STUDY ON THE INFLUENCE OF PCA PRE-TREATMENT ON PIG FACE IDENTIFICATION WITH SUPPORT VECTOR MACHINE (SVM)
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PCA 前处理对 SVM 识别猪脸的影响研究

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ABSTRACT
To explore the application of traditional machine learning model in the intelligent management of pigs, in this paper, the influence of Principal Components Analysis (this method is simply referred to as PCA) pre-treatment on pig face identification with Support Vector Machine (this method is simply referred to as SVM) is studied. By testing method, the kernel functions of two testing schemes, one adopting SVM alone and the other adopting PCA+SVM, were determined to be poly and Radial Basis Function, whose coefficients were 0.03 and 0.01, respectively. With individual identification tests carried out on 10 pigs respectively, the identification accuracy was increased to 88.85% from 83.66% by the improved scheme, also the training time as well as testing time were reduced to 30.1% and 20.97% of the original value in the earlier scheme, respectively. It indicates that PCA pre-treatment had a positive effect on improving the efficiency of individual pig identification with SVM. It provides experimental support for the mobile terminals and embedded application of SVM classifiers.

摘要
为探索传统机器学习模型在生猪智能管理中的应用，本文研究了 PCA 前处理对 SVM 识别猪脸的影响，采用试验方式分别确定仅采用 SVM 以及 PCA+SVM 两种试验方案的核函数为 poly、RBF，其系数为 0.03、0.01，分别对 10 头生猪进行个体识别试验，优化方案将识别准确率从 83.66%提高到 88.85%，训练时间和测试时间缩减为原来的 30.1%、20.97%，结果表明，使用 PCA 前处理对采用 SVM 进行生猪个体识别的效率具有增益作用，可为 SVM 分类器的移动端和嵌入式应用提供试验支持。

INTRODUCTION
The management of individual identification and behaviour analysis of pigs, an important part in the intelligent management of pigs, can be divided into three categories: the first category is based mainly on RFID (Radio Frequency Identification) technology *(Maselyne et al., 2014; Hahnel et al., 2016)*, while the second category is based mainly on traditional machine learning model: LASSO (Least absolute shrinkage and selection operator). Regression and random forest model were used to predict the weight of pigs at 159 days to 166 days under four scenarios *(He et al., 2021)*; random forest and generalized linear regression were used to predict physiological temperature of piglets, though the prediction error was relatively high *(Gorczyca et al., 2018)*; auto-regression model (AR) and improved local linear embedding (LLE) were used to estimate pig weight in actual farm environment *(Wongsriworaphon et al., 2015)*. The third category is based mainly on the application of deep learning model and improved computer vision technology. Tu Shuqing et al. explored a PigMS R-CNN (Region Convolutional Neural Networks) framework based on mask scoring R-CNN (MS R-CNN) to segment the adhesion regions in images for herd pigs as well as identify and locate them *(Tu et al., 2021)*. Zhang Jianlong et al. modified DenseNet201, ResNet152 V2, Xception and MobileNet V2 to be a multi-output regression CNN (Region Convolutional Neural Networks) before getting them trained on modelling data, and modified Xception was selected as the optimal estimation model. In order to improve the real-time performance of the model, Residual learning structure was introduced in, with its MSE (Mean Squared Error) reaching 0.092 *(Zhang et al., 2021)*.

