Chapter VI
Image Classification and Retrieval with Mining Technologies

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ABSTRACT

Mining techniques can play an important role in automatic image classification and content-based retrieval. A novel method for image classification based on feature element through association rule mining is presented in this chapter. The effectiveness of this method comes from two sides. The visual meanings of images can be well captured by discrete feature elements. The associations between the description features and the image contents can be properly discovered with mining technology. Experiments with real images show that the new approach provides not only lower classification and retrieval error but also higher computation efficiency.

INTRODUCTION

Along with the progress of imaging modality and the wide utility of digital image (include video) in various fields, many potential content producers have emerged, and many image databases have been built. In addition, the growth of Internet and storage capability not only increasingly makes images a widespread information format in World Wide Web (WWW), but also dramatically expands the number of images on WWW and makes the search of required images more complex and time consuming. To efficiently search images on WWW, effective image search engines need to be developed.

Since images require large amounts of storage space and processing time, how to quickly and efficiently access and manage these large, both in the sense of information contents and data volume, databases has become an urgent problem to solve. The research solution for this problem, using content-based image retrieval (CBIR) techniques, is initiated in the last decade (Kato, 1992). An international standard for multimedia content descriptions, MPEG-7, is also formed in 2001 (MPEG). With the advantages of comprehensive descriptions of image contents and consistence to human visual perception, research in this direction is considered as one of the hottest research points in the new century (Castelli, 2002; Zhang, 2003; Deb 2004; Zhang 2007).

Among the many research topics in CBIR, automatic image classification (categorization) plays an important role both for Web image searching and retrieving (classification and retrieval are closely related), as it is time consuming for users to browse through and treat the huge data on Web. A successful image classification will significantly enhance the performance of the content-based image retrieval system by filtering out images from irrelevant classes during matching. Classification has been used to provide access of large image collections with more efficient manner because the classification can reduce search space by filtering out the images in unrelated category (Hirata, 2000).

The heterogeneous nature of Web images makes their classification a challenge task. A functional classification scheme should take the contents of images in consideration. Web mining is a tool suitable for helping image classification and retrieval on the Web. It consists of (Scime, 2005):

1. **Pre-processing:** It is one of the most important steps in Web mining. It includes data purging, user recognition, dialog recognition, and event recognition.
2. **Pattern discovering (Mining algorithm):** It uses statistical analysis, association rule, clustering, and classification.
3. **Pattern analysis:** It transforms the rules, patterns and statistical values into knowledge. By using this knowledge, valuable patterns (interesting rules, patterns) can be obtained.

Traditional mining techniques often generate huge amounts of numeric data that could be difficult to interpret and use. Visual mining transforms raw data into visualization and makes it easier to understand the meaning of data and make suitable decisions, in addition to opening the world of visual tools to a much broader audience (Soukup, 2002).

In this chapter, a novel method for image classification based on feature element through association rule mining is presented. The feature elements can capture well the visual meanings of images according to the subjective perception of human beings. In addition, feature elements are discrete entities, and are suitable for working with rule-based classification models. Different from traditional image classification methods, the proposed classification approach based on feature element does not compute the distance between two vectors in the feature space. This approach just tries to find associations between the feature elements and class attributes of the image. Techniques for mining the association rules are adapted and the mined rules are applied to image classifications. Experiments with real images show that the new approach not only reduces the classification errors but also diminishes the time complexity.

The contents of following sections are:

1. In background section, some concepts and definitions about feature-based image retrieval, association rules and rule mining, and classification based on association are introduced.
2. In main thrust section, some techniques and results on feature elements and extraction, database used for testing, feature element based image classification, image classification comparison, feature element based image retrieval, image retrieval comparison, and association feedback are presented in details.

3. In future trend section, several promising directions are pointed out.
4. In conclusion section, few concluding remarks are made.

