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Karawo Motifs Identification based on The Classification of User Characters with Naïve Bayes Method

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Abstract. The general objective of this research is to develop an application that can be used to design patterns and motifs karawo based on motif classification that suits with the character and culture from the people of Gorontalo. This study aims to identify motifs karawo based on user characters using Naïve Bayes classifier (NBC). The character which is used in this research is the Enneagram character. Results from this study is an application template design patterns and motifs karawo. Resulting a template motifs that the attract people to buy and use traditional fabrics karawo.

1. Introduction

Karawo is embroidered cloth typical of the region that is born of craft and perseverance Gorontalo people since the 17th century in embroidering form patterns and motifs, which have become identity and cultural values of Gorontalo. Currently embroidery karawo become the leading commodity in Gorontalo province, so that various development programs karawo embroidery craft that has now obtained a patent from the Government of Indonesia, increasingly empowered to populist economic development while maintaining and preserving the cultural heritage of Gorontalo.

The main problem encountered in the development of embroidery industry karawo is (Provincial Gorontalo, 2012): (1) has not been able to produce in bulk to meet the demand of large scale in a short time; (2) the number of craftsmen who still lacking due to various factors; (3) the number of designer pattern / motif is still lacking; (4) cheapness of bargaining power of the craftsmen karawo. Create a pattern and motif karawo with a variety of interesting and has a high artistic value, embroidered fabric comfortable to wear and follow the trend of today has become a necessity to increase the level of purchases of society to needlepoint karawo, as well as efforts to build a bulwark karawo as cultural identity of Gorontalo.

Based on these problems it is necessary to do a study for design an application template pattern and motif embroidery karawo with previously identified patterns and motifs embroidered karawo which has been developed in various crafts industry karawo and more specifically, to identify patterns and motifs karawo that have resulted from research [1] which is adapted to the nature according Eneagram of karawo users . Furthermore, this study also is an extension of previous research [2] which resulted in a recommendation karawo motif that suits the character of users and types of custom events Gorontalo area that will be followed. With special applications that are used to design the pattern and motif embroidery karawo is expected that industrial society crafts embroidery karawo most of whom live scattered in various villages can use this application to design your own pattern and motif embroidery without hoping to get a copy of the pattern written on the paper chart of the designers, which are still very minimal.

This study aims to identify motifs karawo based on user characters using Naïve Bayes classifier (NBC). The character which is used in this research is the Enneagram character [Lee]. Enneagram character is already commonly used and has been widely implemented into a variety of case studies [Anna].

The Naïve Bayes method chosen as a method of classification because it has a performance level of accuracy is quite high compared with other classification methods [Ting] and has been implemented in a variety of case studies, among others in the field of health [Bhuvaneswari] and image processing [Oujaoura] [8] purpose that Naïve bayes method is kind of module classifier [9] under known priori probability and class conditional probability. It is basic idea to calculate the probability that document D is belongs to class C. There are two event model are present for Naive Bayes [10], [11], [12] as multivariate Bernoulli and multinomial model.

2. Method

The Naïve Bayes Classifier (NBC) is also called as an independent feature models which deals with the simple classification based on Bayes Theorem. The predict the various sets of probabilities based on the condition values in particular class. The independences assumption is a strong base of classification in Naïve Bayes the values of the attributes are in independent irrespective to the other attributes of the variable class [13]. Naïve Bayes Model works with the conditional probability which originates from well-known statistical approach "Bayes Theorem", where as Naïve refers to "assumption" that all the attributes of the examples are independent of each other given the context of the category. Because of the independence assumption the parameters for each attribute can be learned separately and this greatly simplifies learning especially when the number of attributes is large [11], [14].