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Cheng et al. used the deep learning algorithm of recurrent neural network with few layers to identify pigs' preferences for objects. With the full connection layer and Softmax classifier, pigs' preferences were recognized, and the identification accuracy was high; convolutional neural network as well as Long and short term memory Network (LSTM) were combined to identify pigs' aggressive behaviours, with the accuracy reaching 97.2%, though the operation efficiency was only 15 fps *(Cheng et al., 2020)*. To better the interpretability and controllability of the model, Mathieu Marsot et al. used the cascade classifier with Haar features to intuitively see how neural network learns to distinguish parameters by using the category activation diagram generated by Grad-CAM (Gradient-weighted Class Activation Mapping), with an accuracy for 320 test images reaching 83% *(Marsot et al., 2020)*. With GPU being applied, the high precision advantage of computer vision technology has gradually been revealed. In the management of small and medium-sized farms, the needs for mobile terminals and embedded apps has gradually been increasing. For the deep learning model has a high requirement to hardware, it is difficult to adapt to wide application, while the RFID technology is easy to be simulated in the management *(Shi et al., 2012; Zhou et al., 2018)*, also it violates the animal welfare breeding thinking, so it has been gradually eliminated. Only the requirements to hardware by traditional machine learning model conform to the standards for mobile terminals and embedded apps, though there is still room for improvement in its identification accuracy and running time. With principal component analysis, the main features of the images to be tested can be extracted, thus reducing the computation burden, improving operation efficiency, eliminating noise interference and improving identification accuracy.

To promote the application of traditional machine learning model in mobile terminals and embedded apps, in this paper, SVM is adopted for improving the pig face identification efficiency in this study, and its influence on the efficiency of pig face identification is further studied by adding PCA pre-treatment in, which provides experimental support for its application in both mobile terminals and embedded application.

MATERIALS AND METHODS

Sample collection

As shown in Fig.1, the experimental materials of this study were collected on a small farm in Dongsongjiazhuang Village, Jicun Town, Fenyang City, Shanxi Province, China (111º95′ E, 37º26′ N), and the sampling date was in June 2019. Pictures of a total of 10 pigs were collected, including 768 training samples, 85 validation samples and 258 test samples.

Fig.1 - Pig Samples

The computer used in the experiment is configured with 64-bit windows system, Intel Core i7-6700, 8GB memory, 6GB video memory capacity, and Program development uses python v3.5 version language.

Principle of pig face identification with SVM

Support vector machine (SVM) is a machine learning method based on structural risk minimization that is based on statistical learning theory. According to the finite sample information, it seeks the best compromise between the model complexity and the ability to learn to obtain the best generalization ability. In addition, in the process of learning, no shortcomings such as over-fitting and local minimization are there. Thus, it has been widely used in practical identification and control *(Alex et al., 2004; Suykens et al., 1999; Suykens et al., 1999; Suykens et al., 2001)*.

SVM, whose model is related to neural network, classifies by constructing N-dimensional hyperplane. In fact, SVM model adopting S-shape kernel function is equivalent to a two-layer perceptron neural network. In SVM, kernel alternative training methods, in which include polynomial functions, radial basis functions and multi-layer perceptual classifiers, are used. Solution of their network weight is then transformed into the optimization of quadratic programming with linear constraints. With this transformation, it can be ensured that the parameters are the same when two functions get their optimal solutions. The main reason for making this transformation is that mature calculation methods and theoretical support, namely Lagrange optimization theory, are there for quadratic convex functions and constraints. In essence, SVM aims to find a predictive variable called attribute and a transform attribute of hyperplane called feature *(Du et al., 2006)*, also known as feature selection. SVM model has achieved to find the optimal hyperplane, which separates vector clusters in a certain way, and the vectors on different sides of the hyperplane are classified into different categories, while the vectors near the hyperplane are support vectors. SVM was invented by Vapnik *(Vladimir et al., 1979)* in 1979. In its linear form, SVM is a hyperplane that separates a set of positive instances and negative instances. With a maximum margin, it does not minimize training errors. Instead, it minimizes the upper limit of the generalization error and maximizes the margin between the separating hyperplane and the training data.

The key to the classification problem is that to separate the positive and negative instances, it is necessary to set up a traditional classifier. If the data point in the training set is a vector for m numbers, then the task of this kind of classifier is to find a hyperplane that may separate its members, though always linear inseparable data are there, which means that there may be no hyperplane, which can then be solved by SVM classifier nonlinear kernel function. In it, the space of its input instance x⊂R^n is mapped to the high-dimensional feature space, so that the optimal separating hyperplane built on this space has good generalization ability. SVM can select the plane with the maximum margin in the training set, so that it has the maximum generalization ability when unknown data are classified.

