Analysis of an Economic Coupling Relationship Model of the Coastal Ecological Fragile Zone Based on a Machine Learning Model

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1. Introduction

The machine learning model is an integrated learning system that combines a variety of learning methods [1–3]. It is not like the previous data mining decision tree algorithm. Machine learning models gradually appear as decision tree-based classifiers, and data mining-based classifiers are slowly playing an irreplaceable role in the public’s field of vision. At present, machine learning has the research direction of multiple attribute sets. There are not only machine learning algorithms with a single attribute set such as decision trees and logistic regression algorithms but also machine learning algorithms integrated with subsets of attribute sets, such as random forests, attribute set, subset, BDT and so on. The integrated learning algorithm is a method in which the integrated system, the Bagging algorithm, several independent self-service data sets, the data set prediction, the classification results, and the decision tree classifier jointly complete the model work. When the errors of the learners of each integrated system are independent of each other, as the number of independent self-service data sets that make up the integrated system increases, the prediction and classification results of the data sets caused by the integrated system will drop sharply. It even tends to 0 [4–6]. Therefore, the integrated system has a more accurate model work effect than a single Bagging algorithm learner. Since each independent self-service data set-based learner deals with the same work problem at the same time, it cannot achieve completely independent data set predictions. Generally speaking, the higher the accuracy of the ensemble learner, the diversity of the classification results of the base learner will decrease. Accuracy and diversity are the focus of decision tree classifiers. How to balance the relationship between the decision tree classifier and the integrated system and create a good...
2. Machine Learning and Coastal Ecology

2.1. Random Forest. The research of marine economy is more of an adjunct to the advanced complex random forest developed by the decision tree. It mainly focuses on basic issues such as the definition, characteristics, and subject orientation when selecting the attributes of the marine economy. The theory of marine economy will automatically select the best attributes. The base classifier of the random forest algorithm is a decision tree. And it is worth noting that it is not only the decision tree algorithm used but also random attribute selection during model training, as shown in Figure 1 [16–18].

2.2 Extreme Random Tree. Extra tree does not use the best points when selecting branch points but uses the updated random weights to pick out a feature value to divide the tree classifier [19–20]. Let the base classifier focus on training classification, so the whole algorithm is very random, as shown in Figure 2.

2.3. Measurement of the Development of Marine Economy and Resources and Environment. When the marine economy and resource environment are measured, the tuple data is sampled with replacement, and the training set of measurement results is selected to a certain extent. Use the objective and practical base classifier $q$ to train the test data set $A$, and calculate the error of the marine industry-based classifier in the large coastal marine ecosystem. Correspondingly, the relationship between marine economy and marine resources and environment in each region is classified correctly during model training, and the development theory and research methods of the marine eco-economic system should be expanded in the next weight update to reduce the weight of this tuple. Finally, using selective experimental analysis, nonlinear utility functions, establishing statistical models, and updated weights, exponential analysis, comprehensive evaluation, principal component analysis, BP neural network, and general equilibrium models or quantitative methods such as system dynamics allow the base classifier to focus on training classification.
3. Application of the Machine Learning Model in the Economic Coupling Relationship of the Coastal Ecological Fragile Zone

(a) AIC algorithm model [21–23]

\[
\begin{align*}
    dS_t &= \mu S_t dt + \sigma S_t dW_t + H_t dN_t, \\
    dS_t &= \mu S_t dt + \sigma S_t^{\phi/2} (t) dW_t.
\end{align*}
\]
Machine learning model:

\[ W_0 = 0; 0 \leq \beta \leq 2, \]
\[ dr_t = (\theta(t) - ar_t)dt + \sqrt{V_t} dW_t^r. \]

Coastal ecological forecast:

\[ dv_t = a(\beta / \alpha - V_t)dt + \sigma_v \sqrt{V_t} dW_t^v, \]
\[ dS_t = \mu S_t dt + \sqrt{V_t} S_t dW_t^1, \]

Marine resources are produced, exchanged, distributed, and exchanged:

\[ dV_t = k(\theta - V_t)dt + \sigma \sqrt{V_t} dW_t^2, \]
\[ dW_t^1 dW_t^2 = \rho dt, \]
\[ x_t = e^t \sigma_t. \]

(b) SC algorithm model [24–26]

(c) HQ algorithm model [27–30]

\[ h_t^2 = a_0 + \sum_{i=1}^{p} a_i X_{t-i} + \sum_{j=1}^{q} \beta_j h_{t-j}^2, \]
\[ \max_{(p,q)} \sum_{i=1}^{p} (a_i + \beta_j) \leq 1. \]

Economic coupling relationship model:

\[ D(x) = \frac{a_0}{1 - \sum_{i=1}^{p} \sum_{j=1}^{q} (a_i + \beta_j)}, \]
\[ E[W(t)|F(s)] = W(s). \]

Economic coupling relationship of the coastal ecological fragile zone:

\[ E[W(t)] = E[W(0)] = 0, \]
\[ X = e^Y, Y \sim N(\mu, \sigma^2), \]
\[ dX(t) = \mu(t) dt + \sigma(t) dW(t). \]

Prediction of the relationship between marine economy and resources:

Figure 4: K-means cluster analysis.

