Evaluation model for water environment of Eriocheir sinensis ponds based on AdaBoost classifier

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Abstract: In the industry of pond culturing of Eriocheir sinensis, water environment has been exerting great impact on the survival and growth ability of crabs, so it is of great significance to evaluate whether the water environment is suitable for the growth of crabs in every culturing stage. In this paper, we associated the vast water environmental data and the yield of Eriocheir sinensis pond culturing, and proposed evaluation models for water environment in crab farming based on AdaBoost classifier. We started by extracting the features of water temperature and dissolved oxygen data based on the improved support function. Then the classification model was established using the recapture rate, average weight of the captured crabs and per mu yield as the labels based on AdaBoost algorithm, and the feature dimension was reduced using Linear Discriminant Analysis to simplify the model. Finally, the pond water environment was evaluated according to the classification results and the results of the classifiers were compared. The models were verified with the experiments using the water environmental data and the corresponding yield data that have been gathered in Yixing City, Jiangsu Province from 2014 to 2016. The results showed that the models could well evaluate whether the aquatic environment is adapted to the growth of crabs in every culturing stage and provide the basis for making decisions during the culturing process of Eriocheir sinensis.

Keywords: culturing of Eriocheir sinensis, evaluation, water environment, yield, AdaBoost algorithm

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1 Introduction

The Chinese mitten crab Eriocheir sinensis has good nutritional and economic values and is very much welcome by people in Chinese aquatic product market. In 2016, more than 10 million mu of Eriocheir sinensis were raised in China, with an annual output of more than 800 thousand tons (Cheng, 2016). However, with the development of crab industry, there are still some problems such as high breeding costs, great disease risks, and low culturing profits. Water environment is the basic condition for the survival of Eriocheir sinensis and influences their growth (Yuan et al., 2017), so it is of significance to evaluate whether the water environment is suitable for the growth of crabs in every stage of Eriocheir sinensis culturing cycle. The existing methods of constructing water environment evaluation model are mainly expert interviews, questionnaire surveys, on-site investigations and so on (Liu et al., 2011; Shi et al., 2013), but lack of joint analysis of the data from production process and yield. In this paper, we associated parameters of water environment that had been collected by Internet of Things (IOT) in crab pond farming with yield data such as the recapture rate, average weight and per mu yield and constructed the evaluation models for water environment of crab pond, which can evaluate the water environment in each stage of crab culturing, provide assistant information for making production decisions, and benefit for production improvement.

Nowadays, domestic and foreign researches have been carried out on many aspects of the water environment of crab farming. The environmental parameters of aquaculture have some influences on the physiology of Eriocheir sinensis. Fialho et al. (2016) conducted a controlled trial and concluded that in suitable

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temperature range, the higher the temperature comes, the more numbers of times the crabs molt, the more quickly the crabs grow. Gu et al. (2015) demonstrated that the linear correlation coefficients between the average weight of crabs and the water temperature are more than 0.9. Qiu et al. (2011) found that the dissolved oxygen content of water environment affects the reproduction, feeding rate and weight gain rate of crabs. Liu et al. (2011) used expert survey, DELPHI, field research and other methods to analyze the factors influencing water quality of fresh water aquaculture pond and selected five key factors as indexes to establish the water quality evaluation index system. Zhou et al. (2013) detected six crab ponds' breeding condition, carrying capacity and yield in different periods and obtained the non-linear relationship among carrying capacity, yield, feeding quantity and total nitrogen of the water using multiple regression. Li et al. (2015) analyzed and compared the water plants density, water temperature, pH-value, dissolved oxygen, recapture rate, average weight and per mu yield of four farmers' pond, drawing the conclusion that the coverage rate of aquatic plants should be controlled from 50% to 70%.

