

# MINING IMAGE DATASETS

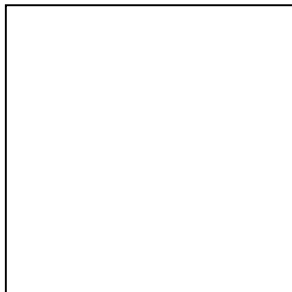
**Mrs. Kajal Salekar,**  
Department of Information  
Technology, Mumbai University/  
Pillai's Institute of Information  
Technology, New Panvel, India,

**Dr. Satishkumar Varma,**  
Department of Information  
Technology, Mumbai University/  
Pillai's Institute of Information  
Technology, New Panvel, India,

**Prof. Rupali Nikhare**  
Department of Computer  
Engineering, Mumbai  
University/Pillai's Institute of  
Information Technology, New  
Panvel,India,

## ABSTRACT

Mining Image dataset is one of the necessary features in the present development. The image datasets are used to store and retrieve the precious information from images, data mining on them. Pixel-wised image features were extracted and transformed into a database-like table which allows various data mining algorithms to make explorations on it. Each tuple of the transformed table has a feature descriptor formed by a set of features in combination with the target label of a particular pixel. With the label feature, we can accept the decision tree algorithm to understand relationships between attributes and the target label from image pixels, and to make a model for pixel-wised image processing according to a given training image dataset. The model can be very efficient and helpful for image processing and image mining.



It is likely that by using the model, various existing data mining and image processing methods could be worked on mutually in different behaviour. Our model can also be used to create new image processing methodologies, refine existing image processing methods, or act as a powerful image filter.

## Keywords

Image mining, Image mining Frameworks Mining techniques, Proposed model.

## 1. INTRODUCTION

Valuable information can be hidden in images, however, few research discuss data mining on them. In this paper, we propose a general framework based on the decision tree for mining and processing image data. Pixel-wised image features were extracted and transformed into a database-like table which allows various data mining algorithms to make explorations on it. Each tuple of the transformed table has a feature descriptor formed by a set of features in conjunction with the target label of a particular pixel. With the label feature, we can adopt the decision tree induction to

realize relationships between attributes and the target label from image pixels, and to construct a model for pixel-wised image processing according to a given training image dataset. Both experimental and theoretical analyses were performed in this study. Their results show that the proposed model can be very efficient and effective for image processing and image mining.

## 2. PROPOSED MODEL

An image mining method that works at a higher generality level for mining image associations is proposed. In contrast to that, our model works on a relative low generality level for image pixel classification. Pixel-wise image classification is an essential part of many image segmentation methods, for example, determining pixels of an edge (corner) in edge (corner) detection methods, pixels of a particular object in objects segmentation based methods, pixels of abnormal tissue of medical image processing [1], and pixel classes in thresholding, etc. The model can be used to mine hidden relationships between an image's pixel and its class label, and determine the interrelated features. Besides, the created model can be applied to perform pixel-wise segmentation on input images.

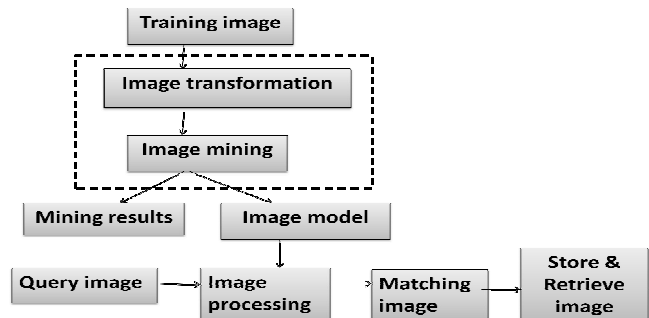


Figure 1. Proposed system

These two phases are: image transformation and image mining.

(1) **Image Transformation Phase:** This relates to how to transform input images into database-like tables and encode the related features.

(2) **Image Mining Phase:** This relates to how to apply data mining algorithms on the transformed table and find useful information from it.

It is remarkable that the segmentation model is efficient, and requires only one scan of the data set. It can be used to effectively solve the time-consuming problem of segmentation with networks. Here we suggest two manners to apply our approach in similar situations.