BACKGROUND

Feature-Based Image Retrieval

Several layers in CBIR can be distinctive, in which feature-based image retrieval (FBIR) lays at the ground (Zhang, 2005). The contents of image are represented and described by different (visual) features. Traditionally, these features form feature vectors, and feature vectors are used for image identification in content-based image retrieval (CBIR). After extracting these features from images, further retrieval is performed with these feature vectors. These feature vectors mark out an image to a point in the feature space. By detecting this point in the feature space, the image can be identified for searching. In addition, the similarity between images that are represented by corresponding vectors is measured by distances between their representing points in the feature space.

In a general sense, features can be found in different levels (Zhang, 2003). Features like color and texture can be directly extracted from image at pixel levels. They can be considered at the lower level. Features like shape are often extracted from objects in segmented images. They can be considered at the middle level. Features like space distribution (or structure relation) are often extracted from multiple objects in segmented images. They can be considered at the higher level. All these levels of features can be extracted from image and used in feature-based image retrieval. However, these feature vectors are often different from the representation and description adapted by human beings. For example, when people look at a colorful image, they hardly figure out its color histogram, but rather concern about what particular colors are contained in certain components of this image. In fact, these color components play the great role in perception and represent useful visual meanings of images. The pixels belonging to these visual components can be taken to form perceptual primitive units, by which human beings could identify the content of images (Xu, 2001).

The feature elements are defined on the basis of these primitive units. They are discrete quantities, relatively independent to each other and have obvious intuitive visual senses. Besides, they can be considered as sets of items. Based on feature element, image classification becomes a process of counting the existence of representative components in images. To this purpose, it is required to find some association rules between the feature elements and the class attributes of image.

Association Rules and Rule Mining

The association rule mining, first proposed by (Agrawal, 1993), is an appropriate tool for pattern detection in knowledge discovery and data mining. Its objective is to extract useful information from very large databases (Renato, 2002). By using rules extracted from images, the content of images can be suitably analyzed, and the information required for image classification can be obtained.

The association rule can be represented by an expression $X \Rightarrow Y$, where X and Y can be any discrete entity. As we discuss image database, X and Y can be some feature elements extracted from images. The meaning of $X \Rightarrow Y$ is: Given an image database D, for each image $I \in D$, $X \Rightarrow Y$ expresses that whenever an image I contains X then I will probably contains Y also. The support of association rule is defined as the probability $p(X \subseteq I, Y \subseteq I)$ and the confidence of association rule is defined as the conditional probability $p(X \subseteq I \mid Y \subseteq I)$. A rule with support bigger than a specified minimum support and with confidence bigger than a specified minimum confidence is considered as a significant association rule.

Since the introduction of the association rule mining by Agrawal (1993), many researches have been conducted to enhance its performance. Most works can be grouped in the following categories:

1. Works for mining of different rules, such as multi-dimensional rules (Yang, 2001).
2. Works for taking the advantages of particular techniques, such as tree projection (Guralnik, 2004), multiple minimum supports (Tseng, 2001), constraint-based clustering (Tung, 2001), association (Cohen, 2001).
3. Works for developing fast algorithms, such as algorithm based on anti-skew partitioning (Lin, 1998).
4. Works for discovering of temporal database, such as discovering temporal association rules (Guimaraes, 2000; Li, 2003).

Currently, the association rule mining (Lee, 2003; Harms, 2004) is one of the most popular pattern discovery methods in knowledge discovery and data mining. In contrast to the classification rule mining (Pal, 2003), the purpose of association rule mining is to find all significant rules in the database that satisfy some minimum support and minimum confidence constraints (Hipp, 2000). It is known that rule-based classification models often have difficulty to deal with continuous variables. However, as a feature element is just a discrete entity, association rules can be easily used for treating images represented and described by feature elements. In fact, a decision about whether an image I contains feature element X and/or feature element Y can be properly defined and detected.