Therefore, Let A be a date type which is described by measurements made on sets of n attributes. Let B be some hypothesis such that data type B that is P(A/(B)) is determined for classification problem. Thus P(B/(A)) is considered as prior probability of A. The posterior probability P(B/A) is based on large information then prior probability P(B) which is not dependent on A [15]. The probability of document (D) containing the vector $V = (x\_1, x\_2, \ldots..x\_n)$ belongs to the hypothesis B as follows.

$$P(B|A) = \frac{P(A|B)P(B)}{P(A|B) + P(A|B_2)P(B_2)} \quad (1)$$

Where, P (B/(A) is considered as posterior probability and P(B) is prior probability associated with hypothesis. For 'n' number of various hypotheses, we consider:

$$P(A) = \sum_{j=1}^{n} P(A|B_j)\, P(B_j) \quad (2)$$

Thus we have

$$P(B|A) = \frac{P(A|B)P(B)}{P(A)} \quad (3)$$

The estimation of $P(A|B)$ is difficult since the number of possible vectors d is too high. This difficult is overcome by using the Naïve assumption that any two coordinates of the document is statistically independent. Using this assumption the most probable category "B" can be estimated [11].

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The procedure of Naïve Bayes Classifier (NBC) method consist of the steps as follows [13].
Step 1: Calculating the frequency of each characteristic in the A on each B
Step 2: Calculating the probability of each B which have the characteristics of A ➔ P (A|B)
Step 3: Calculating the probability of each B ➔ P (B)
Step 4: Calculating the probability of each characteristic A ➔ P (A)
Step 5: Calculating P (B|A) for each B
Step 6: Determining P (B | A) with a maximum value

3. Results and Discussion

3.1. The Result

Let we have 19 user characters (A) in Table 1 and 25 karawo motifs (B) in Table 2.

Table 1. User Characters

Code	Karawo Motifs (B)
K1	Perfectionist
K2	Observer
K3	Helper
K4	Peacemaker
K5	Romantic
K6	Worrier
K7	Adventurer
K8	Warrior
K9	Opportunist

Table 2. Karawo Motifs

Code	Karawo Motifs (B)
M1	Palm Tree
M2	Crown
M3	Crocodile
M4	Rope
M5	Coconut
M6	Palm Sugar
M7	Gate, Portal
M8	Young Coconut Leaf
M9	Banana
M10	Cane
M11	Aliyawo
M12	Eluto
M13	Baladu
M4	Pito
M15	Sabele
M16	Sumala
M17	Banggo

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Table 2. Cont.

M18	Bitu'o
M19	Wamilo
M20	Badi
M21	Yilambua Spear
M22	Pambungo Spear
M23	Tadui-dui
M24	Coin
M25	Nutmeg and Cengkih

However, for training the system construction of vector tables is very important and need to train the system through the vector table.

Table 3. Vector Table A and B

Karawo	**User Characters (A)**								
Motifs (B)	**K1**	**K2**	**K3**	**K4**	**K5**	**K6**	**K7**	**K8**	**K9**
M1	1	0	0	0	0	0	0	1	0
M2	0	0	0	0	0	1	0	0	0
M3	1	0	0	1	0	0	0	0	0
M4	0	0	0	1	0	0	0	0	0
M5	0	1	0	1	0	0	0	0	0
M6	0	0	0	0	0	0	0	0	1
M7	0	0	1	0	0	0	1	0	0
M8	0	0	0	1	0	0	0	0	0
M9	0	0	0	0	0	0	1	0	0
M10	0	0	0	0	1	0	0	0	0
M11	0	0	0	0	0	0	0	1	0
M12	0	0	0	0	0	0	0	1	0
M13	1	0	0	0	0	0	0	1	0
M4	0	0	0	1	0	0	0	0	0
M15	0	0	1	0	0	0	0	0	0
M16	0	0	0	0	0	0	0	1	0
M17	1	0	0	0	0	0	0	0	0
M18	0	0	0	0	0	0	0	1	0
M19	0	0	0	1	0	0	1	0	0
M20	0	0	0	0	0	0	1	0	0
M21	0	0	0	0	0	1	0	0	0
M22	0	1	0	0	1	0	1	0	0
M23	0	0	0	0	0	0	1	0	0
M24	0	0	0	0	0	0	0	0	1
M25	0	0	0	0	0	0	0	1	0

As an example, the character selected by the user through the application karawo, three (3) types of characters, namely: Observer (K2), Peacermaker (K4), and Adventurers (K7). Furthermore, the probability calculation karawo motif for all kinds of motives karawo.

