Image Batik Classification Based using Ensemble Learning

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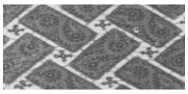
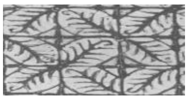
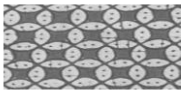
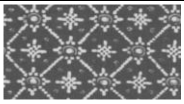
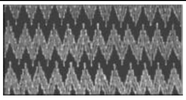
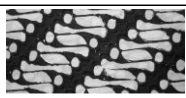
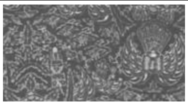
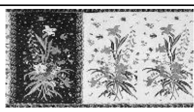
Abstract. Automatic feature descriptor is substantial part of component in the textural image retrieval and classification. Image batik has its unique pattern characteristic such as color intensity, ornament visualisation and ornament size. In motive of batik classificatin rneed feature extraction methods. The scale invariant feature transform (SIFT) can be used for feature descriptor in some applications. In this paper, we presents an efficient based on Bag of Words (BoW) with features of scale invariant feature transform and ensemble classifier for improving classification accuracy.

1. Introduction

Batik is an ancient method of textile decoration which has been admitted by UNESCO as one of national heritage since 2 October 2009. Batik motifs and patterns are dependent on the culture area in indonesia. Indonesia is a country with immense cultural diversity which spread over in the territory of Indonesia The various pattern of batik spread throughout the Archipelago[1], [2]. The word batik is thought to be derived from the word "ambatik" which interpreted means a cloth with little dots" . Also, other words in Javanese culture, batik may be semantically from such as tritik , nitik and klitik. Tritik is the meaning of a resist process by which designs are reserved on textiles by sewing and gathering before dyeing. Nitik is the meaning of batik designs which imitate weaving patterns) and klitik is the meaning of the name of well-known batik design words can be used to refer to drawing. Batik motifs and patterns have been influenced by stylistic and iconographic from Indian, Chinese, Arabic, and European[1] [3],[4]. Batik is named based on its motif, the whole picture ornamenting the cloth. The motif is generally repetitive to cover the whole space of the cloth. In traditional Batik art, there are old basic patterns to assemble Batik motifs. Batik pattern are characterized into two stream; geometry patterns, non-geometry patterns [1][5],[6]. In geometry patterns, a basic pattern appears on cloth regulary. Based on the type of basic pattern and the type of regular appeareance of basic pattern. Geometry motifs are clustered into six motif groups i.e., banji, ceplok, , kawung, lereng, nitik and anyaman[2]. Non-geometry motifs are clustered only based on the appeareance of specific patterns on cloth. These category are clustered two group; "semen" pattern and "buketan" patterns. Examples of two stream patterns such table 1 and fig.1. Beside the two streams, there is also a group of batik motif which can not be identified as geometry or non-geometry motifs, namely special motif or combination motif. The special motif usually combines two motifs or more, for examples like "tambal", ,"Pasisiran", etc, Fig. 2 shows some examples of this patterns. "Pasisiran " pattern or North Coast of Batik – which is associated with vibrant colours, free and dynamic patterns. All coastal patterns show foreign influence during the last centuries.

Table 1. Examples of Batik Motifs.

Motif	Patterns	Examples
Banji	Geometric	
Ceplok	Geometric	
Kawung	Geometric	
Nitik	Geometric	
Anyaman	Geometric	
Lereng	Geometric	
Semen	Non Geometric	
Buketan	Non Geometric	

a. tambal b. Pasisiran

Figure.**1** Examples of combination of geometry and non-geometry motifs, (a) tambal, (b) pasisiran

Plenty of research works had been undertaken to design efficient image batik classification techniques from the image batik databases[7],[8], [9].[10], [11]. They had been explored many points of view to get the best results. Image batik classification is a complex process that may be affected by many factors. This paper examines aspects of features descriptors and ensemble learning for improving accuration of image batik classification