For the linear case, the margin is defined by the distance from the hyperplane to the nearest positive and negative instances, and the output formula for linear SVM is

$$u = w \times x - b \tag{1}$$

where: w represents Normal vector to the hyperplane, [dimensionless];
p represents the Input vector, [dimensionless];
b represents threshold for classification, [dimensionless].

For separating hyperplane, the plane u = 0 and the nearest point is on the plane where u = +1 and u = -1. The margin is

$$m = \frac{1}{\|w\|^2} \tag{2}$$

where: w represents normal vector to the hyperplane, [dimensionless];
m represents the margin of the hyperplane, [dimensionless].

SVM can be further extended to nonlinear classifiers. Lagrange multiplier is adopted to calculate the output of nonlinear SVM

$$u = \sum_{j=1}^{N} y_j a_j K(x_j, x) - b \tag{3}$$

where: K represents function used to measure the similarity or distance between input vector x and all training vectors x_j,[a];
y_j represents the classification tag of the training vector x_j, [dimensionless];
a_j represents the Lagrange multiplier for the j[th] sample, [dimensionless];
b represents the threshold for classification, [dimensionless];
j represents the sample size, [a];
u represents discriminant function, [dimensionless].

In this study, SVM was adopted to realize pig face classification, which is a multi-classification problem. According to its guiding principles, two SVM multi-classification methods are there:

(1) Multi-class identification tasks can be realized by multiple binary classification SVM, and the output result is determined jointly by the results of multiple SVM solutions.

(2) The initial optimization of SVM is changed in some way so that SVM can calculate the multi-classification decision functions to complete the multi-classification task.

This assorting thought was adopted in this study to realize the classification of pig face data. Thus, the original problem as listed above can be rewritten as:

$$min: 1/2\sum_{m=1}^{k}||w_m||^2 + C\sum_{i=1}^{n}\sum_{m\neq y_i}\xi_i^m \quad (4)$$

where: i represents the sample size, [a];

w represents normal vector to the hyperplane, [dimensionless];

m represents the number of categories, [a];

y_i represents the classification tag of the training vector x_i, [dimensionless];

ξ_i represents the Lagrange multiplier for the i[th] sample, [dimensionless].

$$S.T.(w_i \cdot x_i) + b_i \geq (w_m \cdot x_i) + b_m + 2 - \xi_i^m, \quad (5)$$
$$\xi_i^m \geq 0$$

where: i represents the sample size, [a];

w represents normal vector to the hyperplane, [dimensionless];

m represents the number of categories, [a];

x_i represents the i[th] sample, [dimensionless];

b represents the threshold for multiple-classification, [dimensionless];

ξ_i represents the Lagrange multiplier for the i[th] sample, [dimensionless].

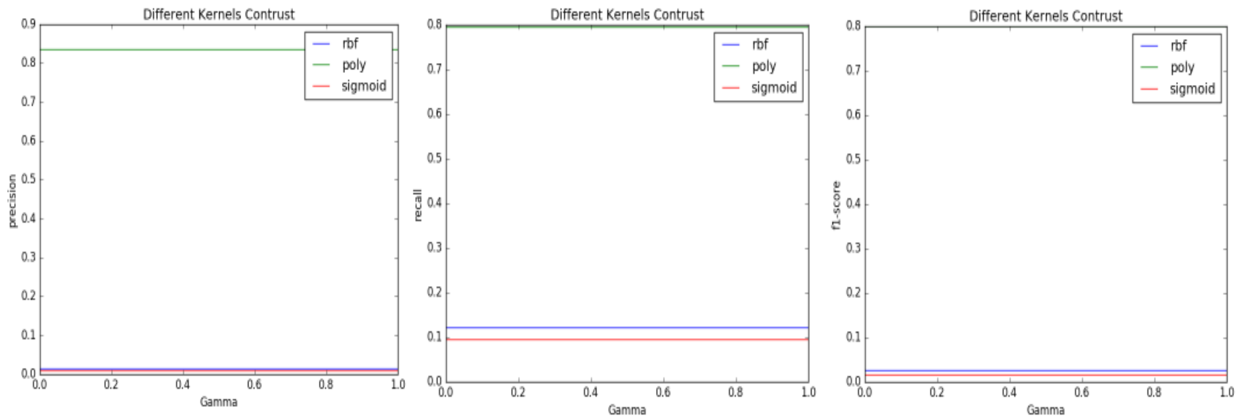
Thus, the decision function $f(x) = max\,[(w_i \cdot x_i) + b_i]$ can be obtained, and the discriminant result is for the i^{th} category.