AdaBoost is a popular ensemble learning algorithm, which trains multiple weak classifiers with different training sets, and then combines these classifiers to form a final strong classifier. The advantages of multiple classifiers combination are that of lowering the requirement and simplifying construction difficulty of a single classifier (Zhou et al., 2016; Kim et al., 2008; Natesan et al., 2012). Some researchers have applied the AdaBoost algorithm to aquaculture, for instance, Liu et al. (2017) took the Penaeus vannamei as the research object, and proposed a recognition method for moving larval shrimp based on the improved PCA (Principal Component Analysis) and AdaBoost algorithm. Hao et al. (2015) quantified the behavioral parameters of young crabs under normal and abnormal salinity using image processing technology and established a salinity prediction model using support vector machine and BP-AdaBoost algorithm.

From the analysis above, it is an important measure for improving the production efficiency of crabs that evaluating whether the aquatic environment of each culturing stage is suitable for the growth of crabs, however, the research of the joint analysis and modeling of the data from actual production process of crab culturing and the data of yield is limited because of lacking of data. In order to describe the features of the water environment in each culturing stage, we made the feature extraction from the water temperature and dissolved oxygen data to establish an evaluation model for water environment more quickly and accurately. AdaBoost algorithm was used to construct the model to classify pond water temperature and dissolved oxygen. This paper made the following contributions: (1) the features of water environment parameters in Eriocheir sinensis ponds was extracted using weighted average method based on improved support function; (2) we associated the vast water environment data collected by the IOT with the yield data and constructed evaluation models for Eriocheir sinensis ponds according to the water environmental features, recapture rate, average weight and per mu yield.

2 Construction of evaluation model

2.1 Overall process

We proposed evaluation models for aquaculture environment of Eriocheir sinensis pond based on the existing research results of water environment of crab culture. Figure 1 shows the overall process.

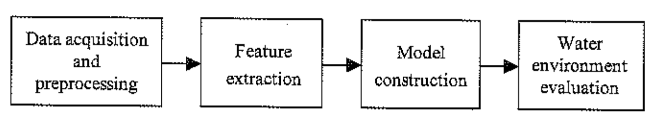

Figure 1 Overall process of evaluation model construction

Data acquisition and preprocessing: Water environmental parameters and the data of yield were collected. The water environmental parameters of culturing process, mainly include water temperature and dissolved oxygen, were collected through IOT. The data were cleaned using a detection method based on sliding window and support vector regression (Duan et al., 2017). Moreover, the abnormal values were eliminated and the missing values were filled. Yield data refer to the recapture rate, average weight and per mu yield of the crabs were also collected.

Feature extraction: Daily, multi-day and abnormal water environment features were extracted and the feature vectors were constructed.

Model construction: The feature vectors constructed above were used as an input and the yield data were used as labels to construct the classification models. Then the water environmental features were reduced to low dimensions to simplify the models.

Water environment evaluation: Water environment was evaluated according to the water environmental classification results

2.2 Feature extraction

The sampling period of IOT for aquatic product is usually 5 minutes or 10 minutes. The water environmental data are of large amount and change in a smooth range in a relatively short period of time. Therefore, it is reasonable to find values to represent the features of water environment during a period of time. In this paper, we extracted daily, multi-day and abnormal water environment features to describe the water environment.

2.2.1 Feature extraction based on improved support function

The daily water environment features are mainly used to describe the features of water environment in a certain day. We find out the periods of time of maximum values and minimum values of water temperature and dissolved oxygen usually appearing by means of statistical tools, and employ the average values of the water temperature and dissolved oxygen in those periods as the daily water environmental features respectively.

Multi-day water environmental features mainly used the weighted average method to describe the features of water environment for several days. The Eriocheir sinensis usually molt five times during a culturing cycle: the first molt is in March to April, the second is in May, the third is in June, the forth is in July to August and the last is in September approximately (Ai et al., 2014). The first and the fourth molt experienced a long time. In order to describe the features of long time water environment more accurately, we separated the two stages by month, thus the culturing cycle of Eriocheir sinensis is divided into 7 stages, each of which is about one month. Water environmental parameters may change greatly in a long period of time and if there are extreme values in a period of time, the average value will be affected by these values, which can't reflect the long-term features of water environmental parameters. The weighted average value of daily water environmental features of several days can reflect the water environmental parameters of continuous days with the relatively close values accounting for larger weights and a few extreme values accounting for smaller weights. The improved support function is employed to calculate the weights.