## MINING IMAGE DATASETS

The first one is using our model to substitute the existing method with the strategies mentioned above. The second one is using our model to quickly filter out the images that need advanced examinations. For example, after singling out suspicious mammograms that might contain pixels of cancer, one can apply the original method for second segmentation. The first manner is suitable for the case that our segmentation method result is better than the original one or the loss of correctness does not make significant difference. The second one is suitable for the case that the segmentation result is used in a critical manner, and the model is unable to reach that Requirement level. The model can easily extend from 2D to 3D image processing without making a revolution and the created model can generate very efficient and compact code.

### 3. IMAGE MINING PHASE

Image mining deals with the extraction of image patterns from a large collection of images. Clearly, image mining is different from low-level computer vision and image processing techniques because the focus of image mining is in extraction of patterns from large collection of images, whereas the focus of computer vision and image processing techniques is in understanding and/or extracting specific features from a single image. While there seems to be some overlaps between image mining and content-based retrieval (both are dealing with large collection of images), image mining goes beyond the problem of retrieving relevant images. In image mining, the goal is the discovery of image patterns that are significant in a given collection of images. This is certainly not true because there are important differences between relational databases versus image databases.

#### 3.1 Absolute versus relative values

In relational databases, the data values are semantically meaningful. For example, age is 35 is well understood. However, in image databases, the data values themselves may not be significant unless the context supports them. For example, a grey scale value of 46 could appear darker than a grey scale value of 87 if the surrounding context pixels values are all very bright.

#### 3.2 Unique versus multiple interpretations

A third important difference deals with image characteristics of having multiple interpretations for the same visual patterns. The traditional data mining algorithm of associating a pattern to a class (interpretation) will not work well here. A new class of discovery algorithms is needed to cater to the special needs in mining useful patterns from images.

### 4. DATA REDUCTION

As given, the input data of the proposed model is formatted as a set of equal sized *raw* and *label* image pairs. The transformation of the input image dataset into a database-like table and subsuming of the related features is described in this subsection. For the sake of clarity, various terms used for this process are defined below. In addition, we propose three kinds of input data sources.

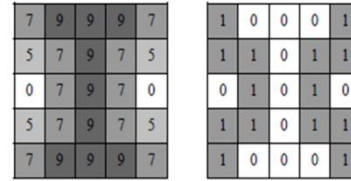
**Definition 1** The **raw image** is a  $d$ -dimensional light-intensity function, denoted by  $R(c1, c2, \dots, cd)$ , where the amplitude (or value) of  $R$  at spatial coordinates  $(c1, c2, \dots, cd)$  gives the intensity of the raw image at that point (or pixel).

**Definition 2** The **label image** is a  $d$ -dimensional light-intensity function, denoted by  $L(c1, c2, \dots, cd)$ , where the value of  $L$  at

spatial coordinates  $(c1, c2, \dots, cd)$  gives the class identifier of the pixel at same spatial coordinates of its corresponding raw image.

**Definition 3** The **database-like table**  $X = \{x1, x2, \dots, xt\}$  is a set of records, where each record  $xr \in \mathfrak{R}k$  is a vector with elements  $\langle a1, a2, \dots, ak \rangle$  being the value of attributes (or features) of  $X$ .

In figure1. Shows, the *raw* image contains the capital English letter “T” with certain degree of blur. Thus, the inside pixels of the letter are darker and the outside pixels are brighter. If a pixel in the *label* image has the value “1”, the pixel in the same position of the *raw* image is a pixel of *outside contour*. It is assumed to be a *pixel of interest* (POI) in this case. In practice, the pixel value of the *label* image is not limited to the binary form but could take any kind of form. In addition, we can have as many *raw* and *label* image pairs at the same time as required for the input.



(a) Raw (b) Label  
Figure 2. The Input of Image Dataset

This process is simple and straightforward. Shows a part of the results of this transformation process according to the data in Figure 2. Each row of such result table stands for a pixel. Hence

its *cardinality* (number of rows) equals the number of total pixels in the *raw* image. In addition, each column of such table represents a feature associated with the given pixels.