Classification Based on Association

Classification based on associations (CBA) is an algorithm for integrating classification and association rule mining (Liu, 1998). Assume that the data set is a normal relational table, which consists of N cases described by distinct attributes and classified into several known classes. All the attributes are treated uniformly. For a categorical attribute, all the possible values are mapped to a set of consecutive positive integers. With these mappings, a data case can be treated as a set of (attribute, integer-value) pairs plus a class label. Each (attribute, integer-value) is called an item. Let D be the data set, I the set of all items in D and Y the class labels. A class association rule (CAR) is an implication of the form $X \Rightarrow y$, where $X \subseteq I$, and $y \in Y$. A data case $d \in D$ means that d contains a subset of items, that is, $X \subseteq d$ and $X \subseteq I$. A rule $X \Rightarrow y$ holds in D with confidence C if C percentages of cases in D that contain X are labeled with class y. The rule $X \Rightarrow y$ has support S in D if the S percentages of cases in D are contained in X and are labeled with class y.

The objective of CBA is to generate the complete set of CARs that satisfy the specified minimum supports and minimum confidence constraints, and to build a classifier from CARs. It is easy to see that if the right-hand-side of the association rules is restricted to the (classification) class attributes, then such rules can be regarded as classification rules to build classifiers.

The classification and retrieve are closely related. The ability to classify images makes it possible to identify different images. Once images can be identified, searching required images becomes an easier task, and retrieving interest images could be conducted.

MAIN THRUST

Feature Elements and Extraction

Various types of feature elements, which put emphasis on different properties of image/object, will be employed in different applications. The extractions of feature elements can be carried out by first locate the perceptual elements and then determine their main properties and give them suitable descriptions. Three typical examples are described in the following.

One process for obtaining feature elements primarily based on color properties can be described by the following steps (Xu, 2001):

1. Images are divided into several clusters with a perceptual grouping based on hue histogram.
2. For each cluster, the central hue value is taken as its color cardinality named as Androutsos-cardinality (AC). In addition, color-coherence-vector (CCV) and color-auto-correlogram (CAC) are also calculated (Greg, 1996; Huang, 1998).
3. Additional attributes, such as the center coordinates and area of each cluster, are recoded to represent the position and size information of clusters.

One type of feature elements highlighting the form property of clusters is obtained with the help of Zernike moments (Xu, 2003). They are invariant to similarity transformations, such as translation, rotation and scaling of the planar shape (Wee, 2003). Based on Zernike moments of clusters, different descriptors for expressing circularity, directionality, eccentricity, roundness, symmetry, *etc.*, can be directly obtained, which provide useful semantic meanings of clusters with respect to human perception.

Wavelet feature element is based on wavelet modulus maxima and invariant moments (Zhang, 2003). Wavelet modulus maxima can indicate the location of edges in images. A set of seven invariant moments (Gonzalez, 2002) is used to represent the multi-scale edges in wavelet-transformed images. Three steps are taken first:

1. Images are decomposed, using dyadic wavelet, into a multi-scale modulus image.
2. Pixels in the wavelet domain whose modulus are locally maxima are used to form multi-scale edges.
3. The seven invariant moments at each scale are computed, and combined to form the feature vector of images.

Then, a process of discretization is followed (Li, 2002a). Suppose the wavelet decomposition is performed in six levels, for each level, seven moments are computed. This gives a 42-D vector. It can be split into six groups; each of them is a 7-D vector that represents seven moments on one level. On the other side, the whole vector can be split into seven groups; each of them is a 6-D vector that represents one moment on all six levels. In this way, 42 feature elements are constructed.

In all above examples, the feature elements have property represented by numeric values. As not all of the feature elements having the same status in the visual sense, an evaluation of feature elements is required to select suitable feature elements according to the subjective perception of human beings (Xu, 2002). Two examples are shown in Figure 1. The left pair of images shows an image with one flower as well as this image after getting 3 feature elements. In this case, the properties of high saturation and center-position help to make the red color flower the most important component of image. The right pair of images shows an image with many flowers and trees as well as this image after getting 3 feature elements. In this case, the importance of red color region and yellow color are similar; while the green color region is located in the background and is splinted into several subclasses due to disperse in color space, thus it has a lower priority level.

