt, H. (2006): Feature Selection for Automatic Image Annotation. In Proceedings of DAGM-Symposium, pp.294-303.

Singh, S. (2009): RGB Color Histogram Feature based Image Classification: An Application of Rough Reasoning, IHCI 2009:Part2, pp.102-112.

Skowron, A.; Pawlak, Z.; Komorowski, J.; Polkowski, L. (2002): A rough set perspective on data and knowledge. Iin W. Kloesgen, J. Żytkow (Eds.) Handbook of KDD, Oxford University Press, pp. 134-149.

Skowron, A. ; Bazan, J. ; Szczuka, M. S.; Wroblewski, J. (2009): Rough Set Exploration System, version 2.2.2, http: //logic.mimuw.edu.pl/~rses/.

Smeulders, A. W. M.; Worring, M.; Santini, S.; Gupta, A.; Jain, R. (2000):Content-based image retrieval at the end of the early years. IEEE Transactions on Pattern Analysis and Machine Intelligence, 22(12), pp.1349–1380.

Tuceryan, M.; Jain A. K.(1998): Texture analysis. Handbook of pattern recognition and computer vision, World Scientific Publishing Co., pp. 207-248.

Wang, C.; Jing, F.; Zhang, L.; Zhang, H.-J.(2006) :Image annotation refinement using random walk with restarts. In: Proceedings of the 14th ACM International Conference on Multimedia, Santa Barbara, CA, USA, pp.647–650.

Wu, L.; Jin R, ; Jain A. K. (2013):Tag completion for image retrieval. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(3), pp. 716 – 727.

Zhang, D.S.; Lu, G. (2000): Content-based image retrieval using gabor texture features. In: First IEEE Pacific-Rim Conference on Multimedia, pp. 392-395.