Figure 1 shows an example of the calculation of the probability of three (3) types of motifs karawo of 25 (twenty five) motifs karawo available, namely Palm Motif (M1), Coconut Motif (M5), and Pambungo Motif (M22), based on three (3) types of characters enneagram that has been selected by the user, have yielded values of different opportunities, and it is known that the motif with the greatest probability value based on the calculation is Pambungo.

- **Motif Pohon Pinang (M1)**, karakter eneargam : **Perfeksionis (K1) dan Pejuang (K8)**

$$P(M1|K2) = \frac{P(K2|M1) * P(M1)}{P(K2)} = \frac{\frac{0}{3} * \frac{1}{25}}{\frac{1}{9}} = \frac{0 * 0.04}{0.11} = 0$$

$$P(M1|K4) = \frac{P(K4|M1) * P(M1)}{P(K4)} = \frac{\frac{0}{3} * \frac{1}{25}}{\frac{1}{9}} = \frac{0 * 0.04}{0.11} = 0$$

$$P(M1|K7) = \frac{P(K7|M1) * P(M1)}{P(K7)} = \frac{\frac{0}{3} * \frac{1}{25}}{\frac{1}{9}} = \frac{0 * 0.04}{0.11} = 0$$

P (Motif : Pohon Pinang) = 0

- **Motif Kelapa (M5)**, karakter eneargam : **Pengamat (K2) dan Pendamai (K4)**

$$P(M5|K2) = \frac{P(K2|M5) * P(M5)}{P(K2)} = \frac{\frac{1}{3} * \frac{1}{25}}{\frac{1}{9}} = \frac{0.33 * 0.04}{0.11} = 0.12$$

$$P(M5|K4) = \frac{P(K4|M5) * P(M5)}{P(K4)} = \frac{\frac{1}{3} * \frac{1}{25}}{\frac{1}{9}} = \frac{0.33 * 0.04}{0.11} = 0.12$$

$$P(M5|K7) = \frac{P(K7|M5) * P(M5)}{P(K7)} = \frac{\frac{0}{3} * \frac{1}{25}}{\frac{1}{9}} = \frac{0 * 0.04}{0.11} = 0$$

P (Motif : Kelapa) = 0.24 (24%)

- **Motif Tombak Pumbungo (M22)**,
  Karakter eneargam : **Pendamai (K4), Pengamat (K2)**, dan **Petualang (K7)**

$$P(M22|K2) = \frac{P(K2|M22) * P(M22)}{P(K2)} = \frac{\frac{1}{3} * \frac{1}{25}}{\frac{1}{9}} = \frac{0.33 * 0.04}{0.11} = 0.12$$

$$P(M22|K4) = \frac{P(K4|M22) * P(M22)}{P(K4)} = \frac{\frac{1}{3} * \frac{1}{25}}{\frac{1}{9}} = \frac{0.33 * 0.04}{0.11} = 0.12$$

$$P(M22|K7) = \frac{P(K7|M22) * P(M22)}{P(K7)} = \frac{\frac{1}{3} * \frac{1}{25}}{\frac{1}{9}} = \frac{0.33 * 0.04}{0.11} = 0.12$$

P (Motif : Tombak Pumbungo) = 0.36 (36%)

Figure 1. Examples of Karawo Motif Probability calculations based on User Characters

The results of this study is an application template design patterns and motifs karawo to classify motives karawo that suits with the character of the user and the type of event that will be followed. Application template design patterns and motifs karawo provides a variety of symbols motif characterized by culture of Gorontalo, the philosophical value such motive nut trees which is "honest, straight and protector"; Wamilo arms motif which means "gentle and happy", and other motifs. The advantages of this karawo template application is the ability to dynamically add a motif that has been available outside the collection.