The support function (Yager et al., 2001; Yager et al., 2010) sup (m, n) indicates the degree of mutual support of two values n and m, that is, the degree of proximity. The following 3 requirements are necessary to be met:

① $\sup(m,n) \in [0,1]$;

② $\sup(m,n) = \sup(n,m)$;

③ if $|m-n|<|x-y|$, then $\sup(m,n)>\sup(x,y)$, $m,n,x,y>0$.

Weights for water temperature and dissolved oxygen data are calculated based on improved support function. The improved support function is calculated as follows (Duan et al., 2017):

$$\begin{aligned}&\sup(m,n) = \mathrm{SN}(m,n,K,\beta) = K \times (1+\beta(m-n)^6)^{-1}\\&K \in [0,1],\ \beta \ge 0\end{aligned} \qquad (1)$$

where, $\sup(m,n)$ represents the support function; K indicates the worth of support, which is generally set to 1. β indicates the attenuation rate of support, and the greater the value of β reaches, the faster the degree of support declines.

2.2.2 Feature extraction of abnormal water environment

The abnormal water environmental features refer to the features of the water environment which are not suitable for the growth of Eriocheir sinensis. The optimum water temperature range for the growth of crab is between 15°C and 28°C. The crabs grow slowly when the water temperature is below 10°C and they are under stress when the water temperature is above 35°C (Gu et al., 2015). As for dissolved oxygen, the water environment is considered to be bad when it is lower than 3 mg/L, and worse when it is lower than 1 mg/L (Liu et al., 2011). In this paper, the total duration of water temperature below 10°C, the total duration of water temperature above 35°C, the total duration of dissolved oxygen below 3 mg/L and the total duration of dissolved oxygen below 1 mg/L are considered as the features of abnormal water environment.

The features of abnormal water environment mentioned above are calculated as follows.

$$sum = \begin{cases} sum + \frac{1}{2}I & x_i > \in S \wedge x_{i+1} \notin S \\ sum + I & x_i > \in S \wedge x_{i+1} \in S \end{cases} \quad (2)$$

$$I = t_{i+1} - t_i,\ i = 1, 2, \ldots, n \quad (3)$$

where, *sum* is the total duration; I is the time interval; x_i represents the sensor data; T represents time; S is the set of the sensor data which match the requirements, and n is the number of samples collected by the sensors.

2.2.3 Feature vector construction

In this paper, the water temperature features and the dissolved oxygen features were extracted to construct the water temperature feature vectors and the dissolved oxygen feature vectors respectively. In order to facilitate the description, the names and symbols of the features of water temperature and dissolved oxygen are defined in Table 1.

Table 1 Definitions of water temperature and dissolved oxygen features

Feature name	Symbol definition
The total duration of water temperature below 10°C	*Temp_Low_10*
The total duration of water temperature above 35°C	*Temp_High_35*
High temperature of multi-day water environmental features in stage *i*	*TH_i*
Low temperature of multi-day water environmental features in stage *i*	*TL_i*
The total duration of dissolved oxygen below 3 mg/L	*DO_Low_3*
The total duration of dissolved oxygen below 1 mg/L	*DO_Low_1*
High dissolved oxygen of multi-day water environmental features in stage *i*	*DH_i*
Low dissolved oxygen of multi-day water environmental features in stage *i*	*DL_i*

The water temperature feature vector and dissolved oxygen feature vector are shown in the following Equations (4) and (5).

$$\mathbf{t} = (Temp\_Low\_10, Temp\_High\_35, TH\_i, TL\_i) \quad i = 1, 2, \ldots, 7 \quad (4)$$

$$\mathbf{d} = (DO\_Low\_3, DO\_Low\_1, DH\_i, DL\_i) \quad i = 1, 2, \ldots, 7 \quad (5)$$

where, $\mathbf{t}$ represents the feature vectors of water temperature, and $\mathbf{d}$ represents the feature vectors of dissolved oxygen and i is the serial number of the culturing stages.