Database Used for Testing

The image database used for the following test consists of 2558 real color images that can be grouped into five different classes: (1) Auto-I: 505 images with autos, (2) Flower-C: 503 images with flower-clusters, (3) Flower-S: 485 images with (single big) flower, (4) Person-P: 565 images with person pictures, and (5) Scenery-I: 500 images with different sceneries (such as sunset, sunrise, beach, mountain, forest, etc.). Among these classes, the first three have prominent objects while the other two normally have no dominant items. Two typical examples from each class are shown in Figure 2.

Among these images, one third images have been used in the test set and the rest in the training set. The images in training set are labeled manually and then used in the mining of association rules, while the images in testing set will be labeled automatically by these mined rules.

Feature Element Based Image Classification

Feature Element Based Image Classification (FEBIC) uses CBA to find association rules between feature elements and class attributes of the images, while the class attributes of unlabeled images could be predicted with such rules. In case that an unlabeled image satisfies several rules, which might make

Figure 1. Typical images and feature elements

Figure 2. Some typical image examples from different classes

(a) *(b)* *(c)* *(d)* *(e)*

this image to be classified into different classes, the support values and confidence values can be used to make the final decision.

In accordance with the assumption in CBA, each image is considered as a data case, which is described by a number of attributes. The components of feature element are taken as attributes. The labeled image set can be considered as a normal relational table, which is used to mine association rules for classification. In the same way, feature elements from unlabeled images are extracted and form another relational table without class attributes, on which the classification rules to predict the class attributes of each unlabeled image will be applied.

The whole procedure can be summarized as follows:

1. Extract feature elements from images.
2. Form relational table for mining association rules.
3. Use mined rules to predict the class attributes of unlabeled images.
4. Classify images using the association of feature elements.

Image Classification Comparison

Classification experiments using two methods with the above-mentioned database are carried out. The proposed method FEBIC is compared to another state-or-the-art method — nearest feature line (NFL) (Li, 2000b). NFL is a classification method based on feature vectors. In comparison, the color feature, such as AC, CCV, CAC, and wavelet feature based on wavelet modulus maxima and invariant moments are used.

Two tests are performed. For each test, both methods use the same training set and testing set. The results of these experiments are summarized in Table 1, where the classification error rates for each class and for the average over the five classes are listed.

The results in Table 1 show that the classification error rate of NFL is about 34.5%, while the classification error rate of FEBIC is about 25.0%. The difference is evident.

Except the classification error, the time complexity is another important factor to be counted in Web application, as the number of images on WWW is huge. The computation times for two methods are compared during the test experiments. The time needed for FEBIC is only about 1/100 of the time needed for NFL. Since NFL requires many arithmetic operations to compute distance functions, while

Table 1. Comparison of classification errors

Error rate	Test set 1		Test set 2	
	FEBIC	NFL	FEBIC	NFL
Auto-I	21.3%	23.1%	18.3%	23.1%
Flower-C	26.8%	45.8%	20.2%	37.0%
Flower-S	32.1%	48.8%	36.4%	46.9%
Person-P	22.9%	25.6%	20.7%	26.1%
Scenery-I	30.7%	38.0%	32.5%	34.3%
Average	26.6%	35.8%	25.4%	33.2%

FEBIC needs only few operations for judging the existence of feature elements, such a big difference in computation is well expected.

Feature Element Based Image Retrieval

On the basis of image classification, image retrieval can also be carried out. Different from many other retrieval methods, the method presented below is also based on feature elements, and can be called Feature Element Based Image Retrieval (FEBIR).

Two types of feature elements, color feature element and shape feature element, have been used. Different distance functions are defined for these two types of feature elements.

