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Pattern Recognition using Multiclass Support Vector Machine Method with Local Binary Pattern as Feature Extraction

Nursyiva Irsalinda¹*, Sugiyarto Surono¹*, Indah Dwi Ratna Sary¹

¹Department of Mathematics, Ahmad Dahlan University, Yogyakarta, 55191, Indonesia ***Corresponding author**: nursyiva.irsalinda@math.uad.ac.id, sugiyarto@math.uad.ac.id

Abstract

Pattern recognition is a scientific discipline usually used to classify objects into a number of categories or classes through a feature extraction method applied to recognize an object accurately. Meanwhile, Local Binary Pattern (LBP) is a texture analysis method which uses statistical and structural models for feature extraction. Moreover, a Support Vector Machine (SVM) method is normally used to solve non-linear problems in high dimensions to obtain an optimal solution by finding the best hyperplane through the maximizing of the margin between two data classes. Pattern recognition in paintings using machine learning has never been done in any research. Meanwhile it is very important in the future to be able to serve as a verification system for novelty works of art at the stage of filing for intellectual property rights. Therefore, this study aimed to apply pattern recognition with LBP feature extraction method and multiclass SVM classification method to classify the flow of several classes of painting works including expressionism, fauvism, naturalism, realism, and romanticism. The best evaluation results using this method were obtained in the training and testing data combination of 90:10 with an accuracy rate of 83%. Therefore, it can be concluded that machine learning in pattern recognition of painting works can be applied.

Keywords

Pattern Recognition, Local Binary Pattern, Support Vector Machine, Multiclass SVM

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1. INTRODUCTION

Technological developments have made data become one of the important components in every human activity. These data can be numeric, categorical, text, images, and others but the most widely used form in recent times is the images which are usually processed to produce a good identification process. Meanwhile, an important method usually used in solving problems in image processing is pattern recognition which is a scientific discipline designed to classify objects into a number of categories or classes (Theodoridis, 2009). Moreover, the numerical pattern recognition which is a statistical approach involves using multidimensional data vector as input where each component is called a feature. The numerical pattern recognition observed to be increasingly used in decision-making processes. Furthermore, a pattern recognition process through feature extraction method such as the Local Binary Pattern method is needed to recognize an object accurately.

Local Binary Pattern (LBP) is a texture analysis method which uses statistical and structural models for feature extraction (Amat et al., 2017; Nugraha et al., 2019). It works by applying a threshold to the surrounding pixels based on the pixels being observed (Galshetwar et al., 2017; Sharma et al., 2020) and also reported to be widely used in applications involving image texture capture and classification (Kaewchote et al., 2018; Prashanth et al., 2020). Some of its advantages includes being fixed to changes in light intensity from the same object and accuracy in recognizing an object (Susanto et al., 2018). Moreover, it can also be implemented easily and fairly quickly for feature extraction using low computational processes (Amat et al., 2017).

Classification is one of the supervised learning methods in data mining. It is usually used to find a model or function of a data set by grouping it into classes such that the data objects determined in each class label indicates they have the same characteristics or similar pattern (Cervantes et al., 2020). The grouping process involves dividing the data into predetermined classes and assigning the classes according to the similarity in characteristics and the patterns in the words (Styawati and Mustofa, 2019).

Support Vector Machine (SVM) was introduced by Vapnik in 1995 is a method widely used in classifying supervised learning (Ay et al., 2019; Komarudin et al., 2020; Wang and Zhao,

2020; Yin and Yin, 2016). SVM is formulated to solve nonlinear problems in high dimensions to obtain optimal solutions (Li et al., 2020; Liu et al., 2017; Pramudita and Musdholifah, 2020; Styawati and Mustofa, 2019; Tang et al., 2019). This method finds the best hyperplane by maximizing the margin between two classes of data (Komarudin et al., 2020). Meanwhile, the margin is defined as the distance between the hyperplane and the support vector which is the closest data from the class to the hyperplane. It is important to note that SVM uses a trick Kernel function to calculate data with non-linear problems in order to obtain classification results with a good level of accuracy. However, it is sensitive to noise and outliers and also reported is less efficient in obtaining complex models for large-scale data sets (Cervantes et al., 2020). Meanwhile, some of its benefits include the ability to minimize errors and higher accuracy when compared with other classifications methods (Utami et al., 2021).