*feature1* represents the gray level and *feature2* the local variation. In order to simplify this demonstration, the local variation in this case is replaced with the average difference of a pixel to its 4-neighbors. Other pixel-wised features such as entropy, contrast, mean, *etc.* can also be encoded into the table as long as they might have affection on the collected dataset.

	feature <sub>1</sub>	feature <sub>2</sub>	.....	feature <sub>n</sub>	label
pixel <sub>1</sub>	7	2	....	value <sub>1n</sub>	1
pixel <sub>2</sub>	9	1.25	.....	value <sub>2n</sub>	0
pixel <sub>3</sub>	9	0	.....	value <sub>3n</sub>	0
.....	.....	.....	.....	.....	.....
pixel <sub>4</sub>	7	2	.....	value <sub>25n</sub>	1

Table 3. Result table of image transformation according to the input

Various encoding strategies such as normalization (*e.g.*, adjusting the value ranging from 0 to 1) or generalization (*e.g.*, transforming the value to high, medium, or low) can be applied when generating the desired features. Moreover, the *label* image was included a column in that table. With the presence of the label

feature, hidden relationships between these two kinds of images can be mined.

## 5. IMAGEMINING FRAMEWORK

Because of the image characteristics, pixels from a neighbouring area will generate similar feature vectors in the transformation process. Under some circumstances, it will cause remarkable redundant information in the result table; for example, an image with a large portion of background.

Here we present some basic types of redundancy and show how they can be eliminated while converting the input image set.

**Definition 4** The **feature scope** of a pixel  $M$  with spatial coordinates  $(c1, c2)$  is an  $n \times n$  pixel area with center at  $M$ , from which all the desired features of  $M$  can be generated.

Usually  $n$  is an odd number, and the sub-image within the feature scope, *i.e.*, pixels within spatial coordinates  $(c1 \pm 12n -, c2 \pm 12n -)$ , is called the **root space** of the pixel  $M$ , denoted as  $\{RSM\}$ .

**Definition 5** Two root spaces  $\{RSN\}$ ,  $\{RSO\}$  are **rotation reachable** if  $\{RSN\} = \{RSO\}R$ , where  $\{.\}R$  stands for a root space after rotating the angle once by  $90^\circ$ ,  $180^\circ$ , or  $270^\circ$ .

**Definition 6** Two root spaces  $\{RSN\}$ ,  $\{RSO\}$  are **mirror reachable** if  $\{RSN\} = \{RSO\}F$ , where  $\{.\}F$  stands for a root space after flipping horizontally or vertically.

Given two pixels  $P$  and  $Q$  at different *spatial coordinates* of an image  $I$ , they are said to be:

1. **equivalent redundant**, if  $\{RSP\}$  is equal to  $\{RSQ\}$ ,
2. **rotation redundant**, if  $\{RSP\}$  and  $\{RSQ\}$  are rotation reachable,
3. **mirror redundant**, if  $\{RSP\}$  and  $\{RSQ\}$  are mirror reachable,
4. **conflict redundant**, if  $\{RSP\}$  and  $\{RSQ\}$  satisfy any one of the first three conditions, but the label information of pixels  $P$  and  $Q$  is not equal to each other.

Users could characterize other types of redundancy according to the image problem they wish to solve. In order to pinch more redundancies, quantization techniques can be applied on the root space. The pseudo code regarding the function of redundancy reduction.

### 5.1 Function-Driven Frameworks

These descriptions are exclusively application-oriented and the framework was organized according to the module functionality. For example, propose an intelligent satellite mining system that comprises two modules,

(a) A data acquisition: Pre-processing and archiving system which is responsible for the extraction of image information, storage of raw images, and retrieval of image.

(b) An image mining system: Which enables the users to explore image meaning and detect relevant events.

### 5.2 Information-Driven Frameworks

While the function-driven framework serves the purpose of organizing and clarifying the different roles and tasks to be performed in image mining, it fails to emphasize the different levels of information representation necessary for image data before meaningful mining can take place proposes an information-

driven framework that aims to highlight the role of information at various levels of representation. The framework, as shown in Figure, distinguishes four levels of information as follows.

(a) Pixel Level, also the lowest level - Consists of the raw image information such as image pixels and the primitive image features such as colour, texture, and shape;

(b) Object Level- deals with object or region information based on the primitive features in the Pixel Level

(c) Semantic Concept Level - takes into consideration domain knowledge to generate high-level semantic concepts from the identified objects and regions

(d) Pattern and Knowledge Level- incorporates domain related alphanumeric data and the semantic concepts obtained from the image data to discover underlying domain patterns and knowledge.

The techniques frequently used include object recognition, image indexing and retrieval, image classification and clustering, association rules mining, and neural network.