For two shape feature elements S_q and S_d, (q stands for querying and d stands for database) the distance between them is computed on the basis of the number of components in shape feature elements, that is:

$$dis(S_q, S_d) = \sum_{i=1}^{14} d(s_{qi}, s_{di}) \tag{1}$$

where

$$d(s_{qi}, s_{di}) = \begin{cases} 1 & if \quad s_{qi} \neq s_{di} \\ 0 & if \quad s_{qi} = s_{di} \end{cases} \tag{2}$$

For two color feature elements C_q and C_r, the distance between them is computed in another way. As described before, the components of color feature elements are the parameters of color regions of image. Suppose that CR_{qi} is the i-th color region in querying image (i = 1, 2, …, m), CR_{dj} is the j-th color region in database image (j = 1, 2, …, n). They form a color region pair (CR_{qi}, CR_{dj}). The distance between two color feature elements is defined as the average value of the differences between all color region pair in two images

$$dis(C_q, C_d) = \sum_{i,j} td(CR_{qi}, CR_{dj}) / N \tag{3}$$

where t is a constant, N is the number of color region pairs, $d(CR_{qi}, CR_{dj})$ is the difference between CR_{qi} and CR_{dj} in a color region pair (CR_{qi}, CR_{dj})

$$d(C_{qi}, C_{dj}) = \left|H_{qi} - H_{dj}\right| \sum_p \left|c_{qi}^p - c_{dj}^p\right| \tag{4}$$

where H stands for hue of color region, c^p stands for other parameters (size, space distribution) of color region. In forming color region pair, the following criteria are used:

1. The color regions to form color region pair should be bigger than a pre-defined threshold in size. Too small regions have very small impact on human vision and can be ignored.
2. The hue difference between two color regions should satisfy

$$\left|H_{qi} - H_{dj}\right| = \min_{1 \le l \le m} \left|H_{ql} - H_{dj}\right| \quad or \quad \left|H_{qi} - H_{dj}\right| = \min_{1 \le l \le n} \left|H_{ql} - H_{dl}\right| \tag{5}$$

3. All color regions in both querying image and database image must be included in one of the color region pairs.

After forming the color region pairs, the distance between two color regions in the color region pairs can be calculated according to equation (3). The value of constant t is selected as

$$t = \begin{cases} 0.5 & if \quad \left|H_{qi} - H_{dj}\right| = \min\limits_{1 \le l \le m} \left|H_{ql} - H_{dj}\right| \\ 0.75 & if \quad \left|H_{qi} - H_{dj}\right| = \min\limits_{1 \le k \le n} \left|H_{qi} - H_{dk}\right| \\ 1 & if \quad \left|H_{qi} - H_{dj}\right| = \min\limits_{1 \le l \le m, 1 \le k \le n} \left|H_{ql} - H_{dk}\right| \end{cases} \tag{6}$$

Once the distance between two color feature elements is obtained, the similarity between the querying image and database image can be calculated by summing all distances between two color feature elements and taking the inverse value of the summation.

Image Retrieval Comparison

A number of experiments have been conducted to evaluate the performance of FEBIR and to compare it with other methods. The method to be compared uses a feature vector, in which the components include color feature CCV, CAC and shape feature based on wavelet and moment (Yao, 1999).

One experiment is described in the following. The query image is shown in Figure 3. In each querying process, 20 retrieval results with the minimum distance to the querying image are obtained. The first is just the original query image, while other 19 images are shown in Figure 4 for FEBIR and in Figure 5 for the comparing method.

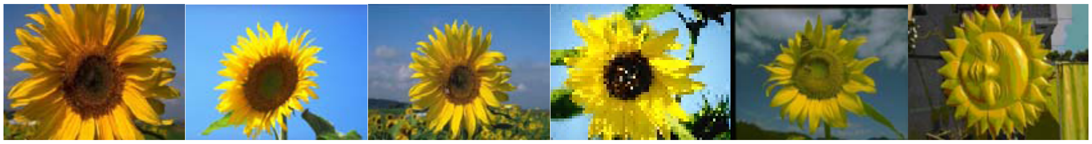
By comparing the numbers of images in each categories, it is clear that the performance of FEBIR is higher than the method based on feature vectors.

