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COMPARISON OF IMAGE CLASSIFICATION TECHNIQUES USING CALTECH 101 DATASET

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ABSTRACT

This paper presents the technique for the classification of single object images. First, this paper aims to introduce the efficient technique in order to classify single object image. Second, each single methods uses in order to propose the techniques were elaborated in this paper. It start from image segmentation, object identification, feature extraction, feature selection and classification. Finally, the best classifier that can provide the best results were identified. The efficiency of the proposed method is define by comparing the result of classification using two different datasets from author's previous paper. The obligation for development of image classification has been improved due to remarkable growth in volume of images, as well as the widespread application in multiple fields. This paper explores the process of classifying images by the categories of object in the case of a large number of object categories. The use of a set of features to describe 2D shapes in low-level images has been proposed. The proposed technique aims a short and simple way to extract shape description before classifying the image. Using the Caltech 101 object recognition benchmark, classification was tested using four different classifiers; BayesNet, NaiveBayesUpdateable, Random Tree and IBk. Estimated accuracy was in the range from 58% to 99% (using 10-cross validation). By comparing with Amazon data, it is proved that the proposed model is more suitable for single object image. Amazon images give higher accuracy with the range from 80% to 99.48%.

Key words: *Image Classification, Feature Extraction, Feature Selection, Classifier.*

1. INTRODUCTION

One of the crucial tasks among computer vision field is an object classification. Image classification is the process of labelling the images into one of a number of predefined categories. The steps of classification include image sensors, image pre-processing, object detection, object segmentation, feature extraction, and object classification. There are numbers of classification techniques that have been developed for image classification [1].

Image classification is a crucial and challenging task in various application domains, including remote sensing, vehicle navigation, biomedical imaging, video-surveillance, biometry, industrial visual inspection, robot navigation, and vehicle navigation [2]. Classification process consists of the following steps [1]:

A. **Pre-processing:** Enhances the quality of the input image such as noise removal, image masking, main component analysis, and others, and locate the data of interest.
B. **Detection and extraction of an object:** Detection contains detection of position and other features of moving object image found from camera. In addition, extraction stage captures the unique characteristics from the detected object guessing the route of the object in the image plane.

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C. **Training:** Selection of the specific attribute which best defines the pattern.
D. **Classification of the object:** Object classification step classifies detected objects into predefined classes by using proper method that matches the image patterns with the target patterns.

From author's previous article [3], they proposed a classification model. The model consists of five main stages, starting from image segmentation, object identification, feature extraction, feature selection and finally, image classification. The model was tested using Amazon images. To make a further comparison, Caltech101 dataset were chosen for this paper.

Shape is one of the objects representation in images with the most significant properties, which is famously used in CBIR (content based image retrieval) and in recognition tasks [4].

The Caltech101 object class dataset consists of 101 class of images. It can be downloaded from [5]. With a wide variety of images in each class, this dataset provides a significant intraclass variant [6]. [7] has mentioned that the name of 101 was accidentally set while the author was flipping through pages of Webster Collegiate Dictionary, and they came out with the idea of listing all 101 categories of images. All images in Caltech101 dataset were downloaded using Google Image search engine.

This paper presents the classification of single object in an image using 4 different classifiers. First, images were segmented for partitioning the meaningful part of the image. Second, object identification was applied to the segmented image to detect the connected line in the image. Then, feature extraction of the object was conducted for encoding the valuable features. Next, the experiments were continued with feature selection using Weka tools. Lastly, the classification accuracies of images using 4 types of classifiers selected earlier were presented.

The focus of this paper is to test the proposed techniques toward Caltech101 dataset and compare with Amazon dataset's results. The results of experiments are presented in the paper, and conclusions are drawn.

2. RESEARCH METHOD AND DESIGN

One of the popular research area throughout current years is content-based image classification using large image databases [8].

The proposed technique aims a short and simple way to extract shape description followed by the classification and annotation processes. The proposed method followed these steps:

Step 1: Image Segmentation

Step 2: Object Identification

Step 3: Image Feature Extraction

Step 4: Image Feature Selection

Step 5: Classification

The process of partitioning images into meaningful region is known as ad image segmentation in the computer vision field [9].

The feature is a measurement process which specifically defines a property of an object based on the characteristics of the object. Shape is one of the crucial visual features because of its primitive feature. Shape can be described in two ways; region-based and contour-based. The method that uses the whole area of an object for shape description is region-based. On the other hand, contour-based method uses the information given from the contour of an image [10]. Normally, shape descriptors are combined to create a more effective shape descriptor because individual simple shape descriptor is not robust [11].