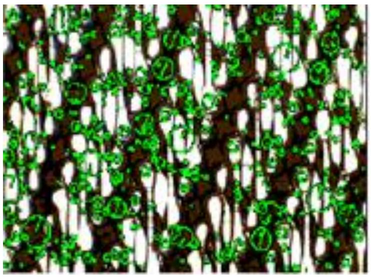
The rest of the paper is organized as follows. In Section 2, we present SIFT descritptor as one of methods to feature extractions . In Section 3, we show how to build dictionary of visual words of images from the extracted features. In Section 4, we explore how to construct an ensemble learning for undertaking the combining of classifier. Then, we establish the proposed method in Section 5. Further, we show result of experiment of proposed methods for improving the classification performance in Section 6. Finally, Section 7 presents the conclusions.

2. SIFT Discriptor

Scale Invariant Feature Transform (SIFT) is algorithm published by David Lowe in 1999 [12] for extracting keypoints and compute its for detecting and describing local features in images[12]. Each SIFT keypoint is a circular image region with an orientation. SIFT detector is invariant and robust to translation, rotations, scaling and partially invariant to affine distortion and illumination changes. SIFT descriptor is widely used to build descriptors of an image as a classification process[13],[9], [14] There are mainly four steps involved in SIFT algorithm

1. Scale-space Extrema Detection: which recognize those locations and different scale of the same object. SIFT algorithm uses Difference of Gaussians which is an approximation of Laplactian of Gaussian as a blob detector which detects blobs in various sizes due to change of scala-space. Difference of Gaussian is obtained as the difference of Gaussian blurring of an image.
2. Keypoint Localization : which eliminates any low-contrast keypoints and edge keypoints and what remains is strong interest points.
3. Orientation Assignment which assign a stable orientation to the keypoints based on local image properties. It creates keypoints with same location and scale, but different directions. It contribute to stability of matching.
4. Keypoint Descriptor : keypoint descriptor is created. Assign A 16x16 neighbourhood around from the keypoint. It is devided into 16 sub-blocks of 4x4 size. This result come up in a feature vector containing 128 elements

Figure 2. shows examples of 500 of SIFT features which are produced for two batik image



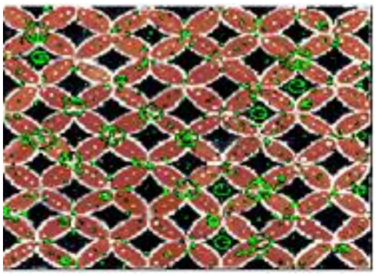


Figure. 2. Examples of SIFT Feature of Batik Parang (left) and Batik kawung (right)

3. Bag of Visual Word in Images

The "bag of visual words" concept is actually taken from the "bag of words" model from the field of text analysis. Bag of visual words model was originally applied to classify and recognize documents in the field of text processing with basic principle is that the document is viewed as a set of disorderly keywords [15], [16]. We simply count the number of times a word appears in a document, and then use the frequency counts of each word as a method to quantify the document. We can apply the same concept in computer vision with only change keywords of each word with image patches and their associated feature vectors as figure 3.

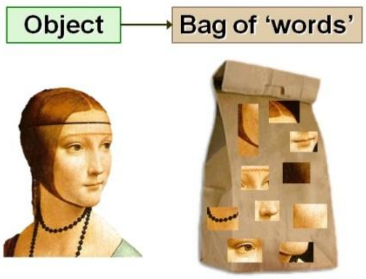


Figure. 3. Bag of visual words of images

In a document, we can easily to count number of times a word appears and construction a histogram of word occurrences. Otherwise, applying the bag of words concept in computer vision we have to quantify and represent an image as a histogram which *simply counts the number of times each visual word appears* based on visual dictionary or codebook of possible visual words as figure 4