Table 3: Comparison of inspection methods.

| Inspection type          | Number of lag periods | Test statistics | P value |
|--------------------------|-----------------------|-----------------|---------|
| ARCH’s LM test           | 1                     | 0.01            | 0.96    |
|                          | 5                     | 0.69            | 0.64    |
|                          | 10                    | 1.21            | 0.28    |
|                          | 1                     | 0.05            | 0.35    |
| Ljung’s Box test         | 5                     | 8.18            | 0.42    |
|                          | 10                    | 15.48           | 0.51    |
|                          | 1                     | 0.03            | 0.96    |
| εLjung’s Box test        | 5                     | 3.28            | 0.66    |
|                          | 10                    | 13.37           | 0.2     |
\[
d \log (S_t) = \frac{1}{S_t} \left( S_t \mu dt + S_t \sigma dB_t - \frac{1}{2} \sigma^2 dt \right),
\]
\[
\frac{dS_t}{S_t} = \mu dt + \sigma dB_t,
\]
\[
df = \left( \frac{\partial f}{\partial t} + \frac{\partial f}{\partial S} S \mu + \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 f}{\partial S^2} \right) dt + \frac{\partial f}{\partial S} \sigma dB.
\]

The classifier is training
\[
\Delta \Pi = -\Delta f + \frac{\partial f}{\partial S} \Delta S.
\]

Compare the result error after training
\[
\Delta \Pi = (e^{\Delta t} - 1) \Pi = r \Delta \Pi,
\]
\[
\frac{\partial f}{\partial t} + rS \frac{\partial f}{\partial S} + \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 f}{\partial S^2} = rf.
\]

### 4. Simulation Experiment

#### 4.1. Feature Screening

Feature selection is to use the method of changing the weight of the base classifier to associate the scope of the ocean economy with the economy directly related to the ocean after the learning algorithm of ocean economics is determined. The research on feature selection
of marine economy can improve the accuracy of ensemble classifiers. When using the base classifier training samples, it mainly focuses on the research of basic issues such as the definition, characteristics, and subject positioning of marine economy. By relatively focusing on error-prone classifiers, by reducing redundant features, using the best feature subset to train the model can improve the accuracy of the model and reduce the running time, as shown in Table 1.

From Table 1, we can conclude that the GARCH model under the generalized error distribution with fixed parameters is the smallest under the three information criteria, and all the coefficients are significant. Normal distribution and generalized error distribution feature screening results are better. In the normal distribution, AIC = 5.169, SC = 5.212, and HQ = 5.186; in the generalized error distribution, AIC = 4.9, SC = 4.943, and HQ = 4.917, as shown in Figure 3.

4.2. K-Means Cluster Analysis. The K-means algorithm is such a clustering algorithm based on centroid partition, using distance as the criterion, indicating the higher degree of similarity, as shown in Table 2 and Figure 4.

4.3. Comparison of Inspection Methods. The test results of the residual sequence establishment with a fixed parameter column are shown in Table 3. Both autocorrelation and heteroscedasticity are better resolved as shown in Figure 5.

The correlation test is based on an improved algorithm based on GBDT. Use the Taylor expansion to expand the LjungBox function to the first order. XGBoost uses Taylor’s formula to expand the objective function to a second-order column with fixed parameters. XGBoost stores a lot of objective function information, which can make the economic coupling relationship model of the coastal ecological fragile zone of the machine learning model have relatively less loss and lower variance, as shown in Figure 5.

4.4. Error Comparison. In order to objectively and accurately evaluate the economic coupling relationship model analysis model of the coastal ecological fragile zone of the machine learning model, compare the result error of the classifier after training and change the weight of the training tuple according to the classifier error. Each tuple of the machine learning model has a probability of being picked out, and the error training several times biases the model to being “error-prone.” At the beginning, the same “error-prone” weight of the biased model is set, so that the probability of training after any one of the biased models is selected as “error-prone” is set by the weight. Regarding the issue of iterative update weights of economic coupling relations in the coastal ecological fragile zone, the classification of the model is “error-prone” as much as possible, as shown in Table 4.

As shown in Figure 6, when the frequency is 60, MSE = 0.1927, MAE = 0.1271, and MAPE = 13.4204; when the frequency is 90, RMSE = 0.1988, MAE = 0.1439, and MAPE = 12.6788; and when the frequency is 180, RMSE = 0.2356, MAE = 0.1524, and MAPE = 11.5405.

4.5. Model Comparison. The machine learning models of the coastal ecological fragile zone economic coupling relationship model analysis of different models are compared, including the AIC algorithm model, SC algorithm model, and Hd algorithm model; prediction results are shown in Table 5. The SC algorithm model is the optimal model. In SC, AR(4) = 3.509, AR(3) = 3.533, AR(2) = 3.531, AR(1) = 3.523, ARMA(1, 1) = 3.532, A(1, 1) = 3.532, A(1, 1) = 3.532, A(1, 1) = 3.532, and A(1, 1) = 3.532; in the AIC algorithm model, AR(4) = 3.596, AR(3) = 3.605, AR(2) = 3.588, AR(1) = 3.567, ARMA(1, 1) = 3.596, AR(2) = 3.588, and ARMA(2, 1) = 3.609; in the algorithm model, AR(4) = 3.544, AR(3) = 3.562, AR(2) = 3.554, AR, AR ARMA(1, 1) = 3.555, ARMA(1, 2) = 3.566, and ARMA(2, 1) = 3.568, as shown in Table 5 and Figure 7.
5. Conclusion

Based on the machine learning model, this study analyzes and predicts the economic coupling relationship of the coastal ecologically fragile zone and builds a machine learning model for human production, exchange, distribution, exchange, and development of marine resources through the decision tree algorithm. By reducing the redundant features and using the optimal feature subset to train the model, the accuracy of the model can be improved and the running time can be reduced. Normal distribution and generalized error distribution are better. The clustering algorithm based on the K-means partition is a number of compact and independent classification clusters based on the K-means partition algorithm. By reducing the redundant features, the optimal number and the optimal statistics are obtained. In order to objectively and accurately treat the machine learning model, an analysis model and economic coupling relationship model were used to evaluate the coastal ecological fragile zone. The future work will focus on the optimization and analysis of the experimental application effect and performance of the model, focusing on the optimization of data sets.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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