The most important step after feature extraction is feature selection. It plays an important role, especially in classification problems. A well-extracted feature must have the value of robustness, discriminative, and easy to compute an efficient algorithm.

The main issue in object detection is to locate the object in an arbitrary image and pose after a non-rigid transformation.

A classifier is chosen after features of an image have been extracted. There are plenty of classifiers that can be used for the experiment.

As stated in Fig.1, Phase 1 is named as data repository, meaning that the process of collecting data takes place before other phases are

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initiated. In this paper, Caltech101 was used for collecting dataset. The collection process showed that Caltech101 was the most suitable dataset that can be used to test the proposed techniques.

The second phase is the training images, which involved the rest of the processes (from segmentation to classification process) to build the training set.

Initially, in Phase 2, which was named as the training phase, the dataset (images) underwent the image pre-processing steps. The purpose of this measure is to substitute the high-dimensional images with lower-dimensional features that capture the main properties of the images and enable the model to forge on the data with limited storage and computational resources. It includes three main processes starting from image segmentation, followed by feature extraction, and end up with image classification. For the purpose of the next phase of the research, all extracted features were stored in the features database. A feature selection step was added before the classification step for comparison throughout the experiments.

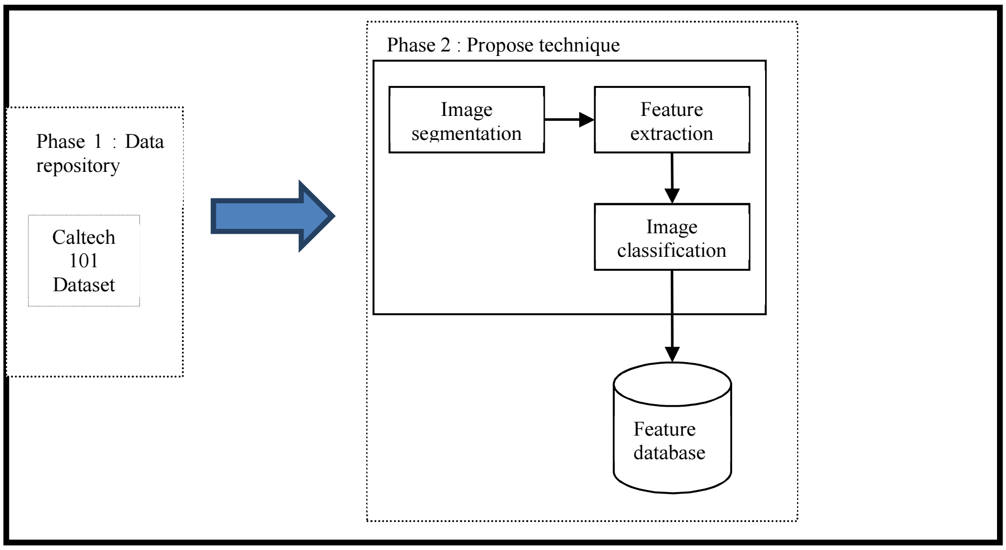

Figure 1: Research method

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3. SEGMENT IMAGES

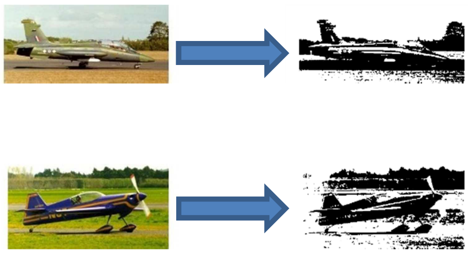

Figure 2: Sample of image classification results using Otsu method

By applying a large dataset from Caltech101, the image data were segmented using thresholding based method. This paper used one of the global thresholding methods, which is Otsu method. [12]. This technique thresholds the entire image with a single threshold value [12], and this system is dependent upon discriminant analysis.

As discussed by [13][14][15], threshold operation can divide the image into two classes; A_1 and A_2, at gray Q such that $A_1 = [22 \ldots , Q]$ and $A_2 = \{Q + 1, Q + 2, \ldots , k\text{-}1\}$, where k is the total number of the gray levels of the image. Let the number of pixels at **i** gray level be n_i, and $N = \sum_{i=0}^{k-1} n_i$ be the total number of pixels in a given image. The probability of occurrence of gray level **i** is defined as $p_i = \frac{n_i}{N}$, $p_i \geq 0$, $\sum_{i=0}^{k-1} p_i = 1$. A_1 and A_2 are normally corresponding to the object of interest and the background. The probabilities of the two classes are:

$P_{A1} = \sum_{i=0}^{Q} p_i$ and $P_{A2} = \sum p_i = 1 - P_{A1}$.