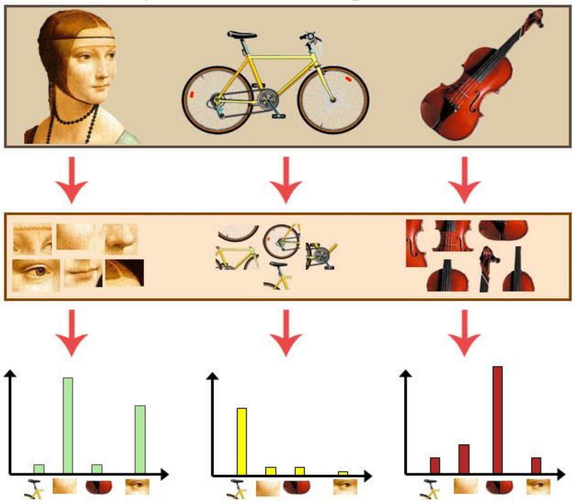


Figure. 4. Histograms of images based on codebook

4. Ensemble Learning

Ensemble learning is a machine learning paradigm for solving the same problem using multiple learners [17–19]. Based on set of learner and combine them, ensemble lerning is usually much stronger than that of base learners for improving performance of models[19]. Ensembles learning was mostly used in the machine learning community for building a prediction model. Generally, an ensemble learning is constructed in two steps.

- Step 1. Generating the base learners. A number of base learners are generated in a parallel style or in a sequential style. The generation of a base learner has influence on the generation of subsequent learners. It is generally believed that the base learners should be as accurate as possible, and as diverse as possible
- Step 2, Combine the base learners. The base learners are combined to use. The majority voting for classification and weighted averaging for regression are among the most popular combination schemes

Figure 5 show framework for constructing ensemble learning.

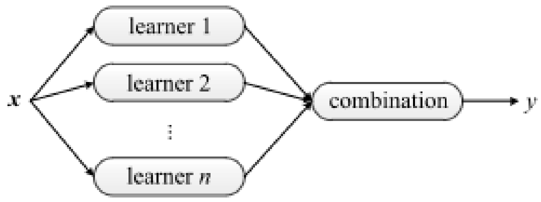


Figure 5. Common ensemble architecture

There are some methods for implementing ensemble learning i.e Boosting, Bagging, Stacking algorithm

5. Proposed Approach

The process of image classification based on BOW with ensemble learning includes the following three steps: feature extraction and description, construct visual dictionary and training classifier. The implement of image batik classification based on BOW and ensemble learning can be described as follow

- Step 1: Feature extraction and description. SIFT descriptor are implemented to extract global dan local features . The feature is characterized by 128-dimension vector.
- Step 2: Construct visual dictionary. This step create cluster a large number of feature points obtained in Step 1 using k-means clustering algorithm. Visual words are represented with cluster, all the words are combined as visual dictionary and the size of dictionary is the number of words. Generaly, histograms of visual words are used for representing images
- Step 3: Training classifier using ensemble learner model. This step builds the process by which multiple models of classifier for the improvement of the performance. This works implement stacking method for constructing ensemble learning.

The following is pseudo-code of stacking methods of ensemble learner

Input : Data set $D = \{(x_1, y_1), (x_2, y_2, (x_m, y_m)\}$
First-level learning algorithms $\mathcal{L}_1, \ldots \mathcal{L}_T$
Second-level learning algorithms $\mathcal{L}$
Process
$t = 1, \ldots \mathcal{T}$:
$h_t = \mathcal{L}_\tau(\mathcal{D})$
end;
$\mathcal{D}' = \phi$
for *i =1...m*
for *t=1..*$\mathcal{T}$
$z_{it} = h_t(x_i)$ %use to classify the training examples
end;
$\mathcal{D}' = \mathcal{D} \cup \{((z_{i1}, z_{i2}, \cdots z_{iT}), y_i)\}$
end;
$h' = \mathcal{L}(\mathcal{D}')$ % Traom the second-leve learner h by apply the second–level learning algorithm $\mathcal{L}$ to the new dataset $\mathcal{D}$
Output : $H(x) = h'(h_1(x), \ldots h_T(x))$