2.3 Water environmental evaluation model

Evaluation model for aquaculture environment of Eriocheir sinensis ponds was established using classification algorithm, in which the feature vectors were used as inputs, and the data of yield were employed as class labels. The water environment was divided into two categories and the output of the classification model is the evaluation result of it.

2.3.1 Establishment of water environmental classification model

In order to improve the classification accuracy and simplify the difficulty of single classifier construction, the AdaBoost algorithm was used to classify the water environment. The two core ideas of the AdaBoost algorithm are as follows (Cao et al., 2013):

(1) It adjusts the sample distribution on each iteration and forces the next sub classifier to focus on the samples that difficult to be classified.

(2) It adopts weighted voting strategy.

The AdaBoost algorithm introduces the idea of the dynamic allocation algorithm, and does not require any prior knowledge of the weak learning algorithm (Cheng et al., 2013). The training process of AdaBoost classifier is: First, a base classifier was trained using the initial training set; then the weight of current classifier was determined and the sample distribution was adjusted according to the performance of the classifier; thirdly, the next classifier was trained on the updated sample distribution; finally, when a specified number of iteration was reached, all classifiers were integrated together based on weighted voting strategy. The construction process is shown in Figure 2.

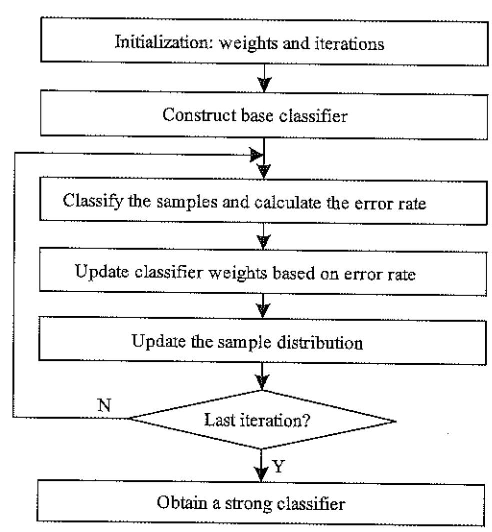

Figure 2 Flow chart of training strong classifier based on AdaBoost algorithm

The weak classifier used in this paper is the decision tree. The principle of decision tree is simple. Moreover, it is not only easy to construct, but also easy to interpret (Liu et al., 1998; Su et al., 2015).

The recapture rate, average weight and per mu yield are three main parameters for evaluating yield in crab farming. The recapture rate refers to the ratio of the number of crabs at the end harvest to the number of crabs at the very start. In this paper, the class of the recapture rate, the average weight and the per mu yield were defined as follows (Wang et al., 2000; Chen et al., 2016).

Table 2 Definitions of the labels of the classification model

Indicators\Labels	Good	Bad
Recapture rate	>70%	≤70%
Average weight	>140 g	≤140 g
Per mu yield	>100 kg	≤100 kg

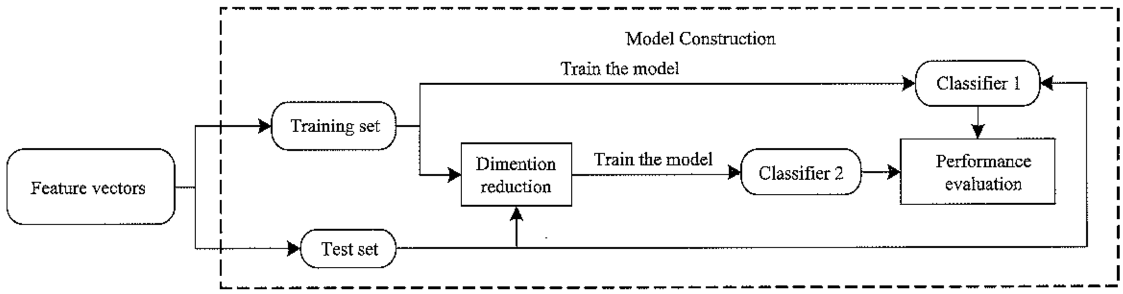

Figure 3 Flow chart of water environmental classification model construction

2.3.2 Water environmental evaluation

We evaluated the water environment in each culturing stage and the complete cycle of culturing using the models constructed above. When evaluating the water environment of a culturing stage, the feature vectors of water environment could not be obtained completely because the culturing cycle is not over. We used historical data to fill up the missing values of the sample feature vectors.