COMPARISON PROCESS IN THE EXPERIMENT

Pig face identification test carried out with SVM alone

SVM model parameter determination

When SVM is used to have pig face data classified, the determination of its kernel function and coefficient is the key to the establishment of an SVM classifier model. In this study, to select the optimal kernel function and its coefficient, the performance of different kernel functions under different coefficients was tested. The RBF radial kernel function, the polynomial kernel function called poly as well as sigmoid kernel function of SVM were selected respectively to ensure that its kernel function coefficient Gamma changes within the range of 0.0~1.0. The curves for classification accuracy, recall rate and *f1* value changing were drawn respectively, as can be seen in Fig. 2.



a. accuracy *b. recall rate* *c. f1 value*

Fig. 2 - The relationship between the evaluation index of SVM model and its kernel function and coefficient

Fig. 2a shows the relationship between the kernel function coefficient Gamma and the classification accuracy. The blue line represents the RBF radial kernel function, while the green line represents the polynomial kernel function called poly, and the red line represents the sigmoid kernel function.

As can be seen from the figure, the three curves were basically smooth and steady, which means that the value of the kernel function coefficient Gamma had little correlation with the classification accuracy. The accuracy of the polynomial kernel function called poly reached 82%, while the accuracy of RBF radial kernel function and sigmoid kernel function was about 1%. Fig. 2b shows the relationship between the kernel function coefficient Gamma and classification recall rate. As can be seen from the figure, compared with the RBF radial kernel function and sigmoid kernel function, the polynomial kernel function called poly had a higher recall rate for pig face data and the identification effect was better. Fig. 2c shows the relationship between the kernel function coefficient Gamma and *f1* value. It can be seen from the figure that the polynomial kernel function called poly had the best classification effect on the pig face data. With all these factors taken into consideration, in this experiment, the polynomial kernel function called poly was adopted as the kernel function for SVM.

Evaluation index of SVM model

By using the parameter determined by the above test, or the polynomial kernel function called poly selected as the kernel function for SVM, the kernel function coefficient was determined to be 0.03 before it was tested on the test set. A confusion matrix was obtained according to the test results, as shown in Fig. 3.

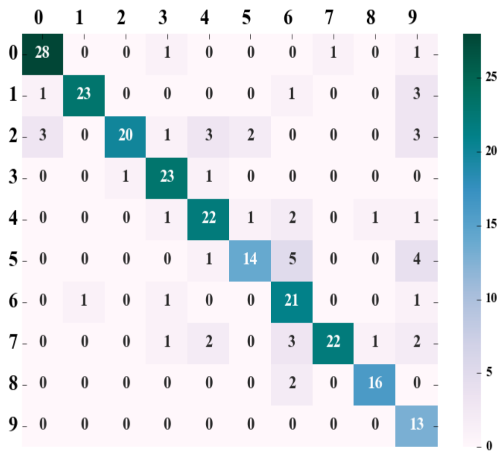


Fig. 3 - SVM prediction result confusion matrix

The leftmost column of the confusion matrix represents the real category, the top row represents the predicted category, and the diagonal line represents the number of correct predictions. The precision, recall and *f1*-core values of ten different pigs were obtained respectively in accordance with the confusion matrix and formulas (6) ~ (8), as shown in Table 1, the precision ratio was defined as:

$$precision = \frac{TP}{TP + FP} \tag{6}$$

Recall ratio was defined as:

$$recall = \frac{TP}{TP + FN} \tag{7}$$

Recall ratio was also called recall rate. Recall ratio and precision ratio changed in opposite trend. The $f1$-score can measure the different preferences of these two indexes, and the formula was as follows:

$$f1 - score = 2 \times \frac{precision \times recall}{precision + recall} \tag{8}$$

where: TP represents the number of positive samples that are actually positive samples, [a];