The mean of A_1 and A_2 classes can be computed as:

$$\mu_{A1} = \sum_{i=0}^{Q} \frac{i^* p_i}{P_{A1}} \qquad (1)$$

$$\mu_{A1} = \sum_{i=Q+1}^{k-1} \frac{i^* p_i}{P_{A2}} \qquad (2)$$

Thus, we can get the equivalent formula:

$$\sigma^2(Q) = P_{A1}P_{A2}(\mu_{A1} - \mu_{A2})^2 \qquad (3)$$

The optimal threshold Q* can be obtained by maximizing the between-class variance.

$$Q^* = Arg \max_{0<Q<k-1} \sigma^2(Q) \qquad (4)$$

4. FEATURE EXTRACTION

MATLAB was chosen as a tool to develop the extraction procedure using built-in Image Processing Toolbox function known as region props. The process of attaining image features from an input image was initiated with the image properties calculation such as area, eccentricity, extent, solidity, filled area, and others. The features were figured using built-in principles in MATLAB.

5. CLASSIFIER

The classifiers that were applied in our research include BayesNet, NaieveBayesUpdateable, Random Tree and IBk.

5.1 weka.classifiers.bayes.BayesNet

Bayesian networks (BNs), also known as belief net-works (or Bayes nets for short), belong to the family of probabilistic graphical models (GMs).

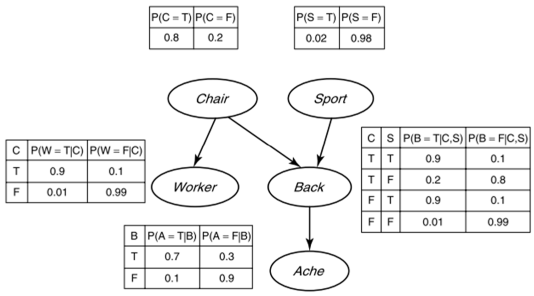

Figure 3: The backache BN example

Figure 3 shows the example of BayesNet process. The parents of the variable *Back* are the nodes *Chair* and *Sport*. The child of *Back* is *Ache*, and the parent of *Worker* is *Chair*. Following the BN independence hypothesis, some independence statements can be detected in this case. For example, the variables *Chair* and *Sport* are slightly independent, but when *Back* is given they are conditionally dependent. This relation is often called explaining away. When *Chair* is given, *Worker* and *Back* are conditionally independent. When *Back* is given, *Ache* is conditionally independent of its ancestors *Chair* and *Sport* [16].

5.2 Weka.Classifiers.Bayes.Naivebayesupdateable

A Naive Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem (from Bayesian statistics) with strong (naive) independence assumptions. A more descriptive

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term for the underlying probability model would be "independent feature model".

The Class is used for a Naive Bayes classifier using estimator classes. This is the updateable version of Naïve Bayes. This classifier will use a default precision of 0.1 for numeric attributes when build Classifier is called with zero training instances [17].

5.3 weka.classifiers.tree.RandomTree

The decision tree (DT) is a multi-stage decision making or classification tool. It is different to other classification model because it uses input-output relationship that can be expressed using human understandable rules. Meanwhile, other classification model is much difficult to describe [11].

A random tree is a tree drawn at random from a set of possible trees. In this context "at random" means that each tree in the set of trees has an equal chance of being sampled. Another way of saying this is that the distribution of trees is "uniform".

5.4 weka.classifiers.lazy.IBk

IBk is called instance-based learning that generates classification predictions using only specific instances. Instance-based learning algorithms do not maintain a set of abstractions derived from specific instances. This approach extends the nearest neighbor algorithm, which has large storage requirements [17].

6. IMAGE CLASSIFICATION (10-Fold Cross Validation)

The cross validation technique works as repeated holdout. It divides dataset into 10 parts (fold) by holding out each part in turn. Then, it will compute the average results where each data point was used once for testing and 9 times for training.