2.3.3 Model simplification

In order to simplify the model structure when the culturing cycle completed, we reduced the dimension of the water environmental feature vectors using linear discriminant analysis method. LDA is a statistical analysis method used to determine a class of a sample, whose basic idea is to project high-dimensional pattern samples into the best discriminant dimension that making the distance between the groups as large as possible (Sharma et al., 2015; Xie et al., 2015). The main difference between LDA and principal component analysis (PCA) is that LDA is a supervised learning method, which takes full consideration of classification performance in projection (Chiu et al., 2015; Elsayed et al., 2015).

3 Experiments

3.1 Datasets

In this experiment, the water environmental data were adopted from the Eriocheir sinensis pond in three towns in Yixing City, Jiangsu Province from 2014 to 2016. The sensors were installed at the direction that wind came, 20 cm of the distance from the bottom of water, and the acquisition period is 10 min. The culture benefit data, such as the recapture rate, average weight of the captured crabs and yield per mu, were obtained by referring the crab farmers' ledgers and the questionnaires filled by the farmers.

The average area of the experimental pond is about 30 mu, and the average water depth is 1 m. The amount of crabs that input at the very start is 1500 to 2000 per mu and the weight of the juvenile Eriocheir sinensis is 6 g approximately. The main feeds are synthetic diet, ice fish and living snails.

3.2 Experimental results and analysis

In this study, the precision, recall and F1-score were used as evaluation criteria for classification model, and their formulas are as follows:

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

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

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{8}$$

where, TP represents the number of true positive instances; FP represents the number of false positive instances, and *FN* represents the number of false negative instance.

In this paper, we used the Matlab 2014 for data preprocessing, sklearn toolbox for model construction. The experimental data were divided into training set and the test set according to the ratio of 3:1. Learning rate of AdaBoost algorithm was set to 1, and the number of iteration steps was set to 400.

3.2.1 Data statistics results

We analyzed three consecutive years' water temperature and dissolved oxygen data that collected by the sensors of 20 farmers. The periods of time of maximum values and minimum values of water temperature and dissolved oxygen usually appearing are listed in the following table.

Table 3 The time of maximum values and minimum values of water temperature and dissolved oxygen appearing

	Maximum values	Minimum values
Water temperature	16:00-18:00	6:00-8:00
Dissolved oxygen	16:00-18:00	6:00-8:00