FP represents the number of positive samples that are actually negative samples, [a];

FN represents the number of negative samples that are actually positive samples, [a].

Table 1

SVM model prediction performance table

Category	Precision [%]	Recall [%]	*f1*-score [%]	Count [a]
1	88	90	89	31

Table 1
(continuation)

Category	Precision [%]	Recall [%]	*f1*-score [%]	Count [a]
2	96	82	88	28
3	95	62	75	32
4	82	92	87	25
5	76	79	77	28
6	82	58	68	24
7	62	88	72	24
8	96	71	81	31
9	89	89	89	18
10	46	100	63	13
average	83.66	79.53	79.95	25

As can be seen from Table 1, the average accuracy of classification and identification of pig face data with SVM adopted reached 83.66%, with the recall rate and the *f1* value reaching 79.53% and 79.95%, respectively.

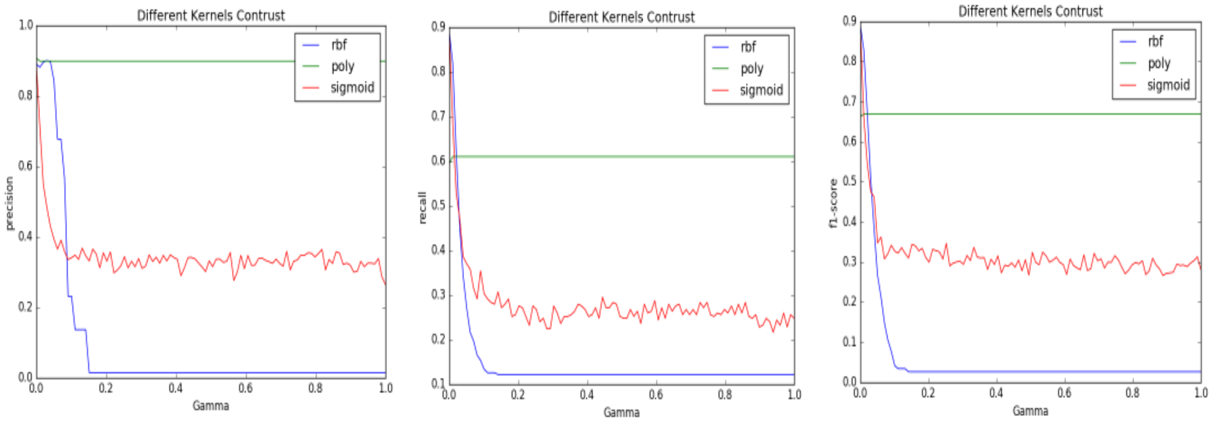
Experiment of pig face identification with SVM + PCA pre-treatment

Determine the *k* value in principal component analysis

At the first stage of the experiment, the number of principal components needs to be determined for principal component analysis. Here the *k* value was taken as 300, with the variance explanation rate reaching over 95%.

Determination of SVM parameters in the optimization plan

Determining the kernel function and the coefficient for support vector machine (SVM) is the key to the establishment of a SVM classifier model. After going through PCA treatment, the data distribution of the pig face images may change in the same way. That is to say, to continue the test with the parameters determined in the above test, it is possible that the optimal result cannot be obtained. That is to say, the kernel function and the coefficient for SVM model needs to be re-determined. With the testing method in "**SVM model parameter determination**" adopted, the kernel function and coefficient for SVM, whose input is the pig face image going through PCA treatment, is determined. The performances under different kernel functions and coefficients were compared, and their relationship is as shown in Fig. 4.



a. accuracy *b. recall rate* *c. f1 value*

Fig. 4 - The relationship between SVM model performance and parameters after pre-PCA processing

In Fig. 4a, the abscissa shows the coefficients for polynomial kernel function, radial basis kernel function and Sigmoid kernel function, the value for which is within the range of 0.0~1.0, while the ordinate shows the precision whose value is also within the range of 0.0~1.0.