7. DATASET

The experiment used Caltech101 dataset as mentioned earlier. Originally, the dataset were collected from Google Image search engine to gather as many images as possible for each group [7]. Fig.3 shows examples of the 101 object categories used in this paper. In addition, the model parts were ordered by their x-coordinate, which was problematic for vertical structures. Therefore, the categories with mostly vertical structure were rotated to a random angle. It is for the sake of programming simplicity. Finally, the images were scaled roughly to around 300 pixels wide, producing Caltech101.

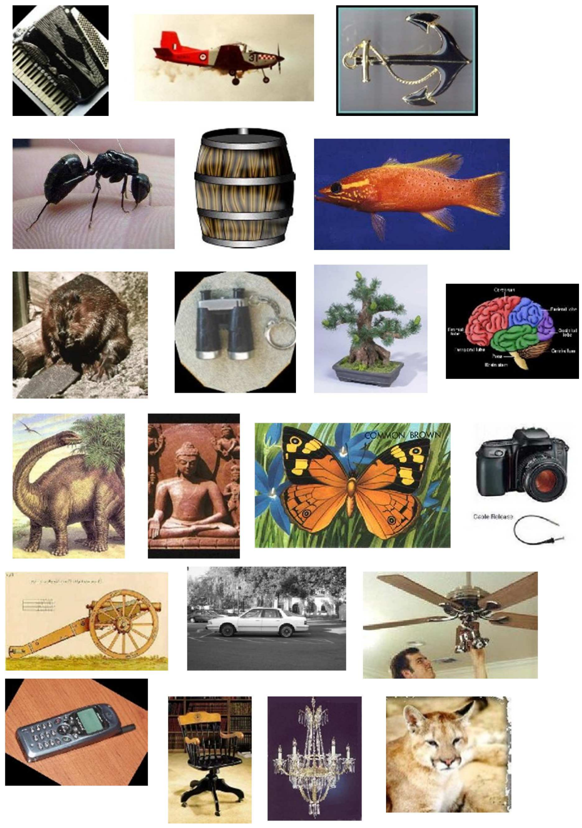

Figure 4: Caltech101 dataset

Figure 5 shows the sample images from Amazon dataset. The images also undergo same steps as Caltech101 dataset because finally the classification results will be compares.

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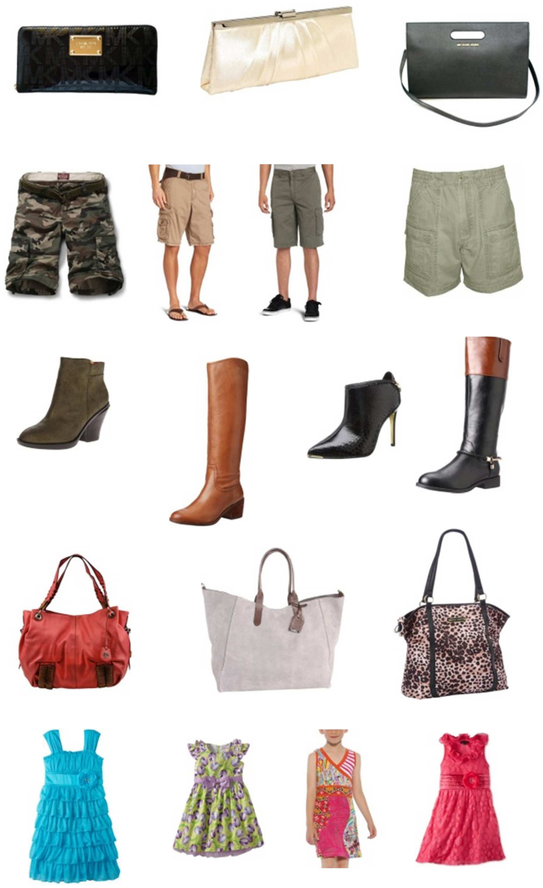

Figure 5: Amazon dataset

8. FEATURE SELECTION

The irrelevant input features may lead to overfitting. Feature selection focuses on the outstanding attributes over the dataset, which offers higher accuracy. There are lots of potential benefits of feature selection such as facilitating data visualization and data understanding, reducing utilization times and techniques, reducing storage requirements and measurement, and defying the curse of dimensionality to improve prediction performance.

CFS (Correlation-based Feature Selection) is an algorithm that couples the evaluation formula that is grounded on ideas from test theory, as well as provides an operational definition of this surmise with an appropriate correlation measure, and a heuristic search strategy.