All the processes described above can be described in outline in figure 6

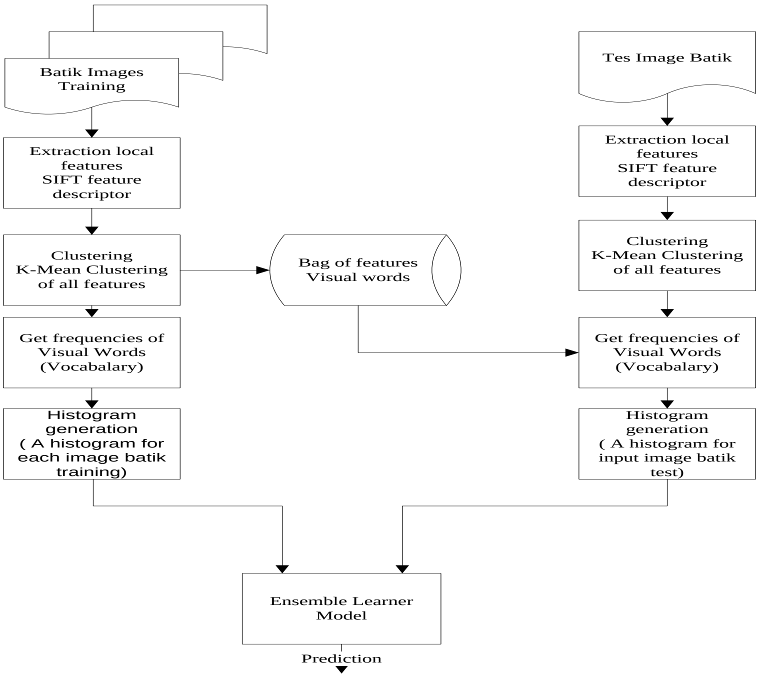


Figure 6. Framework of proposed approach

Several experiments have been conducted to test the performance of the classification results. The reference parameter is the variation of the number of words in the dictionary, the combination of the base classifer at the stacking model [1]. Four classifiers have used as base classifier ie support vector machines (SVM), K-Nearest Neighbor (K-NN), Decision Tree (DT) and Artificial Neural Network(ANN). Stacking with two or three level-0 base learners was employed in our experiments. There are tree experiments were performed with stacking

- Stacking with Support Vector Machine (SVM), K-Nearest Neighbor (K-NN) and Decision Tree (DT). SVM and ANN was used as base classifer at level 0 and SVM was used as classifier at level 1
- Stacking with Support Vector Machine (SVM), Artificial Neural Network(ANN). and Decision Tree (DT). ANN,KNN and DT were used as base classifer at level 0 and SVM was used as classifier at level 1
- Stacking with ANN, K-NN), DT and SVM. ANN,KNN, DT were used as base classifer at level 0 and SVM was used as classifier at level 1

6. Experiment Result

The performance of the batik motifs classification system is evaluated by performing classification on two different batik motifs based on scenario and variation of the dictionary word size. In our experiments, we have only used 2 class motif i.e parang motif and kawung motif. All data batik is 48 parang motif and 28 kawung motif. For training data, the amount of data batik kawung class is 15 and the number of batik parang batik is 24 data. For the test data, the number of kawung motif class is 14 data and the number of parang motif is 14 data. The performance of the proposed system is evaluated based on the average classification accuracy of the two different batik motifs classes using each base classifer and ensemble classifier show in table 2 and table 3

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Table 2. Base Classifier

Base Classifier		
SVM	**K-NN**	**DT**
0.8214	0.6429	0.7857

Table 3. Performance of ensemble classifiers for tree scenario (accuracy)

Level-0	**Level-1**	**Accuracy**
SVM+ ANN	SVM	0.9286
ANN+DT	SVM	0.9643
ANN+KNN+DT	SVM	0.9643

Based on table III representation that combination of base classifier ANN, KNN and DT as base layer and SVM classifer as level-0 classifier are resulting high accuracy of model and have accuracy average is 0.95.