As can be seen from the figure, the polynomial function reached a smooth and steady state quickly, and its precision remained to be at 0.91 as the coefficient increased. The precision of the radial basis kernel function decreased slightly when the coefficient was very small, for which the reason is that when the RBF coefficient was so small, the kernel function could fit all data points, thus over-fitting occurred; though after a slight decrease, it started to rise again, and when the coefficient was 0.01, it reached the maximum, and when the coefficient was over 0.01, it decreased rapidly. The accuracy rate decreased to the lowest---close to 0 when the coefficient was about 0.18. The precision of sigmoid kernel function decreased rapidly as the coefficient increased. When the coefficient was close to 0.05, the precision dropped to about 0.39 and was in an oscillating state. It can be concluded from the above analysis that polynomial kernel function and radial basis kernel function should be selected, and the coefficient shall be 0.01. As the precision for RBF function exceeds that for polynomial kernel function, priority was given to RBF function.

It can be seen from Fig. 4b and Fig. 4c that recall and *f1*-score showed basically the same trend. When the coefficient was very small, their values were relatively high, close to 0.9, though the recall value of polynomial kernel function remained unchanged at 0.61, while the *f1*-score value was a little larger, it remained unchanged at 0.68. The recall and *f1*-score of RBF and polynomial kernel decreased rapidly as the coefficient increased. Recall and *f1*-score reached the lowest values when the RBF coefficient was about 0.1, and they remained unchanged as the coefficient increased. At this time, the precision value was below 0.2, which means that the prediction was meaningless for practice. The performance curve of sigmoid kernel function was in an oscillating state when the coefficient was about 0.05, with recall value remaining around 0.3 and *f1*-score value around 0.35.

With the accuracy, recall rate and *f1* value all considered, when the RBF kernel function coefficient was close to 0.01, the classification performance reached optimum. Therefore, in this paper, the kernel function was taken as RBF and the coefficient 0.01 was selected as a parameter for the SVM validation set to be tested.

Model evaluation index of optimization plan

With the parameters determined in the training set, or RBF selected as a kernel function for SVM, used, the coefficient was taken as 0.01 for the test to be carried out on the verification set. With the prediction accuracy, recall rate and *f1* value of each category calculated, the confusion matrix was drawn, as is shown in Fig. 5.

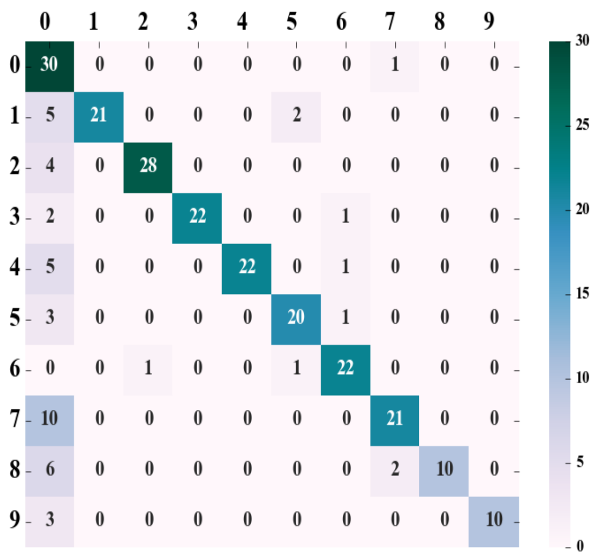


Fig. 5 - PCA+SVM prediction result confusion matrix

The precision, recall and *f1*-core values of 10 different pigs were obtained in accordance with the confusion matrix and formulas (6) ~ (8), as shown in Table 2.