The evaluator cannot work alone. There must be a search method in order to provide a good predictive power. There are three groups of variable subset selections; wrapper, filters, and embedded [18]. This paper used wrapper, which was provided in the Weka tool. Wrappers utilize the machine learning of interest as a black box to mark subsets of variable according to their predictive power. Its methodology offers a powerful and simple way to notify the problem of variable selection regardless of the chosen machine learning.

As already mentioned earlier, 11 features were combined in this experiment. After performing feature selection using CFSSubset evaluator, only 2 features were selected from the overall set of features. They were area and minor axis length. To make it fair, another evaluator was also used in this experiment. Principle components evaluator suggested seven features out of eleven. They were area, major axis length, minor axis length, eccentricity, orientation, convex area and filled area.

At this point, it was clear that 2 main features were suggested by both evaluators, which were area and minor axis length.

9. CLASSIFICATION RESULTS AND ANALYSIS

The main objective of image classification is to calculate the accuracy of classified images based on the categories stated. The tests were performed on the Caltech101 dataset that consist of 12 features for each single image. A series of experiments was conducted using all features, each with a different number of training images per category (only 30 categories were used). There are a total of 2,594 number of images used in this experiment from part of the 101 categories into training and test sets.

Table 1 lists the results of classification accuracy for images using four different classifiers. As stated in the table, the results show that random tree provides the highest accuracy with feature selection CFSSubsetEvaluator, with 99.00%.

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	BayesNet	NaiveBayesUpdateable	Random Tree	IBk
No Feature Selection	95.95	87.36	70.89	58.02
GreedyStepWise + CFSSubsetEvaluator	98.92	97.80	99.00	90.02
Ranker + PrincipleComponent	97.73	92.06	86.89	64.46

Table 1: Result Caltech101

Compare to result in Table 1, Amazon data which is single object image shows higher accuracy when applying CFSSUbsetEvaluator with 99.48%. It shows that the proposed model are more suitable for single object image because most of the accuracy shows in Table 2 is higher compare to Table 1.

	BayesNet	NaiveBayesUpdateable	Random Tree	IBk
No Feature Selection	80.33	90.32	93.81	92.23
GreedyStepWise + CFSSubsetEvaluator	98.12	94.72	99.48	95.20
Ranker + PrincipleComponent	91.53	93.02	98.18	93.99

Table 2: Result Amazon

After comparing both results, it clearly stated that the proposed model is more suitable for single object images. It is because, Caltech images is not a single image. As introduced in section 7, Caltech is an image with various colour of background. It cannot be said it is a single image. It is a multiple images. Compare to Amazon images, it is clearly a single object image with similar background.

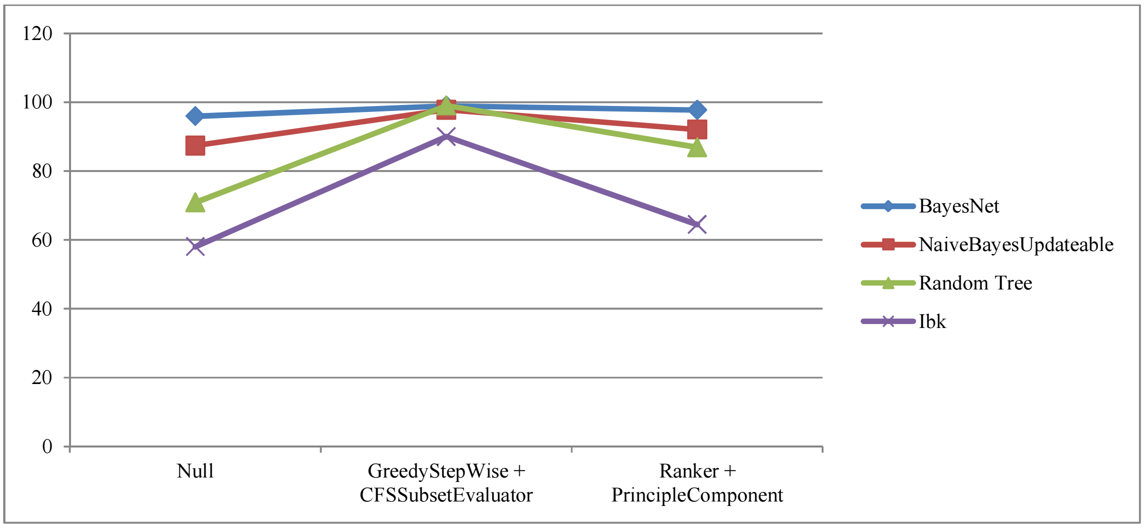

Figure 6:Graph for Table 2

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10. CONCLUSION

We have presented in this paper new image classification technique based on shape for single object image. This paper presents a simple method based on a few set of image features to describe shapes. The contributions of the paper are the proposed technique which contain five steps starting from image segmentation, object identification, feature extraction, feature selection and image classification. Then, we proved that the technique can provide good results and it is can be said that compatible with the dataset. Experimental results using Caltech101 datasets show that the proposed technique achieve better image classification performance when using Random Tree classifier compare to other classifier.