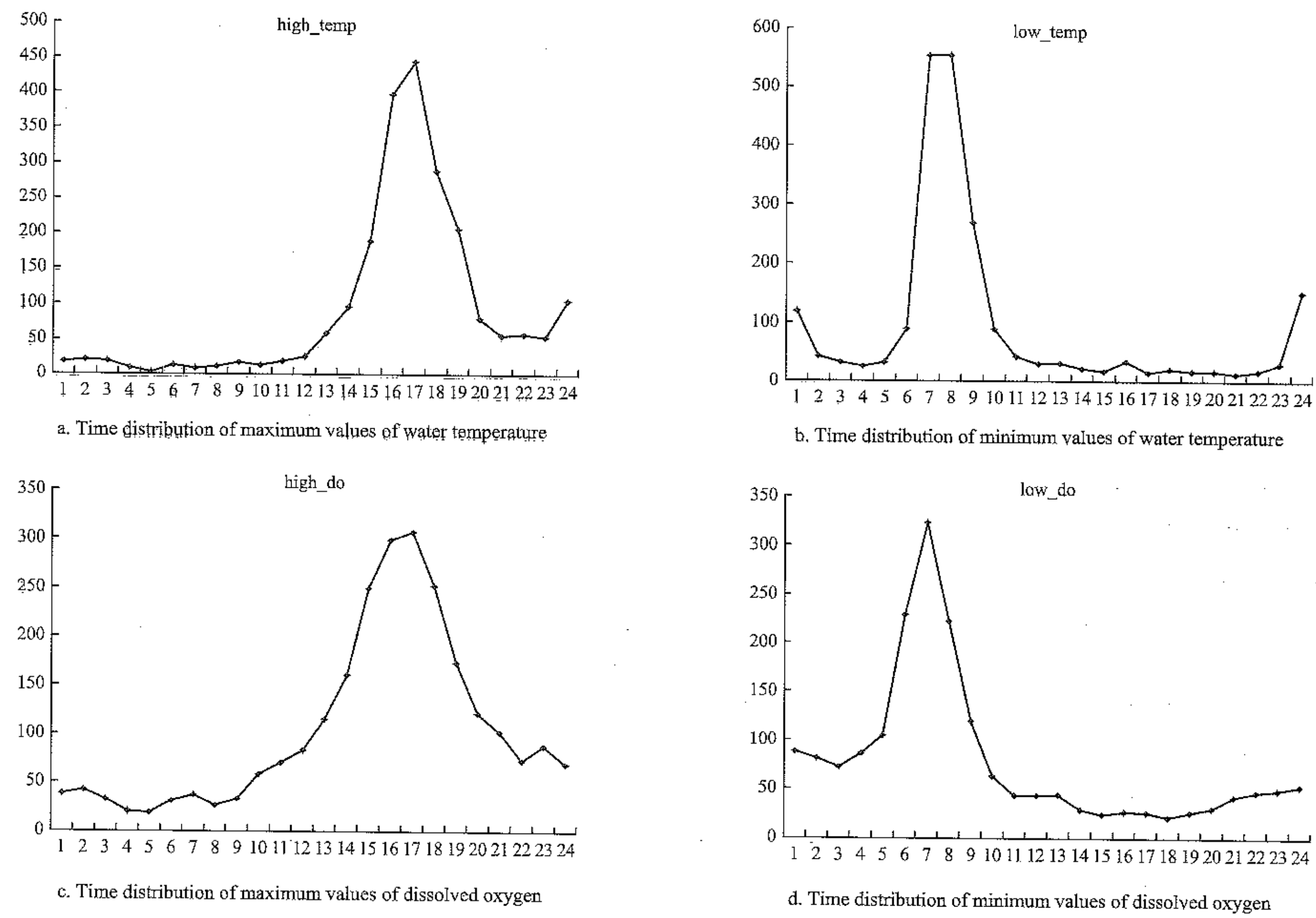

Figure 4 Time distribution of maximum and minimum values of water environmental parameters

3.2.2 Classification results and analysis

The classification models were trained by the feature vectors constructed from the water temperature features and dissolved oxygen features respectively. The models' performance on the test sets are shown in Table 4 and Table 5.

Table 4 Classification results of water temperature

Labels	Precision	Recall	F1-score
Recapture rate	0.720	0.800	0.755
Average weight	0.688	0.560	0.538
Per mu yield	0.808	0.760	0.772
Average value	0.739	0.707	0.688

Table 5 Classification results of dissolved oxygen

Labels	Precision	Recall	F1-score
Recapture rate	0.910	0.800	0.835
Average weight	0.833	0.767	0.758
Per mu yield	0.847	0.867	0.843
Average value	0.863	0.811	0.812

It can be seen from Table 4 that the average precision, recall and F1-score of water environmental classification according to the water temperature are 0.739, 0.707 and 0.688. All the evaluation criteria values are low. It indicates that the effects of water temperature on the recapture rate, average weight and per mu yield of

Eriocheir sinensis pond culturing are indirect or too much information is lost during features extraction. However, when the mu yield is used as a label to classify the water temperature, it can achieve a higher precision (0.808), and its recall ratio and F1-score ratio are also higher than the recapture rate and average weight as the labels.

It can be seen from Table 5 that the average precision, recall and F1-score of water environmental classification according to the dissolved oxygen are 0.863, 0.811 and 0.812. All the evaluation criteria values are higher than the classification according to the water temperature. It indicates that the effects of dissolved oxygen on the recapture rate, average weight and per mu yield of Eriocheir sinensis pond farming are direct.

3.2.3 Feature reduction results and analysis

The results of feature dimension reduction are shown in Table 6 and Table 7.