Pattern recognition and SVM classification methods have been widely used in previous studies. For example, Dias Aziz Pramudita and Aina Musdholifah added a parameter optimization process known as the Gravitational Search Algorithm (GSA) to improve the accuracy of the SVM method in the thyroid nodule classification process (Pramudita and Musdholifah, 2020). L. Jerlin Rubini and Eswaran Perumal also used the Fruit Fly Optimization Algorithm (FFOA) to select the best features in medical data which were later processed using the multiclass SVM method for classification (Jerlin Rubini and Perumal, 2020). Moreover, Diya Wang and Yixi Zhao predicted the feelings of investors towards stock market news using the SVM method in order to make decisions with a high level of accuracy (Wang and Zhao, 2020). Study about SVM also developed to enhance age invariant face recognition performance based on gender classification (Navak and Indiramma, 2021) while Mayur succeeded in showing that CNN-ECOC produced higher accuracy than ordinary CNN classification (Bora et al., 2020). Another research found a higher accuracy of performance for multiclass SVM method when compared with SVM method (Alita et al., 2020). from the studies related to pattern recognition that have been described.

There has been no research on the multiclass SVM method that uses LBP as its feature extraction. By looking at the advantages of LBP and in order to find a method with better results, the researchers combined the multiclass SVM method with LBP to classify pattern recognition. The case study adopted in this research is the classification of paintings into five classes, namely expressionism, fauvism, naturalism, realism, and romanticism. This case study was appointed because pattern recognition in paintings using machine learning has never been done in any research. Meanwhile it is very important in the future to be able to serve as a verification system for novelty works of art at the stage of filing for intellectual property rights. This present study, therefore, uses the Multiclass Support Vector Machine (MSVM) method to classify pattern recognition using the LBP method for feature extraction. The aim was to determine the effectiveness of applying these methods in

classifying the flow in a painting.

2. MATERIALS AND METHODS

2.1 Pattern Recognition

Pattern recognition is a discipline usually used to classify objects into a number of categories or classes (Theodoridis, 2009). The object can be an image, a signal waveform, or any type of measurement that needs to be classified. This means pattern recognition is an important part of a system for decision-making purposes.

2.2 Local Binary Pattern Method

The Local Binary Pattern method was first introduced by Timo Ojala in 1994 as a texture analysis method which uses statistical and structural models (Ojala et al., 2000). It also has the ability to compare the gray values of the surrounding pixels (Abbas et al., 2019; Agbele et al., 2019; Ali et al., 2017; Kwabena et al., 2020; Muqeet and Holambe, 2019; Vidya and Chandra, 2019). The basic LBP operator was configured using 8 pixels around a center pixel and the threshold of the nth surrounding pixel was through the gray value of the center pixel and the thresholding function. The binary code generated by this LBP was, therefore, used to represent the features of the center pixel i_c .

LBP(x_c, y_c) =
$$\sum_{n=0}^{n-1} s(i_n - i_c) 2^n$$
 (1)

$$s(x) = \begin{cases} 1, & x \ge 0 \\ 0, & x < 0 \end{cases}$$
(2)

where

 $\mathbf{x}_c = \mathbf{pixel}$ width

 y_c = pixel height

s(x) = threshold function which is defined by (2)

 i_n = ambient pixels from the center

 i_c = center pixel

LBP is easy to implement, has lower computational level, does not require a long time for feature extraction (Shiyam, 2019), fixed to changes in light intensity from the same object, and accurate in recognizing an object (Gonzalez, 2009).

2.3 Support Vector Machine Method

Support Vector Machine (SVM) is one of the methods usually used classifying supervised learning and reported to be first introduced by Vapnik in 1995 (Ay et al., 2019; Komarudin et al., 2020; Wang and Zhao, 2020; Yin and Yin, 2016) to solve non-linear problems at high dimensions (Abbas et al., 2019; Battineni et al., 2019) in order to obtain an optimal solution. The method finds the best hyperplane by maximizing the margin between two data classes. Meanwhile, a hyperplane is defined as a line or field separating the data between different classes while margin is the distance between the hyperplane and the support vector which acts as the closest data from the class to the hyperplane. For example, the training data set D is

$$D_n = (\mathbf{x}_1, \mathbf{y}_1), (\mathbf{x}_2, \mathbf{y}_2), \dots, (\mathbf{x}_n, \mathbf{y}_n),$$

where $D = b\{(x_i, y_i)\}_{i=1}^n$, $x_i \in \mathbb{R}^d$ is the training data set while x_1 is the input data and $y_1 \in (+1, -1)$ is a class label with an output value of +1 (positive) or -1 (negative).