The success of an image classification depends on several factors. In order to identify or define objects represented in images, shape is one of most valuable features.

11. ACKNOWLEDGEMENT

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REFERENCES:

[1] P. Kamavisdar, S. Saluja, and S. Agrawal, "A Survey on Image Classification Approaches and Techniques," vol. 2, no. 1, pp. 1005–1009, 2013.
[2] D. L. & Q. Weng, "A survey of image classification methods and techniques for improving classification performance," *Int. J. Remote Sens.*, 2007.
[3] Mokhairi Makhtar, Engku Fadzli, and Shazwani Kamarudin, "The Contribution of Feature Selection and Morphological Operation For On- Line Business System ' s Image Classification," *World Appl. Sci. J.*, 2014.
[4] J. F. Nunes, P. M. Moreira, and J. M. R. S. Tavares, "Shape Based Image Retrieval and Classification," 2010, pp. 433–438.
[5] Fei-Fei, Fergus, and Perona, "Caltech 101 dataset," 2004. [Online]. Available: http://www.vision.caltech.edu/feifeili/Datasets.htm.
[6] A. C. Berg, T. L. Berg, J. Malik, and U. C. Berkeley, "Shape Matching and Object Recognition using Low Distortion Correspondences," 2005.
[7] L. Fei-Fei, R. Fergus, and P. Perona, "Learning Generative Visual Models from Few Training Examples: An Incremental Bayesian Approach Tested on 101 Object Categories," *Conf. Comput. Vis. Pattern Recognit. Work.*, pp. 178–178, 2004.
[8] S. Banerji, A. Sinha, and C. Liu, "New image descriptors based on color, texture, shape, and wavelets for object and scene image classification," *Neurocomputing*, vol. 117, pp. 173–185, Oct. 2013.
[9] P. A. B. Miss Hetal J. Vala, "A Review on Otsu Image Segmentation Algorithm," *Int. J. Adv. Res. Comput. Eng. Technol.*, vol. Volume 2, no. Issue 2, 2013.
[10] R. S. Chora, "Image Feature Extraction Techniques and Their Applications for CBIR and Biometrics Systems," *Int. J. Biol. Biomed. Eng.*, vol. 1, no. 1, 2007.
[11] M. M. Dengsheng Zhang n GuojunLu, "A review on automatic image annotation techniques," *Pattern Recognit.*, pp. 346–362, 2012.
[12] P. . Sahoo, S. Soltani, and a. K. . Wong, "A survey of thresholding techniques," *Comput. Vision, Graph. Image Process.*, vol. 41, no. 2, pp. 233–260, Feb. 1988.
[13] N. OTSU, "A Threshold Selection Method from Gray-Level Histograms," *2EEE Trans. SYSTREMS, MAN, Cybern.*, vol. Vol 9, 1979.
[14] A. A. M. Al-kubati, J. A. M. Saif, and M. A. A. Taher, "Evaluation of Canny and Otsu Image Segmentation," pp. 24–26, 2012.
[15] M. Huang, W. Yu, and D. Zhu, "An Improved Image Segmentation Algorithm Based on the Otsu Method," *2012 13th ACIS Int. Conf. Softw. Eng. Artif. Intell. Netw. Parallel/Distributed Comput.*, pp. 135–139, Aug. 2012.
[16] Ruggeri F., Faltin F., and Kenett R., "Bayesian Networks," *Encyclopedia of Statistics in Quality & Reliability*. Wiley & Sons, 2007.
[17] P.Santhi and V. Murali Bhaskaran, "Improving the Performance of Data Mining Algorithms in Health Care Data," *IJCST*, vol. 2, no. 3, pp. 152–157, 2011.
[18] I. Guyon, "An Introduction to Variable and Feature Selection," vol. 3, pp. 1157–1182, 2003.