7. Conclusion

The results of batik image classification are determined by the feature extraction and the appropriate classification model. High accuracy results from batik image classification require the right combination of ensemble classifier

8. References

[1] Elliott I M, 2013 *Batik: fabled cloth of Java* Tuttle Publishing.
[2] Haake A, 1989 The role of symmetry in Javanese batik patterns *Computers & Mathematics with Applications* **17**, 4 p. 815–826.
[3] Stephenson N, 1993 The Past, Present, And Future Of Javanese Batik: A Bibliographic Essay *Art Documentation: Journal Of The Art Libraries Society Of North America* **12**, 3 p. 107–113.
[4] Swallow D, 1987 Javanese batiks: Meaning, intepretation and change *Indonesia Circle* **15**, 42 p. 33–55.
[5] Haake A, Jan. 1989 The role of symmetry in Javanese batik patterns *Symmetry 2* **17**, 4 p. 815–826.
[6] Suciati N Pratomo W A and Purwitasari D, 2014 Batik Motif Classification Using Color-Texture-Based Feature Extraction and Backpropagation Neural Network in *2014 IIAI 3rd International Conference on Advanced Applied Informatics* p. 517–521.
[7] Minarno A E Munarko Y Kurniawardhani A Bimantoro F and Suciati N, 2014 Texture feature extraction using co-occurrence matrices of sub-band image for batik image classification in *Information and Communication Technology (ICoICT), 2014 2nd International Conference on* p. 249–254.
[8] Nurhaida I Noviyanto A Manurung R and Arymurthy A M, 2015 Automatic Indonesian's batik pattern recognition using SIFT approach *Procedia Computer Science* **59** p. 567–576.
[9] Setyawan I Timotius I K and Kalvin M, 2015 Automatic batik motifs classification using various combinations of SIFT features moments and k-Nearest Neighbor in *Information Technology and Electrical Engineering (ICITEE), 2015 7th International Conference on* p. 269–274.
[10] Rangkuti A H Rasjid Z E and Santoso D J, 2015 Batik image classification using treeval and treefit as decision tree function in optimizing content based batik image retrieval *Procedia Computer Science* **59** p. 577–583.

[11] Suciati N Pratomo W A and Purwitasari D, 2014 Batik Motif classification using color-texture-based feature extraction and backpropagation neural network in *Advanced Applied Informatics (IIAIAAI), 2014 IIAI 3rd International Conference on* p. 517–521.

[12] Lowe D G, 1999 Object recognition from local scale-invariant features in *Computer vision,* 1999. *The proceedings of the seventh IEEE international conference on* **2** p. 1150–1157.

[13] Montazer G A and Giveki D, 2015 Content based image retrieval system using clustered scale invariant feature transforms *Optik-International Journal for Light and Electron Optics* **126**, 18 p. 1695–1699.

[14] Azhar R Tuwohingide D Kamudi D Suciati N and others, 2015 Batik Image Classification Using SIFT Feature Extraction, Bag of Features and Support Vector Machine *Procedia Computer Science* **72** p. 24–30.

[15] Huang C-R and Lee L-H, 2008 Contrastive Approach towards Text Source Classification based on Top-Bag-of-Word Similarity. in *PACLIC* p. 404–410.

[16] Ko Y, 2012 A study of term weighting schemes using class information for text classification in Proceedings *of the 35th international ACM SIGIR conference on Research and development in information retrieval* p. 1029–1030.

[17] Dietterich T G and others, 2000 Ensemble methods in machine learning *Multiple classifier* systems **1857** p. 1–15.

[18] Graczyk M Lasota T Trawiski B and Trawiski K, 2010 Comparison of bagging, boosting and stacking ensembles applied to real estate appraisal *Intelligent information and database systems* p. 340–350.

[19] Ponti Jr M P, 2011 Combining classifiers: from the creation of ensembles to the decision fusion in *Graphics, Patterns and Images Tutorials (SIBGRAPI-T), 2011 24th SIBGRAPI Conference on* p. 1–10.

[20] Wang R Ding K Yang J and Xue L, Oct. 2016 A novel method for image classification based on bag of visual words *Journal of Visual Communication and Image Representation* **40**, Part A p. 24–33.