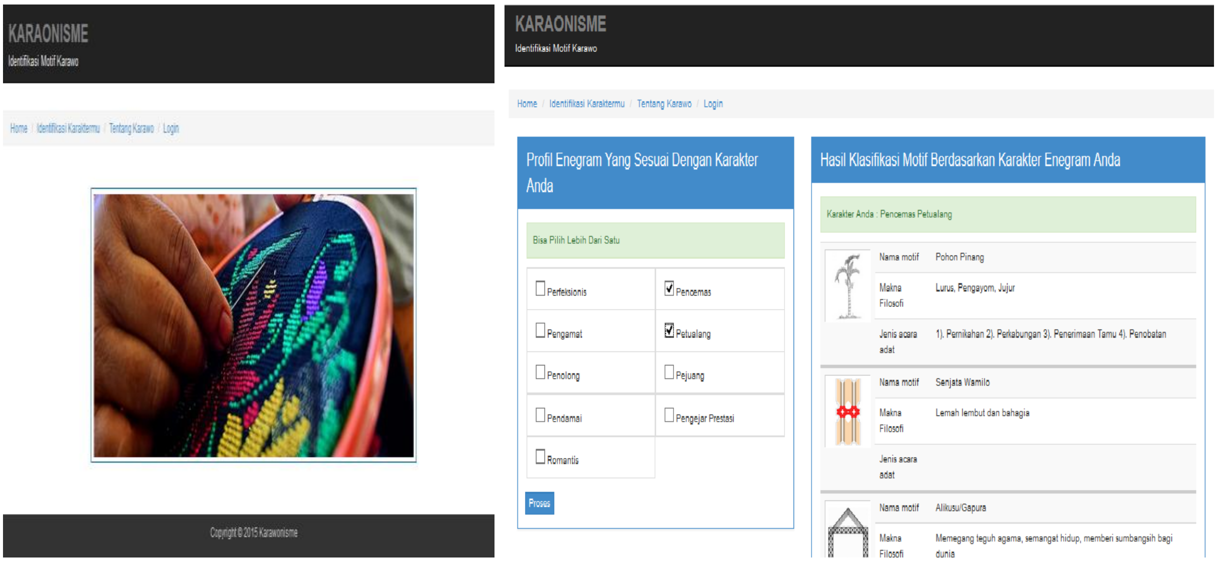

Figure 2. Application template design patterns and motifs karawo

3.2. *Discussion*

The process for making embroidery karawo is quite difficult. One complexity experienced by craftsmen is drawing karawo motif pattern on paper graphics. In addition, the variety of motifs used by the craftsmen karawo in gorontalo very limited, almost exclusively using floral motifs.

In this study has managed to get 25 objects which are elements of traditional indigenous people of gorontalo as traditional weapons, traditional clothing, traditional fruit, and other materials commonly used in the custom event gorontalo society. These objects are then modified into a motive karawo diverse and interesting. The motifs are first classified by enneagram characters that have been obtained in previous studies.

One important step before implement an application template design patterns and motifs karawo is the process of design motifs in the form of pixels. Presentation of motifs in the form of pixels will be easier for karawo craftsmen in embroidering. Figure 3 shows some examples from karawo design motif that has been designed in the form of pixels.

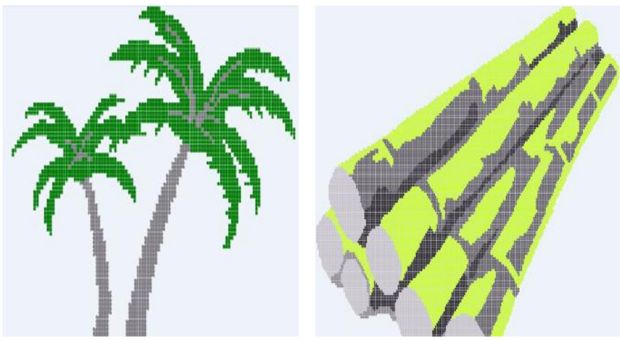

Figure 3. Karawo design motifs in the form of pixels

The application template karawo motif is designed to classify the motifs chosen by the user according to its character. To identify the characters, users can select one or more late enneagram characters that suits him and then processed by the system to get the recommendation of motifs.
In this application, users can access some information about the definition and history of karawo, while users can identify the characters by using karawo. To identify the characters, users can select one or more an enneagram characters that suits him and then processed by the system to get the recommendation of motifs.

4. Conclusion
Based on the result of this research, Application template design patterns and motifs karawo provide many references karawo motifs that can be used by users and craftsmen that suits with the character and the type of event, which has a philosophical meaning contained within each motif.
Application template design patterns and motifs karawo capabilities that can dynamically add new motifs beyond the references provided, thus increasing the interesting and creativity of craftsmen to produce design motif that is interest to use.

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