Association Feedback

High level retrieval often gets help from human beings. Relevance feedback is a popular tool used, which reflects the mind of the user. Association feedback is another way to make retrieval process to be interactive with users (Xu, 2001). In relevance feedback, weights for the feature vector are adjusted according to the use's choice. While in association feedback, vectors are replaced by feature elements. There are cases that user interactions are required in retrieval system and the feedback based on feature elements has advantages:

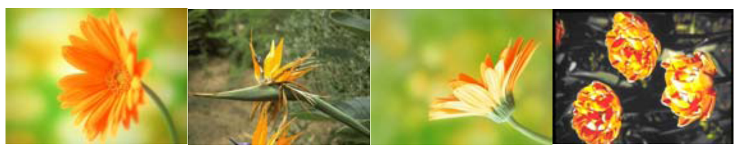
Figure 3. A querying image

Figure 4. Images retrieved by FEBIR



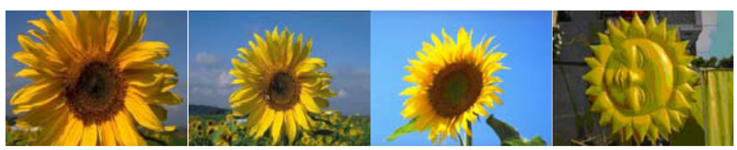
(a) 6 similar images

(b) 9 partially-similar images

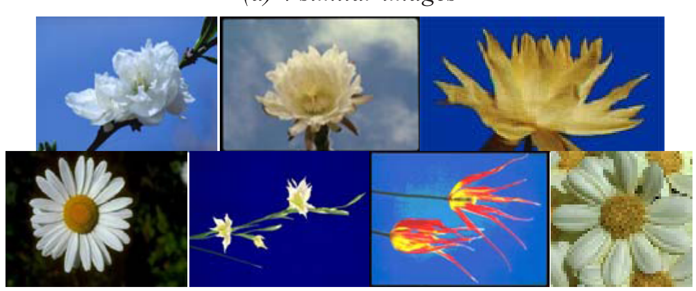


(c) 4 totally-similar images

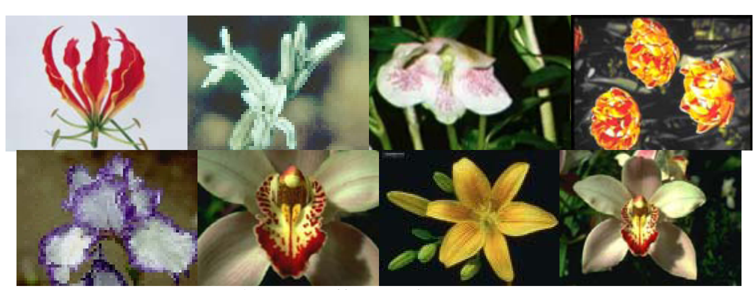
Figure 5. Images retrieved by the compared method



(a) 4 similar images



(b) 7partially-similar images



(c) 8 totally-similar images

1. During the retrieval process, the user may feel not satisfied with the retrieval result provided by the system. The user may mark some result items with “Yes”, while “No” for some others. Then the system would be adjusted to find out which feature elements are the common interest of the user and retrieval result. Then a new round of retrieval is taken place and the new result will be obtained. The process goes iteratively until the user is satisfied.
2. During the retrieval process, the user may also change his mind of attention and switch to other retrieval target. By selecting some result items, which include interesting feature elements, with “Yes”, and de-selecting some result items, which include no-interesting feature elements, with “No”, the process can be shifted to a new direction to catch the new intention through the feedback analysis.