The main concept used in assigning the separator to a linear separable is the dot product between two vectors which is defined as $w^T x = \Sigma_i w_i x_i$. Where, w is the weighting vector and b is the bias. Moreover, the separating hyperplane was used to divide the space into two classes as indicated in the following relationship.

$$h(\mathbf{x}) = \mathbf{w}^T \mathbf{x}_i + b + 0 \tag{3}$$

Meanwhile, the separator function for the two classes is as follows

$$w^T x_i + b \ge +1$$
 for $y_i = +1$

and

$$w^T x_i + b \le -1$$
 for $y_i = -1$

where, $\frac{|b|}{||w||}$ is the perpendicular distance of the dividing plane from the center of the coordinates and ||w|| is the Euclidean distance (Euclidean norm) from w.

Moreover, the Quadratic Programming (QP) problem was the step used in determining the minimum point by considering the equation constraints.

$$\min_{\mathbf{w},\mathbf{b}} \frac{1}{2} ||\mathbf{w}||^2 \tag{4}$$

with constraint function

$$y_i(wx_i + b) - 1 \ge 0, i = 1, 2, ..., m$$

It is also possible to resolve the optimization problem through the use of the Lagrange multiplier as indicated in the following equation:

$$L = \frac{1}{2} ||\mathbf{w}||^2 - \sum_{i=1}^n \alpha_i (\mathbf{y}_i ((\mathbf{w} \mathbf{x}_i + \mathbf{b}) - 1))$$
(5)

Where, α_i is the Lagrange Multiplier which is zero or positive $(\alpha_i \ge 0)$. The problem was, therefore, optimized by minimizing *L* to w and b and maximizing α_i . The equation was later modified as follows with due consideration for the nature of the optimal point *L*= 0: Condition 1

$$\frac{\partial L\mathbf{p}}{\partial \mathbf{w}} = 0 \to \mathbf{w} = \sum_{i=1}^{n} \alpha_i \mathbf{y}_i \mathbf{x}_i \tag{6}$$

Condition 1

$$\frac{\partial L\mathbf{p}}{\partial \mathbf{b}} = 0 \longrightarrow \mathbf{w} = \sum_{i=1}^{n} \alpha_i \mathbf{y}_i = 0 \tag{7}$$

The substitution of w changed the equation into a Lagrange duality Max

$$L_D = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j \mathbf{y}_j \mathbf{y}_j \mathbf{x}_i \cdot \mathbf{x}_j$$
(8)

Condition 1

$$\sum_{i=1}^{n} \alpha_i \mathbf{y}_i = 0$$

Condition 2

$$\alpha_i \ge 0, i = 1, 2, ..., n$$

2.4 Kernel

The Support Vector Machine learning process to determine the support vectors depends on the dot product of the data in the feature space i.e. $\Phi_i(\mathbf{x}_i) \cdot \Phi_i(\mathbf{x}_j)$. It is, therefore, possible to replace this dot product calculations with trick Kernel functions $\mathbf{K}(\mathbf{x}_i, \mathbf{x}_j)$ which implicitly define the transformation and formulated as follows:

$$\mathbf{K}(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{\Phi}_i(\mathbf{x}_i) \cdot \mathbf{\Phi}(\mathbf{x}_j) \tag{9}$$

One of the trick Kernel functions commonly used in the general classification of Support Vector Machines is Radial Basis Function (RBF) which is presented as follows.

$$\mathbf{K}(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{||\mathbf{x}_i - \mathbf{x}_j||^2}{2\sigma^2}\right) \tag{10}$$

Previous studies have already shown that the Radial Basis Function (RBF) Kernel has a better accuracy rate than other Kernels (Caraka et al., 2017). Therefore, it was applied in this research for classification using the Multiclass Support Vector Machine method.

2.5 Multiclass SVM

The Support Vector Machine (SVM) method was first introduced by Vapink only to classify data into two classes. Subsequent research has, however, been conducted to increase its ability to classify data for more than two classes. Moreover, there are two approaches to solve SVM problems for multiclass and the first includes the combination of all data in an optimization problem while the second involves building a multiclass classifier or several binary SVMs. The first approach requires solving a more complex and computationally high optimization problem and this limits its development. Meanwhile, the second such as "One-Against-All" approach is usually used to implement multiclass SVM.