Table 6 Results of dimension reduction of water temperature feature vectors

Recapture rate	Average weight	Per mu yield
Temp_High_35	TH_4	Temp_High_35
TH_3	TL_4	TH_4
TH_4	TH_5	TL_4
TL_4		
TH_5		

As is shown in Table 6, the numbers of water temperature features are reduced from 3 to 5, after reducing the dimension using LDA. The multi-day water environmental features of high and low temperature in culturing stage 4 are both reserved when using the recapture rate, average weight and per mu yield as labels. The results show that these 2 features have great influence on classification results of the three models.

Table 7 Results of dimension reduction of dissolved oxygen feature vectors

Recapture rate	Average weight	Yield per mu
DO_Low_1	DO_Low_1	DO_Low_3
DH_3	DH_3	DO_Low_1
DL_3	DL_3	DH_3
DL_4	DL_4	DL_3

As is shown in Table 7, the numbers of dissolved oxygen features are all reduced to 4, after reducing the feature dimension using LDA. The multi-day water environmental features of high and low dissolved oxygen in culturing stage 3 and the total duration of dissolved oxygen below 1 mg/L are all reserved when using the recapture rate, average weight and per mu yield as labels, which are the factors having great influence on classification results of the three models.

3.2.4 Validation of feature dimension reduction

When the culturing cycle completed, the classification models were trained by the feature vectors after dimension reduction, and the model's performance on the test set is shown in Table 8 and Table 9.

Table 8 Classification result of water temperature after dimension reduction

Labels	Precision	Recall	F1-score
Recapture rate	0.720	0.800	0.755
Average weight	0.688	0.560	0.538
Per mu yield	0.808	0.760	0.772
Average value	0.739	0.707	0.688

It is seen from the comparison of Table 4 and Table 8, the average precision of water temperature classification was reduced by 1.4% after using LDA to reduce feature dimension, while recall and F1-score were raised by 5.7% and 5.5% respectively. The precision, recall, and F1-scores were raised by 2.4%, 9.3% and 7.0%, respectively, when using per mu yield as label.

Table 9 Classification results of dissolved oxygen after dimension reduction

Labels	Precision	Recall	F1-score
Recapture rate	0.910	0.800	0.835
Average weight	0.833	0.767	0.758
Yield per mu	0.847	0.867	0.843
Average value	0.863	0.811	0.812

It is seen from the comparison of Table 5 and Table 9, the average precision, recall and F1-score of dissolved oxygen classification was reduced by 0.4%, 6.7% and 4.2% respectively after using LDA to reduce feature dimension.

It is seen from the comparison of Tables 5, 6, 8, and 9, the average precision of classification according to water temperature and dissolved oxygen are 0.739 and 0.863 respectively, and became 0.728 and 0.859 after feature dimension reduction. Although there is a decline, but it is not large.

From the analysis above, we drew the following conclusions. (1) In the case of non-extreme weather, the daily highest values of water temperature and dissolved oxygen appear between 16:00 and 18:00 and the daily lowest values appear between 6:00 and 8:00. (2) The evaluation models for water environment proposed in this paper has better performance in classifying the dissolved oxygen features. (3) LDA is suitable for the feature dimension reduction for water environmental classification models because precision decreased slightly.

4 Conclusion

(1) In this paper, we proposed evaluation models for water environment of Eriocheir sinensis ponds based on AdaBoost classifier, associated the water environment data that had been collected from the IOT, as well as the recovery rate, average weight and per mu yield jointly. The models made stage evaluations and overall evaluations of the water environment. With an average precision of 0.863 and 0.739, the models have a good performance in classifying dissolved oxygen and water temperature features, which propose a solution to evaluate the water environment in crab farming. The results of the evaluations provided basis for regulation of the water environment, and are helpful to improve the yield.

(2) An extraction method for water environmental features based on the improved support function was designed, helping the classifiers achieving a good performance in classifying the dissolved oxygen features.

(3) The LDA method has a good performance in reducing the feature dimensions under the condition that the precision loss of the classification is less than 2%.

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