Compared with relevance feedback, the association feedback is more intuitive, flexible and much easier to handle. Only with one image marked as “Yes” or “No”, association feedback can be done smoothly, while this would be quite hard for relevance feedback due to the convergence problem.

One example is shown Figure 6.

The user starts from one image of the helianthus under blue sky, and the first round of retrieval gives the results automatically shown in Figure 6(a). The user then wants the images with many little yellow flowers, so “No” is marked for those images with blue sky and one big yellow flower. Then, a few images with many yellow flowers are obtained after the second round of retrieval, as shown in Figure 6(b). The user continues to confirm several images with “Yes”, and the third round of retrieval provides the satisfactory results shown in Figure 6(c).

FUTURE TRENDS

Though the retrieving of image based on different visual features is quite intuitive and is easy to be carried out, there is a considerable difference between users’ interest in reality and the image contents described by using only low-level perceptive features. In other words, there is a large gap (semantic

Figure 6. From one helianthus to many small flowers

(a) *(b)* *(c)*

gap) between content description based on low-level features and that of human beings' understanding. Researches in this direction have been started and some results are obtained (Zhang, 2007). Further effort and impulse are still needed.

The detection and description of feature elements play an important role in providing suitable information and basis to association rule mining. How to adaptively design feature elements that can capture the users' intention based on perception and interpretation needs further research. The proposed techniques can also be extended to the content-based retrieval of images over Internet. As feature elements are discrete entities, the similarity between images described by feature elements can be computed according to the number of common elements.

Image classification/categorization could be treated as an effective solution to enable keyword-based image retrieval. The relation between textural information and visual information, as well as the conversion from text to image and from image to text need to be considered. Different models in this direction has been proposed, for example, integrated patch model (Xu, 2007) and association model (Xu, 2008). Further investigation is even now required.

CONCLUSION

Image classification and retrieval are important tasks in effective search and use of image information. A new approach for image classification and retrieval that uses feature elements and employs association rule mining is proposed. It provides lower classification and retrieval error as well as higher computation efficiency. These advantages make it quite suitable to be included into a Web search engine for images over Internet.

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KEY TERMS

Classification Error: Error produced by incorrect classifications, which consists of two types: correct negative (wrongly classify an item belong to one class into another class) and false positive (wrongly classify an item from other classes into the current class)

Classification Rule Mining: A technique/procedure aims to discover a small set of rules in the database to form an accurate classifier for classification.

Content-Based Image Retrieval (CBIR): A process framework for efficiently retrieving images from a collection by similarity. The retrieval relies on extracting the appropriate characteristic quantities describing the desired contents of images. In addition, suitable querying, matching, indexing and searching techniques are required.

Multi-Resolution Analysis: A process to treat a function (*i.e.*, an image) at various levels of resolutions and/or approximations. In such a way, a complicated function could be divided into several simpler ones that can be studied separately.

Pattern Detection: Concerned with locating patterns in the database to maximize /minimize a response variable or minimize some classification error (*i.e.*, supervised pattern detection), or with not only locating occurrences of the patterns in the database but also deciding whether such an occurrence is a pattern (*i.e.*, unsupervised pattern detection).

Pattern Recognition: Concerned with the classification of individual patterns into pre-specified classes (*i.e.*, supervised pattern recognition), or with the identification and characterization of pattern classes (*i.e.*, unsupervised pattern recognition).

Similarity Transformation: A group of transformations that will preserve the angles between any two curves at their intersecting points. It is also called equi-form transformation, because it preserves form of curves. A planar similarity transformation has four degrees of freedom and they can be computed from two-point correspondence.

Web Image Search Engine: A kind of search engines that start from several initially given URLs and extend from complex hyperlinks to collect images on the WWW. Web search engine is also known as Web crawler.

Web Mining: Concerned with the mechanism for discovering the correlations among the references to various files that are available on the server by a given client. Each transaction is comprised of a set of URLs accessed by a client in one visit to the server.