This One-Against-All (OAA) method is usually used to determine the *k* binary SVM models where *k* is the number of classes (Chamasemani and Singh, 2011; Kumar and Gopal, 2011). It also tests p l with all data from the class with label +1 and those from other classes with label -1. An example of a classification problem with five classes and five binary SVMs is presented on Table 1.

 Table 1. OAA Method

$y_i = 1$	y _i = -1	Hypothesis
Class 1	Not class 1	$f_1(x) = (w_1)x + b_1$
Class 2	Not class 2	$f_2(x)=(w_2)x+b_2$
Class 3	Not class 3	$f_3(x)=(w_3)x+b_3$
Class 4	Not class 4	$f_4(x)=(w_4)x+b_4$
Class 5	Not class 5	$f_5(x)=(w_5)x+b_5$

3. RESULTS AND DISCUSSION

This research used painting works data including expressionism, fauvism, naturalism, realism, and romanticism. A total of 420 images on flow of painting were obtained and these include 70 for expressionism, 100 for fauvism, 80 for naturalism, 70 for realism, and 100 for romanticism. These image data were later divided into training and testing samples at different combinations including 90:10, 75:25, 50:50, and 25:75.

Table 2. LBP Value

Data	Value							
	0	1	2	3	4	5		255
Image 1	833	117	99	79	126	49		937
Image 2	676	86	272	85	86	12		807
Image 3	754	110	96	76	95	42		920
:	:	:	:	:	:	:	•	:
Image 420	393	67	.226	110	57	14		603



Figure 1. Prediction Results and The Actual Data

3.1 Result of Feature Extraction Method LBP

Each of the images was resized and converted to a grayscale in the LBP to determine the pixel values at each point. These values were made into threshold and their binary values encoded to produce LBP values for all pixel points in the image. The final result of the feature extraction is presented on a histogram and one image was discovered to have 256 values based on the frequency of occurrence from 0 to 255. These outputs are also indicated in the on Table 2.

The data from the LBP extraction process were used as the input for the classification conducted through the Multiclass Support Vector Machine (MSVM) using the Radial Basis Function (RBF) kernel. The results of the prediction against the actual data for each of the proportions are, therefore, shown in the following graphic images:

Figure 1 shows the 90:10 combination produced predictions which are almost the same as the actual data. Moreover, the classification results for each training and testing data combination were evaluated using a confusion matrix to determine the deviations in the prediction process and the findings are presented as follows.



Figure 2. (a) Confusion Matrix Generated by 90:10 Partitioned Data. (b) Confusion Matrix Generated by 75:25 Partitioned Data. (c) Confusion Matrix Generated by 50:50 Partitioned Data. (d) Confusion Matrix Generated by 25:75 Partitioned Data

Figure 2 shows the correct prediction results are located in the diagonal part of the table. Moreover, the performance of the MSVM classification model was determined based on precision, recall, and accuracy as indicated in Figure 3:



Figure 3. Evaluation Model on Each Data Partition

Figure 3 illustrates the evaluation classification that has been produced by the combination of the LBP method with MSVM to classify the data of works of art in the form of painting. From the four partition combination experiments that is 90:10, 75:25, 50:50 and 25:75 the accuracy, precision and recall values are obtained as shown in Figure 3. From the bar charts, it can be seen clearly that the data partition is 90:10 more has the highest value in terms of accuracy, precision and recall. While the 25:75 data partition has the lowest model evaluation value among the others.

4. CONCLUSIONS

Data analysis and discussion showed that pattern recognition through Local Binary Pattern feature extraction and Multiclass Support Vector Machine were used to classify works of art into five classes which include expressionism, fauvism, naturalism, realism, and romanticism. It was discovered that the classification made by combining training and testing data at 90:10 had an accuracy rate of 83%, 75:25 had 81%, 50:50 had 81%, and 25:75 had 51%. Therefore, the best evaluation of pattern recognition classification in this data case using Multiclass Support Vector Machine with Local Binary Pattern as feature extraction were obtained through training and testing data combined at 90:10. Based on the results of the study, it was concluded that the pattern recognition process using the Local Binary Pattern method for feature extraction and the Multiclass Support Vector Machine method can be used to classify works of art into five classes, namely expressionism, fauvism, naturalism, realism, and romanticism. Therefore, this study needs to be further developed by adding more types of paintings to be used as a novelty verification system for works of art at the stage of filing intellectual property rights.

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