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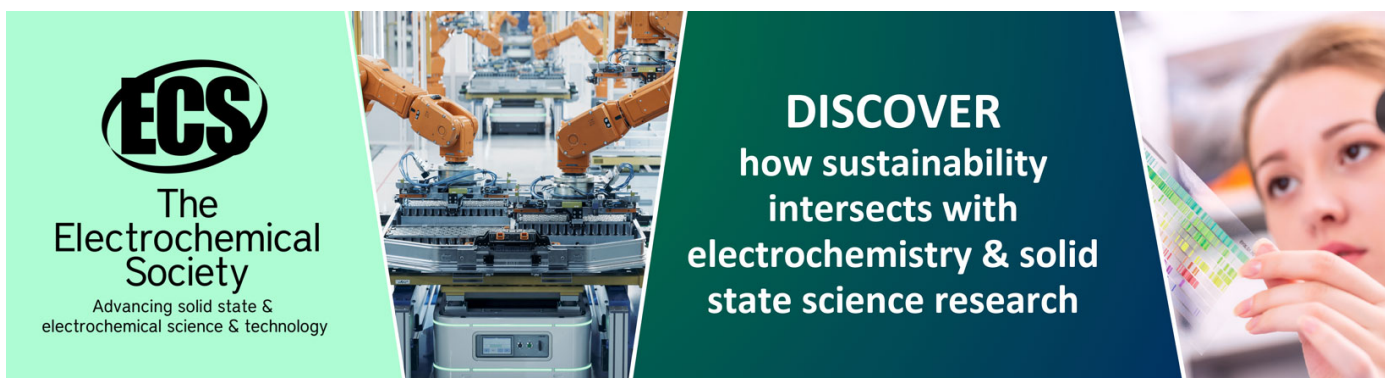
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Application Support Vector Machine on Face Recognition for Gender Classification

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Abstract. Face recognition system is capable of generating a variety of information about a person's identity quickly and accurately. One of them, face recognition is able to provide information about the gender (male or female) of each person. Gender classification has become an area of extensive research due to its increasing application in existing human-computer interaction (HCI) systems, advertising, biometrics, surveillance systems, content-based indexing and searching. This paper presents face recognition for gender classification using Support Vector Machine (SVM). Support Vector Machine are a system for efficiently training the linear learning machines which can be used for as powerful classification methodology. In this research, we have obtained face recognition accuracy rates for gender classification using Support Vector Machine (SVM) with different kernels. When training data were used 40 to 90 percent, SVM method with RBF kernel and also Polynomial kernel has achieved the same maximum accuracy that is 100 percent.

1. Introduction

The human face becomes an important and valuable source of information in the process of face recognition [1]. The proportion and expression of human faces are one of the most influential things to identify origins, expression, age, gender and some social information [2]. Face recognition for gender classification has a major role in a variety of potential applications. In the field of advertising, the gender classification is one of the strategies used to display ads that are relevant to the person viewing the billboard. Then in the biometric field, gender classification is used for the process of identification and access control. Furthermore, the gender classification is useful for limiting the area to only one subject, for example, when in a dormitory or train. In addition, gender classifications are also useful in content-based indexing and search, with the widespread use of electronic devices such as cameras, a large number of digital media are produced. Indexing or records of information about the number of people in the image or video, age and gender will become more noticeable with automated systems that use computer vision. In addition, for content-based searches such as finding a person's photo, classifying gender as a pre-processing step will simplify the search process and can reduce the number of searches required in the database [3]. It is therefore important to do research on gender classification in order to support its role in various fields and to produce an improved level of accuracy.

In the early stages will be collected data in the form of facial images consisting of male and female. Furthermore, the face image will be converted into a matrix form to facilitate the classification process. The classification method used is the Support Vector Machine (SVM). In the final stage will result in a comparison of the level of accuracy or success rate in the process of gender classification



using Support Vector Machine (SVM) with different kernels. In this paper consists of introduction, data, related works, methodology, experiment and results, and conclusion.

1.1 Data

In this research the facial image data used comes from one benchmark face recognition is computer science research projects <https://cswww.essex.ac.uk/mv/allfaces/index.html> [4]. In the database, the available face images are images with the .jpg format and the face images have RGB color. Facial image data used in this study consisted of 10 male and 10 female, with each person having 10 facial images with slight expression differences. So the total image of facial images used as much as 200 images faces with a balanced composition of 100 male face images and 100 images of female faces with the number of features is 15,625.