## 6. IMAGE MINING TECHNIQUES

### 6.1 Object Recognition

Object recognition has been an active research focus in field of image processing. Using object models that are known a priori, an object recognition system finds objects in the real world from an image. This is one of the major tasks in the domain of image mining. Automatic machine learning and meaningful information extraction can only be realized when some objects have been identified and recognized by the machine. The object recognition problem can be referred to as a supervised labelling problem based on models of known objects. Specifically, given a target image containing one or more interesting objects and a set of labels corresponding to a set of models known to the system, what object recognition does is to assign correct labels to regions, or a set of regions, in the image. Models of known objects are usually provided by human input a priori.

In general, an object recognition module consists of four components, namely, model database, feature detector, hypothesizer and hypothesis verifier. The model database contains all the models known to the system. The models contain important features that describe the objects. The detected image primitive features in the Pixel Level are used to help the hypothesizer to assign likelihood to the objects in the image. The verifier uses the models to verify the hypothesis and refine the object likelihood. The system finally selects the object with the highest likelihood as the correct object.

### 6.2 Image Retrieval

Image mining requires that images be retrieved according to some requirement specifications. The requirement specifications can be classified into three levels of increasing complexity:

(a) Level 1 comprises image retrieval by primitive features such as color, texture, shape or the spatial location of image elements. Examples of such queries are "Retrieve the images with long

thin red objects in the top right-hand corner" and "Retrieve the images containing blue stars arranged in a ring"

(b) Level 2 comprises image retrieval by derived or logical features like objects of a given type or individual objects or

## MINING IMAGE DATASETS

persons. Examples include “Retrieve images of round table” and “Retrieve images of Jimmy”

(c) Level 3 comprises image retrieval by abstract attributes, involving a significant amount of high-level reasoning about the meaning or purpose of the objects or scenes depicted. For

example, we can have queries such as “Retrieve the images of football match” and “Retrieve the images depicting happiness”.

### 6.3 Image Indexing

Image mining systems require a fast and efficient mechanism for the retrieval of image data. Conventional database systems such as relational databases facilitate indexing on primary or secondary key(s). Now, the retrieval of most image retrieval system is, by text, similarity-based retrieval. In this case, indexing has to be carried out in the similarity space. One promising approach is to first perform dimension reduction and then use appropriate multi-dimensional indexing techniques.

Indexing techniques used range from standard methods such as signature file access method and inverted file access method, to multi-dimensional methods such as KD- B tree, R-tree, R\* -tree and R+-tree.

### 6.4 Image Classification

Image classification and image clustering are the supervised and unsupervised classification of images into groups respectively. In supervised classification, one is provided with a collection of labelled (pre-classified) images, and the problem is to label newly encountered, unlabeled images. Typically, the given labelled (training) images are used to do the machine learning of the class description which in turn are used to label a new image.

## 7. CONCLUSION

The results have shown clearly that the model can mining and process image data well. The experiments have verified the flexibility of the model for various kinds of image processing problems, including image enhancement, image restoration, and image segmentation. In addition, the benefits resulting from application of the model have been accessible.

The model requires label information of image pixels in advance; however, in some situations this label information may be unavailable or undecided. from time to time, it might be necessary to find the actual hidden label properties, and our future work is to refine the model to an unsupervised one, which can automatically analyze and determine the label information for further use. In contrast, we are trying to tailor this general framework like function driven framework and information driven framework to a particular case. The specialization of model will involve more issues such as generation of *raw* image features, transformation of *label* image properties, integration of different masks, and support of existing methods.

## REFERENCES

- [1] J. Zhang, W. Hsu, And M. L. Lee, “Image Mining: Issues, Frameworks And Techniques,” In *Proceedings Of The 2nd International Workshop Multimedia Data Mining*, Pp. 13-20.
- [2] J. P. Eakins and M. E. Graham. Content-based image retrieval: a report to the JISC technology applications program. *Northumbria Image Data Research Institute, 2000.*
- [3] Kun-che Lu And Don-lin Yang “*Image Processing And Image Mining Using Decision Trees*” Journal Of Information Science

And Engineering 25, 989-1003

[4] K. C. Lu, D. L. Yang, And M. C. Hung, “Decision Trees Based Image Data Mining And Its Application On Image Segmentation,” In *Proceedings Of International Conference On Chinese Language Computin*

[5] K. C. Lu, *Image Processing and Image Mining Using Decision Trees: Fusing Data Mining and Image Processing*, a publication of master thesis by VDM Verlag, 2008.