Table 2

PCA+SVM model prediction performance table

Category	Precision [%]	Recall [%]	$f1$-score [%]	Count [a]
1	44	97	61	31
2	100	75	86	28
3	97	88	92	32
4	100	88	94	25
5	100	79	88	28
6	87	83	85	24
7	88	92	90	24
8	88	68	76	31
9	100	56	71	18
10	100	77	87	13
average	88.85	81.10	82.69	25

SVM classifier with PCA pre-treatment adopted was used for individual pig identification, which not only improved the identification accuracy but also reduced the training time as well as testing time of the model. The specific test indexes for the two schemes are as shown in Table 3.

Table3

The optimization result of SVM model by PCA pre-processing

model	precision [%]	precision change	test_time [ms]	test_new/ old[%]	train_time [ms]	traintest_ new/old[%]
SVM	83.66		329		12,823	
PCA+SVM	88.85	+5.19	69	20.97	3,861	30.10

RESULTS AND DISCUSSION

As can be seen in Table 2, the classification effect of PCA+SVM classifier is significantly better than that of SVM classifier alone, with the accuracy of the 2nd, 4th, 5th, 9th and 10th categories reached 100% in accuracy while the average accuracy was 88.85%. As can be seen in Table 3, for PCA+SVM scheme, the training time was 3,861 ms, the identification time was 69 ms, while the corresponding indexes for the SVM classifier alone scheme were 83.66%, 12,823 ms and 329 ms respectively. With PCA+SVM scheme employed, the accuracy of the classification test got improved by 5.19 percentage points, while its training time and the identification time were only 30.1% and 20.97% of the SVM classifier alone scheme, respectively. Although the identification accuracy was increased by only 5.19 percentage points, it was difficult to improve from 83.66% to 88.85%. The operation efficiency of the algorithm was obviously improved, and the identification time was only 20.97% of that of SVM classifier alone scheme. This provides theoretical support for the embedded application of the algorithm.

The operating efficiency of the algorithm got improved mainly for three reasons: first, after features of pig face samples were selected via principal component analysis, features participating in calculation were reduced, thus reducing the amount of calculation, which means that the running time of the algorithm was bound to get reduced; second, while the main features were selected via PCA, the secondary features were filtered, also the noise interference was eliminated, thus there would be no over-fitting in the model training, which was beneficial to not only the reduction of running time but also the improvement of identification accuracy, as has been verified by the experimental results; third, for PCA treatment, indeed additional time cost was needed, though the additional time cost can almost be ignored considering the overall operating efficiency of the algorithm. This method can be used to identify pigs through their face pictures, improve the efficiency of identification by adding PCA pre-processing, and realize the personalized feeding of pig breeding more effectively, so as to provide a reference for intelligent pig breeding.

CONCLUSIONS

In this paper, the influence of PCA pre-treatment mode on the efficiency of identification of 10 different pigs with SVM classifier was studied. The kernel function and the coefficient of the classifier were determined via tests. With the influence of two test schemes on identification efficiency compared, in which one adopting the SVM classifier alone and the other adopting PCA+SVM, we got the following conclusions:

(1) When SVM classifier was used for individual pig identification, the selection of kernel function was related to the pre-treatment method. When the SVM alone scheme was adopted, the poly function was appropriate and the coefficient shall be 0.03; while the PCA+SVM scheme was adopted, RBF function was appropriate, and the coefficient shall be 0.01.

(2) PCA pre-treatment can benefit the efficiency of individual pig identification with SVM adopted, with the accuracy increasing to 88.85% from 83.66%, and the training time as well as testing time reduced to 30.1% and 20.97% of the original values respectively.

(3) This method can improve the recognition accuracy and reduce the recognition time, SVM classifier going through PCA pre-treatment is more suitable for mobile terminals and embedded application, and it can improve the efficiency of intelligent pig breeding.

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