In this research, training data and testing data were divided randomly. Training data starts from 10 percent to 90 percent. When the training data used 10 percent means the test data used is 90 percent, when the training data used 20 percent means the test data used is 80 percent, when the training data used 30 percent means the test data used is 70 percent, when the training data used 40 percent means the test data used is 60 percent, when the training data used 50 percent means the test data used is 50 percent, when the training data used 60 percent means the test data used is 40 percent, when the training data used 70 percent means the test data used is 30 percent, when the training data used 80 percent means the test data used is 20 percent, so until the training data used is 90 percent means the test data used is 10 percent.

1.2 Related Works

1.2.1 Supervised Learning

The learning method that maps input to output based on the example is called supervised learning. The input and output pairs are referred to as training data. In the process, data is labelled to facilitate customized goals or outputs. In general, supervised learning aims to predict the value of response variables or labels based on the variables or features inputted [5]. Supervised Learning is usually used in classification, approximation, control, modelling, signal processing and identification [6]. Grouping of men and women on the basis of facial recognition is a classification problem, so supervised learning is an appropriate type of learning for use in this research.

1.2.2 Support Vector Machine (SVM)

Support Vector Machines (SVM) is a learning approach originally developed by Vapnik and colleagues. Support Vector Machines (SVM) is a data-learning method based on statistical learning theory. This method belongs to the category of supervised learning used to predict both classification and regression. The SVM mechanism is to find an optimal classifier function that can separate two sets of data from two different classes. Basically, there are many separating fields that can separate data from two different classes but there is only one separating field that can optimally separate the data and minimize misclassification. The optimal classifier field is called hyperplane. This hyperplane can be found by maximizing the margin. Margin is the perpendicular distance between the hyperplane and the closest data of each class. Data from each class close to the hyperplane is called a support vector [7]. It was once discussed on [10-14]

Suppose a given set of data pairs $\{\mathbf{x}_i, y_i\}_{i=1}^N$ with x is the input vector in the form of a row vector and $x \in R^D$ so that $\mathbf{x}_i$ is the input vector of the sample, and dimension D (number of features), then $y \in \{-1, +1\}$ is a class label for each data sample. The point x on the hyperplane satisfies the following equation [8]:

$$f(x) = \langle \mathbf{w}, \mathbf{x} \rangle + b = 0 \quad (1)$$

with w representing a vector perpendicular to the hyperplane or referred to as a normal vector, and b is a constant which is a bias parameter, $\frac{|b|}{\|w\|}$ is the perpendicular distance between the points on the hyperplane (H) to the origin, and $\|w\|$ is the Euclidean norm of w [9]. The optimal hyperplane (H) will divide the data into positive and negative classes, assuming that all training data satisfies the following equations [8]:

$$\langle w, x_i \rangle + b \geq 1 \text{ for a positive sample} \quad (2)$$

$$\langle w, x_i \rangle + b \leq -1 \text{ for a negative sample} \quad (3)$$

The form of inequality can be rewritten as follows:

$$y_i(\langle w, x_i \rangle + b) - 1 \geq 0 \quad (4)$$

To get the optimum hyperplane can be done by completing the following functions:

$$\min \left[\frac{1}{2} \|w\|^2 \right] \quad (5)$$

with constraints

$$y_i(\langle w, x_i \rangle + b) \geq 1, y_i \in \{-1, 1\}, i = 1, 2, \dots, N \quad (6)$$

The following are defined lagrange functions:

$$L(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^N \alpha_i [y_i(\langle w, x_i \rangle + b) - 1] \quad (7)$$

Here are the conditions of Karush-Kuhn-Tucker (KKT) that must be fulfilled:

$$(y_i(\langle w, x_i \rangle + b) - 1) \geq 0 \quad (8)$$

$$\alpha_i (y_i(\langle w, x_i \rangle + b) - 1) = 0 \quad (9)$$

$$\alpha_i \geq 0, i = 1, 2, \dots, N \quad (10)$$

Thus, obtained the dual Lagrange form of the primal optimization problem as follows:

$$\max \left(\sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle \right) \quad (11)$$

with constraints

$$\alpha_i \geq 0 \quad (12)$$

$$\sum_{i=1}^N \alpha_i y_i = 0 \quad (13)$$

2. Method

There are several face recognition steps for male and female classification:

- Face Image Collection: collection of facial images consisting of male and female
- Digital Image Pre-processing: the data in the form of accumulated facial images is converted into matrix form in order to process
- Training and Classification: male or female

3. Results and Discussion

In this study used an image of a facial recognition dataset. In the dataset there are some face image folder that is faces94, faces95, faces96, and grimace. In this research using facial recognition dataset from folder faces94. The data used amounted to 200 face images. The collection of face images consists of 100 male faces and 100 female face images with JPG image format and 180 x 200 dimensions. This data collection technique is known as image acquisition. Then, do image pre-processing, the image of the face dimension 180 x 200 or portrait shaped converted into square shape with the dimensions of the image 125 x 125. After the image of the face is square, the image of the face with JPG format is converted into a form of matrix by using the algorithm built in *Matlab* program with the aim to facilitate the next process. The next stage is training, which is part of the classification process. From this training process we can get a predictive parameter and model. So, we can classify the data testing appropriately and get the smallest possible errors.

Classification is a grouping problem based on training. In this research, the classification method used is Support Vector Machine (SVM). To classify the data testing, we must get the optimum hyperplane that can separate the two classes. Suppose a sample will be classified on a particular class, the sample is in pairs (x_i, y_i) , where x_i is the input and y_i is the output. Thus, the classification of two classes is a learning problem for finding a function that can map every x_i to y_i , with y_i consisting of only two values or two classes. Hyperplane is defined as follows $w \cdot x + b = 0$ with w is the weight vector, b is the bias parameter, and x is the point located on the hyperplane. After the classification is done, then the next stage is to evaluate. This evaluation is useful to know how well the performance of a classification program we have built. Evaluation can be seen from how much data testing is correctly classified and how much data testing is misclassified. The evaluation can be done with a confusion matrix. Then we can calculate the level of accuracy with the following formula:

$$accuracy = \frac{\text{number of correct predictions}}{\text{number of predictions}} \times 100\% \quad (14)$$

The test results in this research is a level of accuracy obtained from the classification process of Support Vector Machine (SVM) by using RBF kernel and Polynomial kernel. Test results will be presented in tabular form.

The following is a trial result using all features that is 15625 features, classification process using Support Vector Machine (SVM) method with RBF kernel ($\sigma = 0.05$) and classification process using Support Vector Machine (SVM) method with Polynomial kernel ($d = 5$). Training data and testing data were divided randomly, training data diverse from 10 to 90 percent.

Table 1. Accuracy Result of Gender Classification using SVM with kernel: Polynomial, parameter: constantly 5 and using SVM with kernel: RBF, parameter: constantly 0.05, training data: diverse from 10 to 90

Training Data (%)	Polynomial ($d = 5$)	RBF ($\sigma = 0.05$)
	Accuracy (%)	Accuracy (%)
10	88.88889	85.55556
20	95.625	87.5
30	95.714	85.71429
40	100	100
50	100	100
60	100	100
70	100	100
80	100	100
90	100	100

Based on the results presented in Table 1, it can be seen when using SVM with kernel Polynomial that the best accuracy result is 100 percent obtained when the training data used is 40 to 90 percent. When training data is used 10 to 30 percent, the accuracy is 88 to 95 percent. Next, based on the results presented in Table 1, it can be seen when using SVM with kernel RBF that the best accuracy result is 100 percent obtained when the training data used is 40 to 90 percent. When training data is used 10 to 30 percent, the accuracy is 85 to 87 percent.

4. Conclusion

In this research, we have classified gender using Support Vector Machine (SVM) method with RBF kernel ($\sigma = 0.05$) and Polynomial kernel ($d = 5$). When training data were used of 10 to 30 percent, the SVM method with the polynomial kernel ($d = 5$) has better accuracy than the SVM method with the RBF kernel ($\sigma = 0.05$). Furthermore, for training data 40 to 90 percent, SVM method with RBF kernel ($\sigma = 0.05$) and also polynomial kernel ($d = 5$) has achieved the same accuracy that is 100 percent.

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